City Aldermen and Twitter Usage

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I. Introduction

The 2016 U.S presidential election featured an unprecedented use of Twitter by eventual winner and President Donald J. Trump. For the first time in history, a political candidate won a major election of a global power in which he used social media to express highly controversial opinions and attitudes. Furthermore, prior to his victory, the majority of critics believed Trump's seemingly wild and impetuous tweeting would be his downfall and this opinion was confirmed by countless polls from a variety of organizations. Despite these opinions, Trump won the Electoral College by a significant margin and the predictions tools were clearly flawed. This gap between what was expected and the result means political scientists and policy analysts must now develop new ways of evaluating politician behavior. Understanding the role social media played in his victory is a crucial part of explaining that gap.

Democrats in the 2016 election were blindsided by the power of republican voters that flew under the radar. Polls across the U.S. predicted Hillary Clinton was going to win a variety of states she ended up failing to win. In a recent analysis, Wright and Wright demonstrated some of this bias may be attributed to poor polling aggregation methods (Wright, 1). But, as always, predictions are easier to make after the events happen. Although traditional blue urban areas voted democrat (e.g. California, Illinois, New York), democrats failed to anticipate anti-establishment sentiments prevalent throughout much of the country. For instance, the large support Trump received from white women despite the 'pussygate' scandal. In other words, the ideals pushed by democrats failed to connect with many voters who voted democrat in 2012 and represents a lack of understanding of the cultures, attitudes, and values of these population subsets. Therefore, understanding how cultural factors impact both policy and politician behavior is critical. We need tools that will take local information and start to provide in-depth analysis of how local cultures reflect politician behavior and how this matches with their success.

Another key aspect of Trump's behavior was his communication style and the *way* he used Twitter. For example, Paulhus and colleagues demonstrated that Trump's grandiosity, informality, and dynamism played an important role in setting him apart from traditional candidates and this helped make him more successful (Paulhus, 1). This undoubtedly manifests in his tweeting behavior. Trump's success in marketing himself not only can be captured in his personality but in the types of tweeting behaviors he exhibited. His tweeting behavior represents a divergence from the norm and we need new methods that will permit us to categorize and understand the behavior of such politicians. Furthermore, these methods should not only work for one politician, but be able to efficiently categorize many politicians with an enormous total quantities of tweets.

My paper seeks to combine two innovative types of analysis to tackle these complex goals with the overall objective of exploring new ways of analyzing politician tweeting behavior. To generate large quantities of behavioral information, my analysis employs the machine learning tools created by Libby Hemphill et al. to produce data about the tweets that can be analyzed. I retain their coding framework and use the exact classifiers as developed in their study (Hemphill, 2013, 1). To provide substantive information about the properties of local cultures, I analyze the Twitter data in relation to data from *Scenescapes*, a recent work pioneered by Daniel Silver and Terry Clark. Their 15 dimensions for characterizing local cultures provides an excellent framework for exploring what local cultural factors might drive and explain differences in politician tweeting behavior.

Most existing research has focused on national-level politics, so to be contrarian I elected to study local politicians. Understanding city politicians presents an opportunity to examine how the contents of tweets relate both to a national and local level. For example, one key question is do politicians communicate about national issues with their constituents through twitter? My study looks at the occurrence of national trends in aldermen and mayors tweets to determine the extent to which these issues are discussed. At a local level, analyzing aldermen also permits study of how local cultural variables influence tweeting dynamics. Can we take information Silver and Clark have gathered about local cultures and use their framework to make predictions about how politicians tweet and what they are tweeting about? In short, picking this unit of analysis presents interesting opportunities for integrating political science as well as sociological research.

II. Literature Review

Twitter and Politics Research

Andreas Jungherr wrote one of the first major literature reviews on the use of Twitter in politics (Jungherr, 1). Since the role of Twitter in politics is a relatively new field, the research is fragmented and at times papers fail to link their current research to existing literature effectively. His review took a first step towards integrating different perspectives by characterizing the different clusters of research to make understanding different research areas easier to navigate.

Classes of Studies

Among all the Twitter-politics research, Twitter's use by politicians and campaigners has received by far the most attention (Jungherr, 25). These studies fall into three categories. Type 1 are that studies analyze the factors that influence the propensity of a politician to use Twitter. Type 2 are studies that analyze the effects of politicians' Twitter messages on those who follow them. Type 3 are studies that focus on how politicians use Twitter, either by analyzing how they use a particular technical feature (e.g. retweeting) or by manually coding functions and features of message contents (Jungherr, 25). My study falls into this last category.

Among examples cited in his review is a study by Beth Anne Conneway et al. during the 2012 US presidential primaries. They analyzed the twitter feeds for the Democratic, Libertarian, and American Elect parties and found high tweet count did not predict success in the primaries, despite considerable differences in tweeting frequency amongst the politicians. Furthermore, the number of followers and accounts followed was highly skewed among the candidates, but no systematic connection between these metrics and election success was found. However, they did discover a strong association between number of followers and number of accounts followed (Jungherr, 42-43). Their work thus provides one example of research that has been done into the predictive power of tweet count, something I will explore in my paper. For more information on this as well as a general overview of other types of studies, refer to Jungherr's literature review.

Types of Data Collection Methods

According to Jungherr, there are two distinct approaches to automated data collection. The first type query Twitter's API or scrape Twitter's website while the second type use third-party software or packages for collection (Jungherr, 14). Currently, there still remains no systematic comparison between data sets collected through various API accesses and third-party software solutions. This makes knowing the optimal tools to use hard to determine. Jungherr also notes a large number of studies do not report their method of data collection, indicating this field still needs common standards for reporting (Jungherr, 17).

Categorizing Tweet Behavior

Jennifer Golbeck and colleagues developed a behavioral coding system and analyzed tweets posted by U.S. Congress members between 2008 and 2009 (Golbeck, 1). They coded messages with regard to how congress people were using the service. Example categories included 'direct communication', 'personal message', 'requesting action', and 'fundraising' (Golbeck 4-5). They found that most tweets predominately contained information about the political activities of the congressperson, often accompanied with links to further information (Golbeck, 14). They also showed evidence for congressmen dialoging with other Twitter users (Golbeck, 16). They concluded this was an indicator congresspeople use Twitter for outreach (Golbeck, 15)

Building on this idea, Hemphill et al. established a similar coding framework and built machine learning classifiers to categorize tweets using data from 380 members of Congress' Twitter activity during the winter of 2012. To train and evaluate their classifiers, they used MALLET (Machine Learning for LanguagE Toolkit) and developed three distinct classifiers, with the maximum entropy classifier performing best (Hemphill, 2013, 4). Thus, the major innovation Hemphill and colleagues provided was creating a robust method for systematically sorting tweets into categories that can be applied at scale in contrast to Golbeck's which was done by hand.

Hemphill et al. gathered 791 tweets from the top and bottom 10% of politicians ranking in number of tweets, followers, and friends. They used this sample to help define their coding scheme. By choosing such the extremes of tweeting behavior in these categories, they thought this would give the classifiers a better sample then pure random sampling. They then gathered another 526 tweets to double check their coding scheme and used the 526 tweets to train the classifiers.

To formulate coding categories, they went through three rounds of inductive coding, meaning they started without any preconceived notion of what categories to use. They subsequently created a scheme involving six codes, including one "other" category that simply means the tweet did not get categorized (see Figure 19). Codes were not mutually exclusive, meaning a given tweet could be classified as both narrating and positioning if relevant information to each was present in the tweet. They measured inter-coder agreement using Cohen's kappa score and provided this information for each category to give a sense of how much the coded tweets used by the classifier align with the coders' opinions.

Silver and Clark's *Scenescapes* (2016)

Daniel Silver and Terry Clark's recently published book *Scenescapes* provides a critical framework used in my analysis. My study took his variables and used them to understand politician twitter behavior. Therefore, a thorough understanding of their methods is required to appreciate the context of my study.

Defining Key Terms in 'Scenescapes'

Silver and Clark define a scene roughly as a specific place or neighborhood with a distinct character where the people have a shared interest in a specific activity (Silver, 1-2). They elaborate this definition into specific 15 dimensions and for each dimension coded indicators, making their model measurable. Silver and Clark used two main data sources, Zip Code Business Patterns (BIZZIP) and Yellow Pages (YP). The Census Bureau collects information about local businesses for each zip code and categorizes these using NAICS classification. BIZZIP provided Silver and Clark with comprehensive general information about the zip codes but not specific enough for Silver and Clark's purposes. To add information about the style and aesthetics of organizations, they combined this with information from YP. YP provided them with more "experiential" differences between the organizations to distinguish scenes more precisely.

Silver and Clark use the term "amenity" to enlarge the scope of their indicators so as not to limit themselves to just businesses and organizations. Loosely speaking, an amenity is something that provides value or enjoyment to people, which includes services. They use this term to refer to the entities they counted in their study, which formed the structure for their indicators.

Structure of Silver and Clark's Measurements

The 15 dimensions used were *traditionalistic, self-expressive, utilitarian, charismatic, egalitarian, neighborly, formal, glamorous, exhibitionist, transgressive, local, ethnic, state, corporate,* and *rational*. They created a list of the amenities types associated with each dimension and counted the occurrences in their data set, bringing measurability to their study. For each type of amenity, they assigned weights to each dimension, creating a weight set unique to that amenity. For example, cafes might be denoted as follows:

$$\mathbf{w}_{\text{cafes}} = \{w_{\text{cafes}}^{\text{Tradional}}, w_{\text{cafes}}^{\text{Formal}}, \dots, w_{\text{cafes}}^{\text{Glamor}}\}$$

For a given zip code, they counted the number of occurrences of that amenity category, e.g. n_{cafes}. They then picked a dimension of interest (e.g. glamour) and summed $n_{\text{cafes}} * w_{\text{cafes}}^{\text{Glamor}}$ over all amenities for a particular dimension, giving an "intensity score." Let A_{glam} be the set of amenity types and a be an amenity in the set.

$$\text{Intensity Score for Glamorous} = \sum_{\forall a \in A_{\text{glam}}} n_a w_a^{\text{glam}}$$

Since each weight is different, each amenity contributes a different amount to the particular dimensions intensity score.

$$\text{Performance Score} = \frac{\text{Intensity Score}}{\substack{\text{Total number of amenities} \\ \text{for a given zip code}}}$$

Performance scores provide a measure of the average value of dimension's score for amenities in a zip code. For instance, one might find a glamour score of 3.4 per amenity in a particular zip code. This is the main tool they settled on to use to measure differences between areas (Silver, 333). Silver and Cark treat 3 as a neutral score and the range of possible scores must be between 1 and 5, with any decimal amount being allowed. Phenomena that are 'high weight' contribute positively and raise the score closer to 5 whereas phenomena that are lower the score towards 1.

Utilitarian and Traditional Dimensions

My paper selected BIZZIP Utilitarian and YP Traditional as the two dimensions to focus on because they yielded the most interesting correlations (as will be shown later). To preface this discussion, I provide the background information to understand what information these dimensions provide.

Silver and Clark describe the *traditional* dimension as a measure of how “organically connected” a given scene is to a historical narrative that continues to play a prominent role in the local culture’s identity (Silver, 52). High-traditional indicators included Bibles, synagogues, heritage buildings, opera companies, etcetera (Silver, 110). Low-weight traditional phenomena include management consulting, business centers, wireless communications, sex shops, R&D, etc. Nationally, Silver and Clark found that traditional scenes occurred more outside of major cities and less traditional ones within them (Silver, 109). They then used other dimensions such as neighborly and self-expressive to highlight crucial differences driving the local antitradtionalist cultures. In Chicago, the South and West Sides had the most neighborly scenes while those of the Near North Side where highest in self-expression (Silver, 112).

Silver and Clark describe the *utilitarian* dimension as a measure of how much the surrounding amenities cultivate a culture of profit-orientation, cost-reduction, discipline, and delayed gratification (Silver, 337). Example indicators include fast food restaurants, trade schools, warehouse clubs and superstores, convenience stores, management consulting services, and exam preparations (Silver, 101). I could not find a great application of utilitarian in the text, but the reader can refer to Figure 02 for a histogram of BIZZIP Utilitarian Performance Scores to see the distribution across the U.S.

II. Methodology

My data analysis had several stages: (1) collect the twitter data, (2) generate machine learning behavioral categorizations of the tweets using mallet, (3) compile two data sets, one of tweets and one of aldermen and mayors containing all this information, (4) add *Scenescapes* information to the aldermen/mayor data set, (5) generate keyword variables, (6) mine the data for interesting correlations.

My study concentrated on alderman and mayors of large cities. To increase the robustness of my analysis, I chose data from three cities instead of just one, selecting the three largest U.S. cities: New York, Los Angeles, and Chicago. Given the highly unusual election, I thought analyzing the tweets during the election cycle would provide interesting insight into how the local officials responded to national issues. I therefore chose a sampling frame from January 20, 2016 00:00:00 to January 20, 2017 00:00:00. Since I included all the politicians and their accounts, the aldermen and mayors constitute the entire population of possible officials for these cities and are not a sample.

Twitter Data Set

Collecting Twitter Data

The politician twitter account list was compiled by hand. First, I went to the city council websites for Chicago, Los Angeles and New York and got a list of the council members' names and corresponding districts. After compiling this list, I googled each of the politicians' names to find their Twitter accounts, using search variations to ensure I found extra accounts. Figure 16 lists the specific politicians and accounts not included in the study as well as the reasons why. To understand better why some politicians have protected accounts and why some have no accounts, I called the different offices and asked them.

NEED FOR EXCLUSION	REASON PROVIDED BY OFFFICES
Protected Accounts	None of the protected accounts responded to requests for information as to why their accounts are protected. Protected accounts were excluded from the study because they are not accessible to the general public and therefore constitute an interaction of a separate nature.
No Accounts	Two of the politicians' offices, Zalewski and Quinn, did not give reasons for their lack of accounts. The official from Barron's office: "She doesn't do social media. She doesn't feel it is the appropriate platform for expressing her views." The official from Maisel's office: "We have a more senior population in our district who are not as active on Twitter. But we do have a Facebook account and maintain an active presence there. There is also the Council's website."
Accounts without Tweets in Range	Some of the accounts had not been active in the past year at all. By construction therefore, they do not appear in the study. I did not call these offices as there were too many, I had limited time, and it didn't seem crucial for the purposes of my research.

Raw Tweet Data Aggregation

Once I had the names of accounts, I needed to aggregate the tweet information. Hemphill initially gave me her scripts for her analysis, but they used an API written for Python 1 and not Python 3. This created a problem as the packages she used for the API were no longer available. Therefore, I wrote new scripts using the Tweepy API with Python, which is newer and compatible with Python 3. The scripts I wrote downloaded the tweet information and stored it in a CSV format.

Machine Learning Analysis of Behavioral Data

To perform the machine learning analysis, I used Hemphill's machine learning classifiers developed in the critical paper mentioned in the literature review. Her research indicated the "maximum entropy" method performed best, so I chose to do all my analysis with this model. Hemphill's classifiers are written in MALLET.

The MALLET classifier unfortunately cannot handle CSV files unless they are stripped down and formatted into "instance files," which are more cumbersome. Ordinarily, languages such as R, Python, or Stata can perform operations on subsets of data using the CSV file as given. But the simplicity of the MALLET language did not permit this. Consequently, I had to store each politicians' tweets separately, which yielded roughly 130 separate files. Each of these had to be inputted into the classifier, which is operated using MALLET in the system basic command line (Windows, in my case).

Given the diversity of characters posted on social media, the input files had to be cleaned because the MALLET classifier rejected some of the characters (e.g. emojis). Once cleaned, the classifier ran smoothly. The result was 5 distinct behavioral outputs, resulting in therefore roughly 650 output files. Future work should find a better way of doing this.

I then used R to upload the individual output files into a data frame that contained all the other raw information. Figure 17 shows a screen shot of what the data looked like once compiled. Each of these columns contained the probability the tweet belonged to the Hemphill et al. behavioral categorization. I decided to regard $\mathbb{P}(\text{tweet falls in category}) \geq 0.5$ as the cutoff for a tweet belonged to the category and generated a binary variable for each category to indicate this.

Key Word Analysis

I download the R package “tm”, which is designed for advanced corpus analysis. Due to my limited time and understanding of the package, I found it was overly-complicated and inefficient because the corpus analysis dropped much of the crucial information available in my data set I would need to stratify it later. Therefore, I elected to use a simpler approach and just searched using the *grep* function within each tweet for the keywords of interest. This method worked very nicely.

For each keyword, I generated a binary variable with 1 indicating ‘keyword present’ and 0 indicating ‘keyword absent.’ Using R’s table functions, I was then able to generate counts as well as percentages for the tweets for a variety of variables. Keywords included were Trump, ban, Muslim, Christ-, vot-, and others. Capitalization was ignored.

Aldermen and Mayors Data Set

As previously mentioned, I began by compiling a list of the alderman and their account information. I also included their city, political party, and sex. For council members with protected accounts or who had no account, I manually created binary variables to store this information in the data set. I used R to generate binary variables for whether each account contained no tweets in the range or had less than 100 tweets. Based on all the binary variables, I generated a binary variable “in study” to permit me to isolate only the politicians with accounts in the study. This permitted the data set to be easily subsetted for research while keeping track of all the total number of accounts and council members not included in the study. Using the Twitter Data file, I generated counts for total numbers of tweets and total number for each of the behavioral categories.

"1-to-1 Council Member to District Office" Method

Incorporating the *Scenescapes* data presented a significant sampling method problem. The *Scenescapes* data contains 42192 zip codes and the entire data set is organized according to them. However, political wards and districts do not overlap with zip codes. I could not think of a method to determine "how much" of a zip code and all the ensuing variables belongs to a particular ward.

As a first attempt to work around this, I proposed using the zip code for the district office to represent the politicians in my study. For each politician, I found the district office zip code and then located the corresponding zip code in Clark's data set. I then added the data to the Alderman file, providing me with *Scenescapes* data for each politician. Los Angeles presented a problem because there is not a 1-to-1 correspondence (see Figure 18). There are only 5 district offices and some serve the same district. Terry Clark and I agreed to incorporate this data even though the methodology presented problems. In particular, for Districts 4,5, and 6 there were multiple possible office zip codes to choose from. I used a random number generator to select the zip codes in these cases.

Correlation Analysis

With these two files, I calculated Pearson correlations between a select variables of interest. In particular, correlations were computed between (1) all scenescapes performance scores for BIZZIP and YP data and (2) tweet count, narrative count, position count, provinfo count, reqaction count, and thanks count (see Figure 19 for categories). To elucidate more specific correlations, I stratified the data by income and education. I generated 4 types of these variables: All Cities, New York, Los Angeles, and Chicago. This gave me a total of 8 variables to stratify my analysis with.

Although I could in principle segment by both income and education, the population size was too small and this either meant the correlation was undefined or too low to be meaningful at all (e.g. 4 members). Therefore, my analysis stuck strictly to stratifying only by education or by income alone. Correlations between keywords were also computed.

III. Results

The results are broken down into two sections. The first section presents an analysis of national trends and the second presents an analysis of the *Scenescapes* variables in relation to the Twitter variables. For the purposes of my discussion, see Figure 20 for my definitions of correlation strength used here.

National Trends

Keyword analysis yielded several interesting results. To start with, I will address national trends in general. Figure 47 presents an entire table of various keywords and the percentage of tweets that contained the keyword each month. Comparing Jews, Christians, and Muslims, we find 'Jew' appears most, considerably more than 'Muslim' or 'Christ-'. Unsurprisingly, 'Trump' appears more frequently than 'Hillary'/'Clinton', but 'Hillary'/'Clinton' appears even less than 'Ban.' Thus, either 'Hillary'/'Clinton' appears a surprisingly low amount or 'Ban' appears a surprisingly high amount.

In terms of correlations between the keywords, all of them were nonexistent. The table is provided here for convenience:

Keyword 1	Keyword 2	Pearson Correlation
Muslim	Terror-	0.03807
Trump	Muslim	0.03142
Trump	Police	0.02529
Immigra-	Muslim	0.01499
Ban	Muslim	0.00916
Trump	Ban	0.00825
Ban	Terror-	0.00410

Police and Shootings

Since shootings have played such a large role in Chicago in recent years, I made a special effort to explore this topic by examining the correlation between the number of shootings and the frequency the word 'police' is mentioned in tweets. Figures 01 displays the number of tweets containing police for each month and the number of shootings for each month. But Pearson correlation was a trivial 0.16, indicating when shootings increase that it is not accompanied by an increase in occurrence of 'police.'

The data also shows politicians did respond to the 2016 Dallas shootings of police officers. As can be seen in Figure 01, the number of tweets containing 'police' spike in July 2016. Furthermore, across all cities, July 2016 showed a major spike in tweets containing Dallas (1.2%) which is two orders of magnitude greater than the other months. See Figure 46 for a bar graph representation of the spike. Thus, the data indicates that, for particularly salient extreme events like high-profile killings, politicians do react.

Scenescapes Analysis

All Cities (NY,LA,Chicago)

Figures 02-05 (Utilitarian) and 07-10 (Traditional) show histograms comparing performance scores of all zip codes with each of the cities. The mean, median, standard deviation and population sizes are also included in Figures 06 (Util) and 11 (Trad). Chicago has the highest median BIZZIP utilitarian performance score (2.86903) and all three cities are above the median for all zip codes

(2.75). Chicago also has the highest median YP traditional performance score (3.336938) but all three cities fall below the median for all zip codes (3.33913). See Figures 06 and 11 for specific numbers.

Stratifying by education yielded no correlations between tweet count and BIZZIP utilitarian performance score, with all of them less than 0.15 in magnitude (see Figure 37). However, tweet count and YP traditional performance scores displayed higher correlations, the largest in magnitude being low-moderate education group (corr: -0.36685) (see Figure 41). Thus, while BIZZIP utilitarian performance scores had minimal predictive power, YP traditional performance scores performed slightly better. Stratifying by income yielded mixed results without a distinct pattern. For BIZZIP utilitarian performance scores, the low-moderate income group was the only one that displayed a moderate correlation, with all the others being weak or trivial (see Figure 40). For YP traditional performance scores, both the low income and low-moderate income groups displayed much larger correlations (negative) than the high-moderate and high income groups (see Figure 43).

In terms of the machine learning variables, stratifying by education produce no interesting correlations in relation to BIZZIP utilitarian performance scores (see Figure 38), but stratifying by income yielded weak magnitude correlations in every category except providing info (corr: 0.445916) for the low-moderate income group (see Figure 38). This group seemed to stand out in contrast to the others in that there were clearer associations between behavior and BIZZIP utilitarian performance scores. By contrast, YP traditional performance scores yielded larger correlations. Both stratifying by income (see Figure 44) and education (see Figure 42) produce many weak correlations as well as a few moderate ones. However, no overall distinct pattern was clear.

New York

In terms, of tweet count, stratifying by education revealed a dichotomy between utilitarian and traditional performance scores. The data demonstrated how New York politicians governing low-educated districts displayed a higher tweet count if the surrounding community was more utilitarian (corr: 0.65961) and less traditionalistic (corr: -0.29702) (see Figures 21 and 25 respectively). In contrast, in highly educated areas displayed a higher tweet count if the surrounding community was more traditionalistic (corr: 0.51697) and less utilitarian (corr: -0.51725) (see Figures 21 and 25). Stratifying by income did not produce an obvious relationship between the two dimensions as most groups displayed low or no correlation between performance score and tweet count (see Figures 21, 23, 25, and 27 complete tables with quantiles defined).

Regarding the machine learning behavioral variables, the low-education group had high positive correlations between BIZZIP utilitarian performance scores in every variable except providing information, which stands out with an almost zero correlation indicating no relationship (see Figure 22). BIZZIP Utilitarian performance scores are therefore poor predictors of low income providing information behaviors but good predictors for other categories. The low-moderate education group did not display any significant correlations. The high-moderate education group display moderate positive correlations in every category, indicating that utilitarian performance scores are good indicators of tweeting volume across categories (hence a corr of 0.48 for tweet count). Finally, the high-educated group displayed moderate negative correlations in every category except narration (corr: -0.22675), suggesting potentially narration and utilitarianism have a more complex relationship for the high education group (see Figures 22 and 26 for the specific correlations).

Since several of the variables for the low-education group seemed to all have roughly the same magnitude and sign correlation, I was concerned they were correlated with each other. To verify this was not the case, I generated a correlation matrix between all the Twitter variables and found all had trivial correlations, with most of them being negative (see Figure 45 for correlation diagram).

In terms of income stratification, the low-income group had trivial correlations in most categories, none significant enough to interpret. The low-moderate income group had moderate positive correlations in every category except requesting action (corr: 0.16746) (see Figure 24). The high-moderate income group displayed moderate negative correlations in positioning and providing info, with the rest being negative but of insignificant magnitude. Finally, the high-income group yielded moderate negative correlations for in providing info and thanking, again the rest being insignificant. Interestingly, segmenting by income revealed no correlation or extremely weak correlation across all groups with request for action (see Figure 24 and 28 for complete data).

Chicago Data

In terms, of tweet count, stratifying by education yielded some large magnitude correlations with BIZZIP utilitarian performance score (e.g. low education 0.63129). However, unlike the New York data the low and high education groups did not display an obvious pattern. Whereas in New York high educated districts showed high negative correlation, Chicago high income wards display no correlation. Therefore, although both educational stratifications yielded useful information, the two cities differed considerably in this regard.

Income stratification produced a clear monotonically decreasing trend in correlation between tweet count and BIZZIP utilitarian performance score (see Figure 31). Low income groups display moderate positive correlation while high income groups display moderate negative correlation. In terms of YP traditional, although there were several significant magnitude correlations, no obvious trend exists as income increases. Contrasting the utilitarian and traditional variables however, we can see low income strata that are utilitarian have higher tweet counts (see Figure 31) while those that are traditional display lower tweet counts (see Figure 33).

In terms of machine learning variables, stratifying by education yielded the highest correlations with BIZZIP utilitarian performance scores but there were very few and no obvious pattern exists (see Figure 30). Stratifying by income demonstrated a clear monotonic decreasing trend in the providing info category as income increases. The low income group demonstrates a strong link whereby higher BIZZIP utilitarian performance scores yield higher amounts of providing information while the opposite proved true for high income group (see Figure 32). The YP traditional performance score displayed a monotonically increasing relationship between correlation and education level. Aldermen in high education traditional wards displayed less obvious tendency to avoid providing information whereas in lower educated traditional groups, providing information was strongly inversely correlated with YP traditional performance scores (see Figure 34).

Los Angeles Data

I could not get the code for this data to work in time to generate results. I will have to present this information at a later time.

IV. Discussion

The discussion is similarly broken down into national trends and *Scenescapes* analysis.

National Trends

Despite 2016 being a major election year with several hot issues, politician tweeting behavior did not show high correlations between major key words. This trend was consistent across different topics including police, terrorism, Trump, Muslims, and bans. The fact these correlations are so low suggests there is not a strong discussion of these issues amongst politicians. For example, suppose politicians were debating the constitutionality of a "Muslim ban." We would expect to see these words highly correlated, whenever one appears the other would too. But this is not the case and, in mainstream media, the predominant association with "ban" is "Muslim." This one example illustrates the general point for all these correlations: they should be higher if the issues are being discussed. As another point of evidence, given the turmoil surrounding Muslim ban, it seems unreasonable that Jew appears more often than Muslim if politicians used Twitter to discuss national issues. The fact the correlations are low provides reasonable evidence to justify further research into whether this claim can withstand more precise analysis. This conclusion could be consistent with Hemphill's finding that local politicians are more engaged in social conversations rather than formal politicking (Hemphill, 2012, 3). Whereas national issues would come up more when discussing politics, conversations about local issues might deviate considerably.

Police and Shootings

Unlike the other national issues, the low, positive correlation found between number of shootings and police was substantially higher. However, it is still so low that it is insignificant and, like the other trends, suggests politicians do not use Twitter as a platform for discussing this issue either. If they did, when shootings spiked, so should the number of tweets containing reference to police. But this is not the case.

To be clear, this analysis merely provides initial evidence Chicago politicians do not increase their discussions of police when more shootings occur on *Twitter*. But there are many media outlets and they may choose to disseminate their opinions through other channels rather than through

Twitter. All this study has shown is that Twitter does not seem to be the medium for such discussions, if they happen at all.

Scenescapes Analysis

Analysis of the New York data yielded an interesting dichotomy between traditional and utilitarian measures. Both traditional and utilitarian are measures of what Clark terms "legitimacy," in *Scenescapes* and the fact both of these dimensions had high magnitude correlations is interesting because they are supposed to naturally work together to help characterize the legitimacy of a culture. The data demonstrates this and therefore is consistent with Silver and Clark's hypotheses and applications of the concepts. New York high utilitarian neighborhoods displayed higher tweet count for low educated groups except for providing information.

Consider a business district that has a high utilitarian performance score full of highly educated and high income residents. Intuitively, we would suspect these individuals would not need help information from their aldermen. They are already well informed about their surroundings and have a grasp of how to handle their lives. Thus, the aldermen in the neighborhoods with higher income and education residents have a tendency to provide less information in their tweets than alderman of lower income groups (see Figure 24 and 32). By contrast, low income and low education aldermen thus spend more time disseminating information. These individuals do not have the same advantages as those in richer and more educated strata so consequently they rely on their aldermen more for opportunities and information about the happenings around them. The opposing relationship could be observed when considering the YP traditional correlations. Traditional low income areas paid less attention to their aldermen (Figure 28). This is one example of how understanding tweeting behavior can help us understand at a local level why aldermen are reacting the way they do and Clark's scenescape dimensions help us make this interpretable. These results also held for the Chicago data (Figures 32, 34). Thus, one main finding of this analysis was that traditional and utilitarian dimensions could help differentiate how much aldermen provide information to different cultures within particular income and educational strata. This replicates the power of Clark's analysis but now in the context of tweeting.

Overall, the correlations were much weaker when the cities were combined. The total number of aldermen and councilmen were greater, but they are still sufficiently low it is hard to tell yet what the predictive power of BIZZIP utilitarian and YP traditional performance scores. The results would be more meaningful with larger N. The low population size is concerning because it is harder to establish how likely the correlations are to be valid. Why do the patterns disappear when the cities are combined, particularly since Chicago and New York shared some similar magnitude and sign correlations in the data? Although this could strictly be because of having a low N, adding more cities could also improve the analysis and make it easier to see why the magnitude of correlations went down when the three cities were combined. Further research is therefore need to test the efficacy of my methodology.

In retrospect, running correlations between performance scores and tweet counts for the behavioral variables may not be the best way to utilize this analysis. Since our objective is to observe differences in behavior, the total count is probably less important than the proportion of tweets that are narrative out of the whole set. In other words,

$$\frac{\text{Narrative Tweet Count}}{\text{Total Tweet Count}}$$

might be a more meaningful measure of tweeting behavior and permit more easily interpreted results.

Los Angeles Data

There is nothing to analyze because I could not provide the data on time. However, nonetheless, I would like to make a few remarks regarding the zip code sampling methodology.

My LA Scenescapes zip code sampling method seems highly flawed. If we look at the histograms for BIZZIP Utilitarian Performance Scores (Figures 02-05) we can see how abnormal the LA histogram looks. To be fair, LA only has 15 council members, but undoubtedly the individual zip codes for these districts display a high degree of heterogeneity and this is masked by the "1-to-1 District Office to Politician" method because multiple districts are served by the same office. This conflates the scenescape data, making it seem like completely different districts have exactly the same scenescape information, when in reality this is not the case. Therefore, I do not believe this data is reliable and should be redone with a better sampling methodology for choosing zip codes.

One possibility is to identify zip codes that lie completely within districts and use these to represent the district data by taking averages of them.

$$\text{Average Scenescape Variable} = \frac{\begin{array}{c}\text{Sum of variable values for all zip codes} \\ \text{that fall completely within the district}\end{array}}{\begin{array}{c}\text{Total number of zip codes falling} \\ \text{completely within district}\end{array}}$$

This would be a better methodology. To apply it in mass, I would need maps both of the zip codes and the districts. I could then presumably use some sort of mapping or Geographical Information System packages to identify the zip codes that lie entirely within a district. This methodology could be tested in subsequent studies.

V. Conclusion

My paper has introduced a novel methodology combining machine learning as well as scenescape analysis to interpret the tweeting behavior of politicians. Although the method is experimental, I believe the findings presented in the results as well as the interpretation in the discussion section provide sufficient evidence that Silver and Clark's conclusions to merit further additional consideration. The methodology will need to be tested further to solidify its usefulness, but this paper has provide initial evidence for its efficacy. Given my unit of analysis, the national trends information provided critical insights about the absence of discussion amongst politicians of key issues. In sum, these tools provide us with critical tools that going forward can be expanded to incorporate more cities as well as potentially used to analyze other types of individuals, such as businessmen or leaders of particular amenities.

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Appendix

Figure 01 Chicago, number of tweets mentioning 'police'
and number of shootings per month

MONTH	NUMBER OF TWEETS MENTIONING 'POLICE'	heyjackass.com's listing of Chicago SHOOTINGS
January 2016 (last 11 days)	N/A	246
February 2016	59	156
March 2016	71	282
April 2016	90	274
May 2016	64	339
June 2016	63	373
July 2016	72	382
August 2016	62	398
September 2016	54	301
October 2016	52	348
November 2016	32	324
December 2016	22	240

(note: for accuracy, numbers excluded for first month since full month of tweets not collected)

Source: "2016 Stats." Hey Jackass!; Web; 1 Mar. 2017; <http://heyjackass.com/category/2016-stats/>.

Figure 02

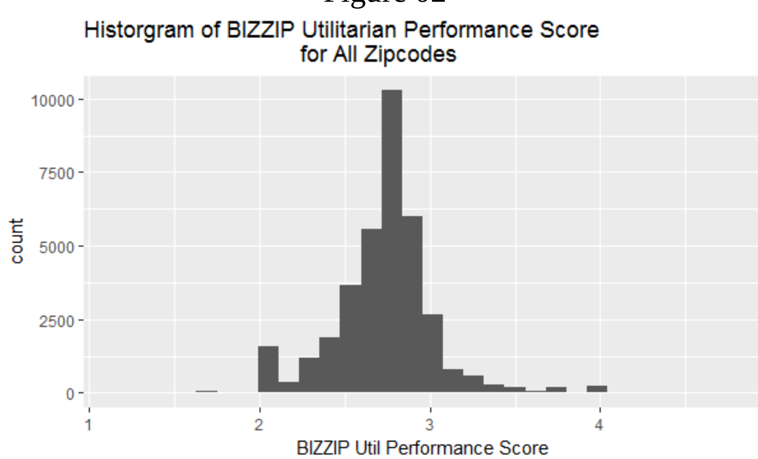

Figure 03

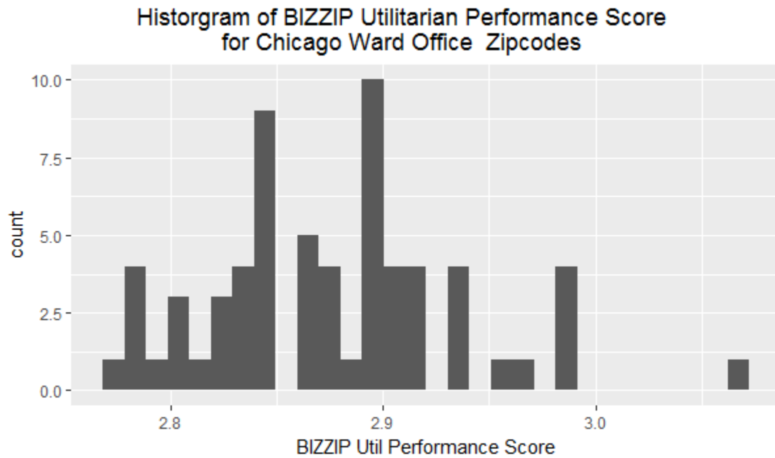

Figure 04

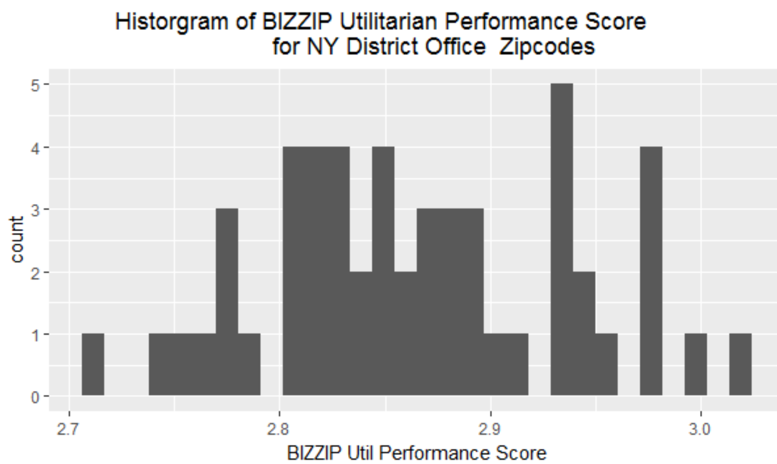

Figure 05

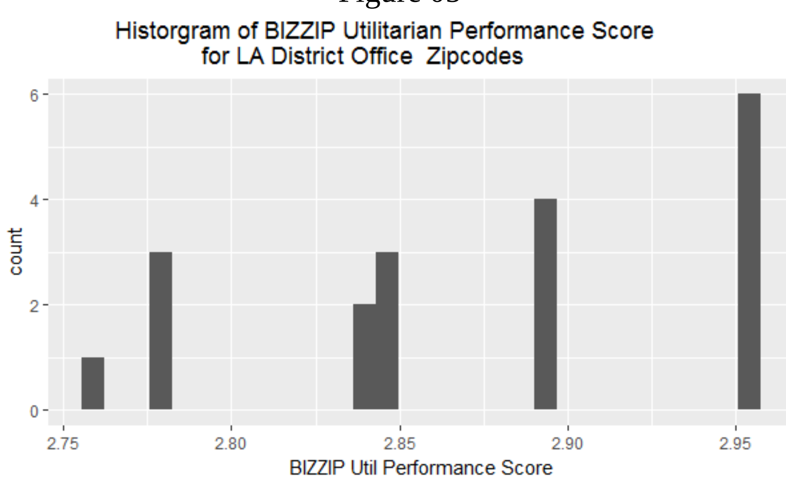

Figure 06 Mean, Median, Standard Deviation of Utilitarian Performance Scores
For Different Groups (of those included in study)

GROUP	Mean BIZZIP Util Perf Score	Median BIZZIP Util Perf Score	Standard Deviation BIZZIP Util Perf Score	Population Size
All Zip Codes	2.72977	2.75	0.3041607	35675
New York Offices	2.866492	2.855556	0.07279364	51
Chicago Offices	2.876186	2.86903	0.06014368	48
Los Angeles Offices	2.870273	2.868712	0.07111569	16

Figure 07

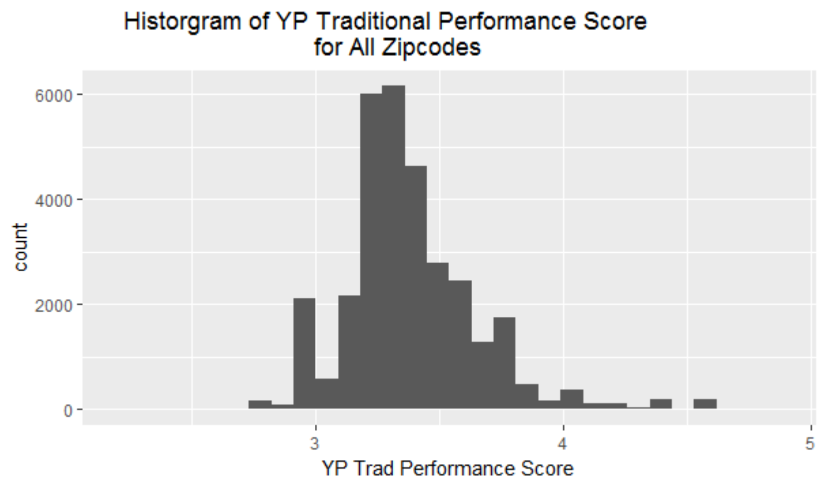

Figure 08

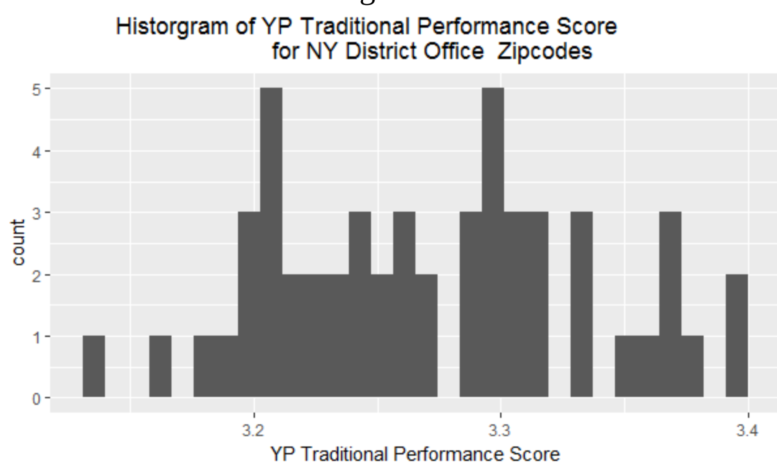

Figure 09

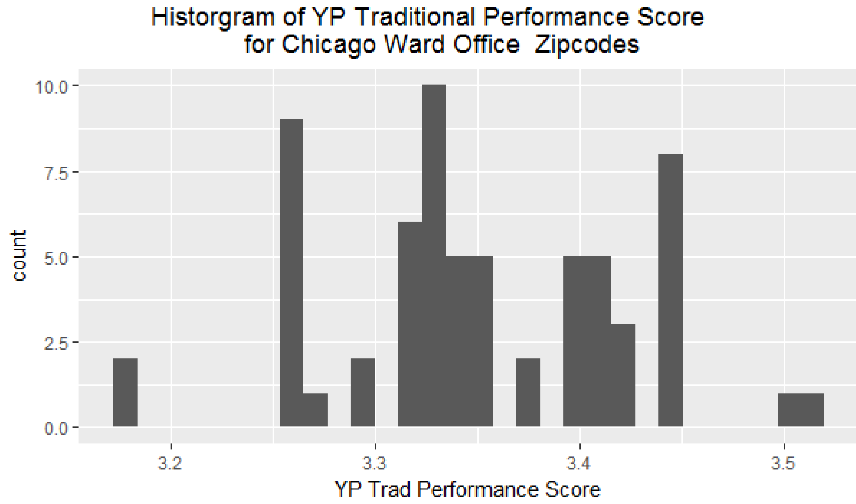

Figure 10

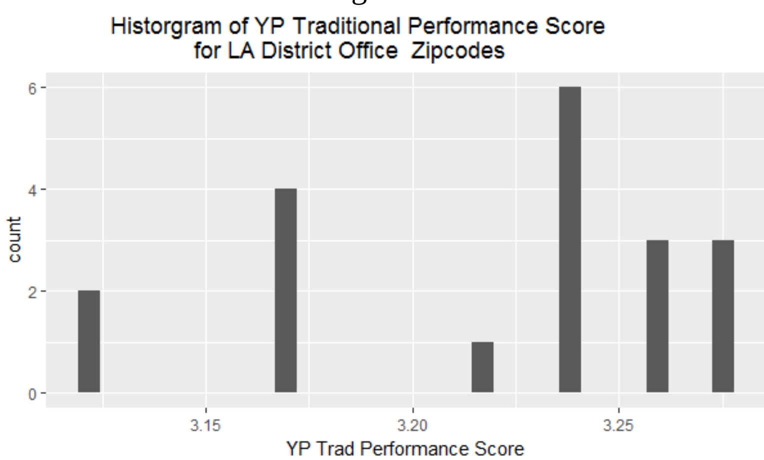

Figure 11 Mean, Median, Standard Deviation of Traditional Performance Scores
For Different Groups (of those included in study)

GROUP	Mean YP Trad Util Perf Score	Median YP Trad Util Perf Score	Standard Deviation YP Trad Util Perf Score	Population Size
All Zip Codes	3.388599	3.33913	0.2691111	31874
New York Offices	3.27234	3.271831	0.06121745	51
Chicago Offices	3.349242	3.336938	0.06479462	48
Los Angeles Offices	3.218889	3.236364	0.05231086	16

Figure 12

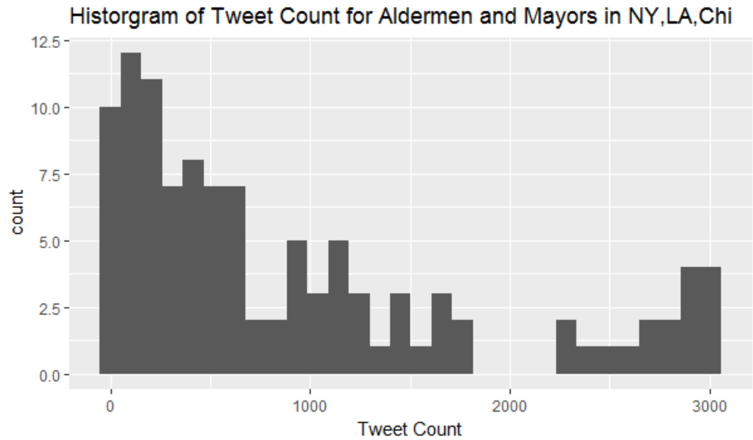

Figure 13

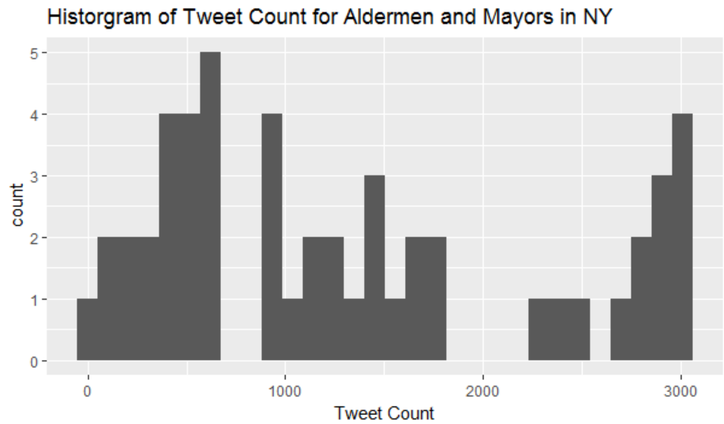

Figure 14

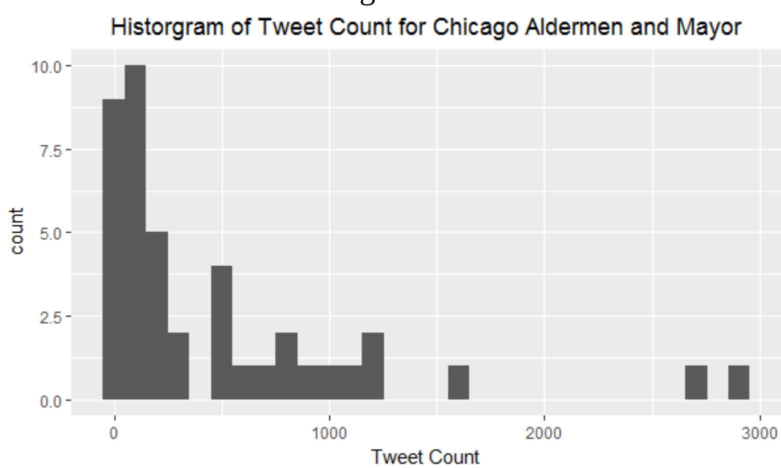

Figure 15

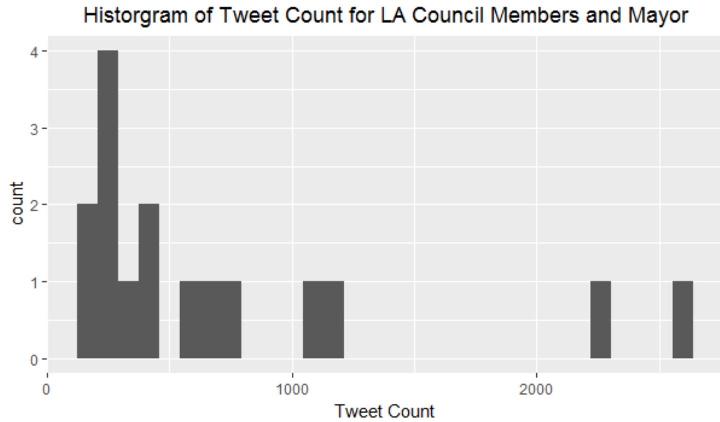

Figure 16 Districts and Accounts Not Represented in Study

Vacant	NY – District 9 LA – District 7
Protected	Chicago, Emma Mitts Account: EmmaMittsAld37 Chicago, Edward Burke Account: EdwardMBurke Los Angeles, Gilbert Cedillo Account: gilcedillo
No Account	NY, Inez Barron NY, Alan N. Maisel Chicago, Michael R. Zalewski Chicago, Marty Quinn
No Tweets in Range	Not enough space to include.

Figure 17 Screen shot of Twitter Data File

	index	id	created_at	text	retweets	favorites	hashtags	urls	user mentions	Narrative P(1)	Position P(1)	ProvInfo P(1)	ReqAction P(1)	Thanks P(1)	user_name	city
1	1	8.221280e+17	2017-01-19 17:05:59	Stay up to date! Subscribe to receive weekly email newsl...	0	0	0	0	0	0.2206898442	0.116808403	0.127798573	0.021021775	0.048581649	r33rdWard	Chicago
2	2	8.221122e+17	2017-01-19 16:03:07	Spread the word about our next Transportation Action C...	2	2	0	1	0	0.0648085166	0.119304351	0.722833390	0.091258225	0.032621651	r33rdWard	Chicago
3	3	8.217801e+17	2017-01-18 18:03:26	You still have time to volunteer for the 2017 Homeless C...	1	0	0	1	0	0.0198643350	0.236361873	0.276868591	0.010136703	0.029868355	r33rdWard	Chicago
4	4	8.217647e+17	2017-01-18 17:02:21	Create public art in the City. Applications accepted by @...	0	0	0	1	1	0.0445837812	0.078517280	0.282185028	0.069774939	0.059856853	r33rdWard	Chicago
5	5	8.217498e+17	2017-01-18 16:03:03	Support community resource @ConcordiaPlace at BrewF...	0	1	0	1	2	0.3638210661	0.022889780	0.135361062	0.072690720	0.022504910	r33rdWard	Chicago
6	6	8.215194e+17	2017-01-18 00:47:41	Do you qualify for the City's Emergency Heating Repair P...	2	1	0	1	0	0.0101888494	0.007173366	0.513102034	0.051989629	0.063186965	r33rdWard	Chicago
7	7	8.214174e+17	2017-01-17 18:02:32	Attend our next Transportation Action Committee meeti...	0	0	0	1	0	0.1822622555	0.060615948	0.499974109	0.111389537	0.025000964	r33rdWard	Chicago
8	8	8.210248e+17	2017-01-16 16:02:09	Learn more about the City's Checkout Bag Tax, which go...	1	0	0	2	0	0.0087583728	0.024439451	0.864393286	0.049122732	0.012419261	r33rdWard	Chicago
9	9	8.210247e+17	2017-01-16 16:02:04	Grab a friend and help out with the 2017 Homeless Cou...	0	0	0	1	0	0.1746666653	0.028386584	0.031971931	0.058381736	0.019829980	r33rdWard	Chicago
10	10	8.210095e+17	2017-01-16 15:01:30	Our office is closed today (Monday, January 16th) for th...	0	0	0	0	0	0.0169450815	0.187424109	0.148104063	0.040437349	0.029088829	r33rdWard	Chicago
11	11	8.206922e+17	2017-01-15 18:00:42	Heads-up! Our office will be closed tomorrow (Monday, ...	0	0	0	0	0	0.0144435700	0.135503273	0.036189319	0.214040521	0.012954889	r33rdWard	Chicago
12	12	8.203404e+17	2017-01-14 18:42:49	Our office will be closed on Monday for the MLK holiday...	0	0	0	0	0	0.0208029963	0.110321752	0.054705501	0.205768911	0.013228229	r33rdWard	Chicago
13	13	8.199676e+17	2017-01-13 18:01:29	The next Chicago Services Fair is January 26th. Learn mo...	1	0	0	0	0	0.0176842783	0.037405361	0.480307313	0.030414199	0.052507481	r33rdWard	Chicago
14	14	8.199526e+17	2017-01-13 17:01:49	Apply to create public art in the City. Applications accept...	0	0	0	1	1	0.0663837973	0.107951147	0.210589873	0.056369803	0.065949470	r33rdWard	Chicago
15	15	8.199375e+17	2017-01-13 16:02:00	The next Transportation Action Committee meeting is sc...	0	0	0	1	0	0.0248773605	0.124785645	0.582824507	0.068571166	0.026029694	r33rdWard	Chicago
16	16	8.199225e+17	2017-01-13 15:02:18	Help strengthen the services in our City by participating ...	0	0	0	1	0	0.0325019503	0.199341986	0.106906503	0.137294766	0.034918148	r33rdWard	Chicago
17	17	8.199223e+17	2017-01-13 15:01:36	Learn about the City's Emergency Heating Repair Progra...	0	0	0	1	0	0.0609760394	0.014162649	0.418773997	0.023514908	0.028074330	r33rdWard	Chicago
18	18	8.199223e+17	2017-01-13 15:01:36	The winter session of the pilates class at Horner Park ha...	0	0	0	1	0	0.0224688562	0.037009612	0.421831582	0.047986837	0.029824739	r33rdWard	Chicago
19	19	8.199223e+17	2017-01-13 15:01:36	Stay in the loop! Subscribe to receive our 33rd Ward ne...	1	0	0	0	0	0.1632793737	0.141695952	0.190295683	0.045867961	0.079960695	r33rdWard	Chicago
20	20	8.199072e+17	2017-01-13 14:01:29	Free events for kids and parents ---> https://t.co/Fc27...	0	0	0	1	1	0.1068891352	0.179650481	0.328480522	0.024325724	0.021982815	r33rdWard	Chicago
21	21	8.199072e+17	2017-01-13 14:01:29	The City's Checkout Bag Tax begins February 1st. Learn ...	0	0	0	1	0	0.0150673978	0.110842620	0.384768720	0.031567004	0.058926565	r33rdWard	Chicago

Figure 18 Los Angeles District Offices

DISTRICT OFFICE	Districts Served
West Valley	3,5,6,12
East Valley	2,4,5,6,7
Hollywood-Wilshire	4,10,13
Central	1,9,14
Western	5,11
Southern	8,15

Figure 19 Coding Scheme by Hemphill

Code	Definition	Example	Cohen's kappa	N (%)
Narrating	Telling a story about their day, describing activities	"headed up to the Fox News camera for an interview" (Rep. Ron Paul, R-TX)	0.83	2,069 (7%)
Positioning	Situating one's self in relation to another politician or political issue, may be implied rather than explicit	"A9: Theoretically, not realistically. HC spending is growing 4x inflation and driving our debt. Let's tackle the real threat. #ryanttv" (Rep. Paul Ryan, R-WI)	0.87	6,728 (22%)
Directing to information	Pointing to a resource URL, telling you where you can get more info	"Harkin Announces More Than $300,000 for Housing in Tama County http://1.usa.gov/lf6Aem" (Sen. Tom Harkin, D-IA)	0.70	12,468 (41%)
Requesting action	Explicitly telling followers to go do something online or in person (not just visiting a link but asking them to do something like sign a petition, apply, vote) - look for action verbs	"RSVP to my Immigration Forum with Rep. Luis Gutierrez this Saturday in Brooklyn http://t.co/qTcWugs" (Rep. Yvette Clark, D-NY)	0.70	299 (1%)
Thanking	Says nice things about or thanks someone else, e.g. congratulations, compliments	"@rmartindc Thanks. MoC's handwriting is probably on par with M.D.'s. Glad I could make your job easier." (Rep. John Shimkus, R-IL)	0.90	667 (2%)
Other	Doesn't fit in any other Action category, or one can't tell what they're doing	"@jfor441 Will do!" (Rep. Jason Chaffetz, R-UT)	N/A	N/A

Note. Cohen's kappa values refer to the reliability of hand-coded tweets used to train the classifier. N (%) reports the output of the automatic classifier.

Source: Hemphill, Libby, Jahna Otterbacher, and Matthew Shapiro; "What's congress doing on twitter?"; *Proceedings of the 2013 conference on Computer supported cooperative work*; ACM, 2013.

Figure 20 Definitions of Correlation Strength Terms

TERM	DEFINITION (ignoring sign)
No Correlation	[0,0.15)
Weak Correlation	[0.15,0.4)
Moderate Correlation	[0.4,0.7)
Strong Correlation	[0.7,1.0]

Figure 21 New York Education Quantiles and Tweet Count Correlations, Utilitarian

GROUP	Number of Bachelor's Degrees per Zip Code (1990)	Population Size	Correlation between Tweet Count and BIZZIP Util Performance Score
Low Education	[373, 2110)	13	0.65961
Low-Moderate Education	[2110,3084)	12	-0.15975
High-Moderate Education	[3084,5325)	13	0.48285
High Education	[5325, ∞)	13	-0.51725
Overall	**----**	**----**	**−0.06508217**

Figure 22 New York Education Machine Learning Variable Correlations, Utilitarian

	CORRELATIONS				
EDUCATION	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	0.879226	0.847786	0.06819437	0.997257246	0.955959
Group 2	-0.12305	-0.17	-0.1240218	-0.18795739	-0.19752
Group 3	0.414148	0.515227	0.4590016	0.466274679	0.432725
Group 4	-0.22675	-0.43289	-0.5064263	-0.40354779	-0.47507

Figure 23 New York Income Quantiles and Tweet Count Correlations, Utilitarian

GROUP	Income (USD) per Zip Code	Population Size	Correlation between Tweet Count and BIZZIP Util Performance Score
Low Income	[9033,14215)	13	-0.062165
Low-Moderate Income	[14215,17923)	12	0.62897
High-Moderate Income	[17923,27338)	13	0.45769
High Income	[27338, ∞)	13	-0.23400
Overall	**----**	**----**	**−0.06508217**

Figure 24 New York Income Machine Learning Variable Correlations, Utilitarian

	CORRELATIONS				
INCOME	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	-0.05937	-0.17036	-0.048784178	-0.111108449	0.307464
Group 2	0.547693	0.505995	0.501798585	0.167459839	0.66454
Group 3	-0.30055	-0.4681	-0.415568608	-0.199210333	-0.21026
Group 4	-0.05867	-0.03455	-0.439749046	0.032487387	-0.46606

Figure 25 New York Education Quantiles and Tweet Count Correlations, Traditional

GROUP	Number of Bachelor's Degrees per Zip Code (1990)	Population Size	Correlation between Tweet Count and YP Trad Performance Score
Low Education	[373, 2110)	13	-0.29702
Low-Moderate Education	[2110,3084)	12	-0.47458
High-Moderate Education	[3084,5325)	13	0.51544
High Education	[5325, ∞)	13	0.51697
Overall	**----**	**----**	**−0.07107844**

Figure 26 New York Education Machine Learning Variable Correlations, Traditional

	CORRELATIONS				
EDUCATION	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	0.640807	-0.3087	-0.667648135	0.164811032	0.512019
Group 2	-0.51667	-0.54191	-0.473791261	-0.516808903	-0.33409
Group 3	0.456195	0.459947	0.472757725	0.329672148	0.525857
Group 4	0.233363	0.431019	0.598830789	0.428003418	0.557346

Figure 27 New York Income Quantiles and Tweet Count Correlations, Traditional

GROUP	Income (USD) per Zip Code	Population Size	Correlation between Tweet Count and YP Trad Performance Score
Low Income	[9033,14215)	13	0.10983
Low-Moderate Income	[14215,17923)	12	0.27872
High-Moderate Income	[17923,27338)	13	0.49864
High Income	[27338, ∞)	13	0.073883
Overall	**----**	**----**	**−0.07107844**

Figure 28 New York Income Machine Learning Variable Correlations, Traditional

	CORRELATIONS				
INCOME	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	0.071174	0.048697	0.07799654	0.082019328	0.276342
Group 2	0.176074	0.104095	0.31896979	-0.203111721	0.473112
Group 3	0.202939	0.44263	0.51804317	0.225890841	-0.02532
Group 4	-0.11086	-0.0387	0.30311788	0.002743261	0.318854

Figure 29 Chicago Education Quantiles and Tweet Count Correlations, Utilitarian

GROUP	Number of Bachelor's Degrees per Zip Code (1990)	Population Size	Correlation between Tweet Count and BIZZIP Util Performance Score
Low Education	[0,1390.75)	12	0.63129
Low-Moderate Education	[1390.75,3912)	10	-0.45079
High-Moderate Education	[3912,4925)	13	0.33271
High Education	[4925, ∞)	13	-0.06099
Overall	**----**	**----**	**0.20713**

Figure 30 Chicago Education Machine Learning Variable Correlations, Utilitarian

EDUCATION	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	0.700742	0.716538	0.64382414	0.398558996	0.377412
Group 2	-0.49172	-0.20095	-0.1538782	-0.13406544	-0.18311
Group 3	-0.26162	-0.14851	-0.3463679	-0.2176719	-0.24695
Group 4	0.216111	0.099363	-0.3046608	-0.24118528	0.020893

Figure 31 Chicago Income Quantiles and Tweet Count Correlations, Utilitarian

GROUP	Income (USD) per Zip Code	Population Size	Correlation between Tweet Count and BIZZIP Util Performance Score
Low Income	[0,13184.75)	12	0.58587
Low-Moderate Income	[13184.75,17102)	12	0.33046
High-Moderate Income	[17102,21633.75)	12	0.07238
High Income	[21633.75, ∞)	12	-0.52348
Overall	**----**	**----**	**0.20713**

Figure 32 Chicago Income Machine Learning Variable Correlations, Utilitarian

INCOME	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	0.620177	0.629645	0.652280709	0.560433948	0.308828
Group 2	-0.11317	0.110369	0.523551961	0.471532062	0.261948
Group 3	0.142316	0.095178	0.09263461	-0.125170228	0.086547
Group 4	-0.33223	0.070515	-0.506912033	-0.067809104	-0.20315

Figure 33 Chicago Education Quantiles and Tweet Count Correlations, Traditional

GROUP	Number of Bachelor's Degrees per Zip Code (1990)	Population Size	Correlation between Tweet Count and YP Trad Performance Score
Low Education	[0,1390.75)	12	-0.83424
Low-Moderate Education	[1390.75,3912)	10	-0.62303
High-Moderate Education	[3912,4925)	13	-0.40468
High Education	[4925, ∞)	13	-0.12679
Overall	**----**	**----**	**−0.5254896**

Figure 34 Chicago Education Machine Learning Variable Correlations, Traditional

	CORRELATIONS				
EDUCATION	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	-0.636105	-0.72108	-0.877461	-0.8613421651	-0.715136
Group 2	-0.534924	-0.570262	-0.3815544651	-0.66898001	-0.616895
Group 3	-0.455272	-0.482407	-0.1826164110	-0.3944326309	-0.400502
Group 4	-0.112319	-0.109863	-0.0817983176	0.384027259903	0.0099430

Figure 35 Chicago Income Quantiles and Tweet Count Correlations, Traditional

GROUP	Income (USD) per Zip Code	Population Size	Correlation between Tweet Count and YP Trad Performance Score
Low Income	[0,9033)	12	-0.63433
Low-Moderate Income	[9033,14215)	12	-0.88741
High-Moderate Income	[14215,17923)	12	0.23833
High Income	[21633.75, ∞)	12	-0.19817
Overall	**----**	**----**	**−0.5254896**

Figure 36 Chicago Income Machine Learning Variable Correlations, Traditional

	CORRELATIONS				
INCOME	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	-0.597237	-0.650217	-0.6835323	-0.64152025	-0.260337
Group 2	-0.706581	-0.826337	-0.8377841	-0.849156299	-0.860742
Group 3	0.019096	0.016369	0.41442154	0.4659173961	0.129168
Group 4	-0.037604	-0.468646	0.07583418	-0.275566908	-0.21514

Figure 37 All Cities Education Quantiles and Tweet Count Correlations, Utilitarian

GROUP	Number of Bachelor's Degrees per Zip Code (1990)	Population Size	Correlation between Tweet Count and BIZZIP Util Performance Score
Low Education	[0,1564)	28	-0.08117
Low-Moderate Education	[1564,3474)	27	-0.02775
High-Moderate Education	[3474,4925)	29	0.06467
High Education	[4925, ∞)	31	-0.1434
Overall	**----**	**----**	**-0.0006215243**

Figure 38 All Cities Education Machine Learning Variable Correlations, Utilitarian

	CORRELATIONS				
EDUCATION	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	-0.08083	-0.09829	0.041826	0.155129	0.027985
Group 2	-0.06743	-0.00646	0.05825	-0.0883	0.028887
Group 3	0.044121	0.129752	0.073834	-0.02366	0.123135
Group 4	-0.02025	-0.0764	-0.12808	-0.16388	-0.17708

Figure 39 All Cities Income Quantiles and Tweet Count Correlations, Utilitarian

GROUP	Income (USD) per Zip Code	Population Size	Correlation between Tweet Count and BIZZIP Util Performance Score
Low Income	[0,13359)	25	0.022278
Low-Moderate Income	[13359,17514)	30	0.41860
High-Moderate Income	[17514,25216)	33	0.02597
High Income	[25216, ∞)	27	-0.25960
Overall	**----**	**----**	**-0.0006215243**

Figure 40 All Cities Income Machine Learning Variable Correlations, Utilitarian

	CORRELATIONS				
INCOME	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	-0.00765	0.036354	0.108072	-0.04123	0.02712
Group 2	0.261734	0.323049	0.445916	0.284966	0.382789
Group 3	0.041966	-0.02948	0.135684	0.001884	-0.09545
Group 4	-0.23853	-0.11973	-0.28191	0.07717	-0.19766

Figure 41 All Cities Education Quantiles and Tweet Count Correlations, Traditional

GROUP	Number of Bachelor's Degrees per Zip Code (1990)	Population Size	Correlation between Tweet Count and YP Trad Performance Score
Low Education	[0,1564)	28	-0.24854
Low-Moderate Education	[1564,3474)	27	-0.36685
High-Moderate Education	[3474,4925)	29	-0.17329
High Education	[4925, ∞)	31	0.092531
Overall	**----**	**----**	**-0.1987882**

Figure 42 All Cities Education Machine Learning Variable Correlations, Traditional

	CORRELATIONS				
INCOME	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	-0.20551	-0.25661	-0.28246	-0.45158	-0.05683
Group 2	-0.36491	-0.28685	-0.26073	-0.42059	-0.34713
Group 3	-0.20613	-0.19064	-0.12216	-0.28361	-0.10575
Group 4	-0.12046	0.100091	0.218638	0.151682	0.084922

Figure 43 All Cities Income Quantiles and Tweet Count Correlations, Traditional

GROUP	Income (USD) per Zip Code	Population Size	Correlation between Tweet Count and YP Trad Performance Score
Low Income	[0,13359)	25	-0.27619
Low-Moderate Income	[13359,17514)	30	-0.41446
High-Moderate Income	[17514,25216)	33	0.067507
High Income	[25216, ∞)	27	0.048622
Overall	**----**	**----**	**-0.1987882**

Figure 44 All Cities Income Machine Learning Variable Correlations, Traditional

	CORRELATIONS				
INCOME	Narr Ct	Posit Ct	ProvInfo Ct	ReqAction Ct	Thank Ct
Group 1	-0.33549	-0.41198	-0.27287	-0.35767	-0.03165
Group 2	-0.30771	-0.30808	-0.3896	-0.48015	-0.37718
Group 3	-0.01945	0.103779	0.11582	0.082833	-0.07719
Group 4	-0.13243	-0.01428	0.187752	-0.08142	0.048368

Figure 45 Correlation Matrix Between Machine Learning Variables

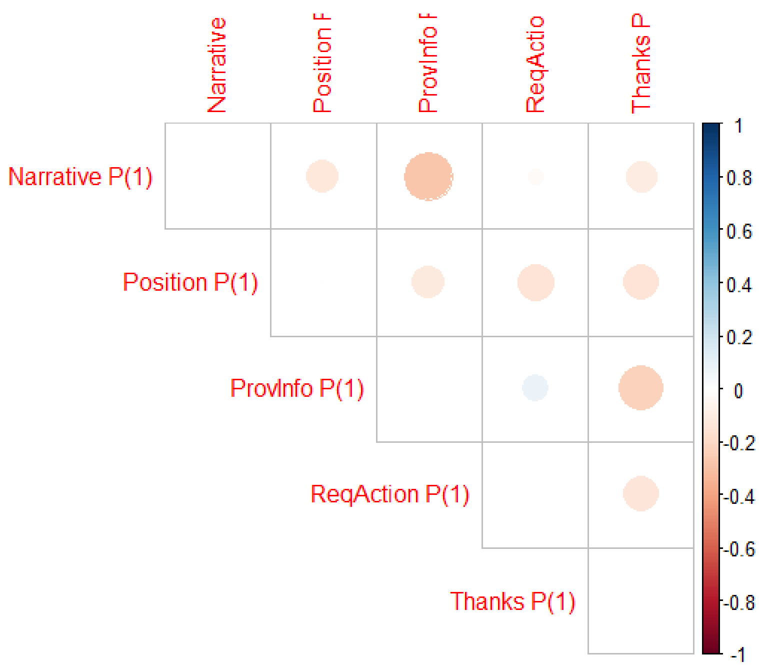

Figure 46

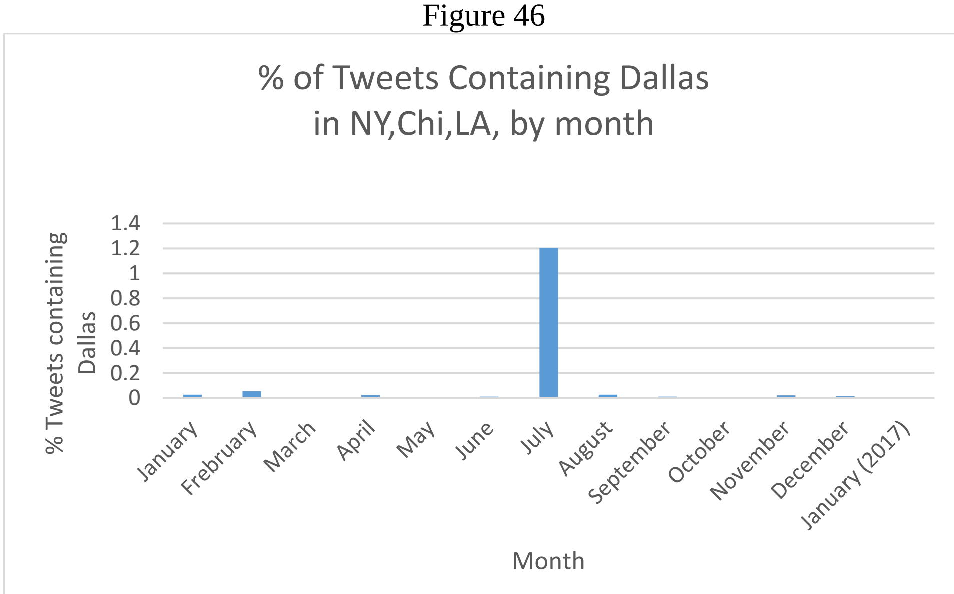

Figure 47 Table of % of Tweets Containing Keyword, by Month

	% tweets Containing....								
	immigra-	Muslim	Jew	Christ (excluding names)	Trump	Hillary or Clinton	vot-	Terror	Ban
January 2016 (last 11 days)	0.4178	0.02611	0.23499	0.078328982	0.443864	0.52219321	0.861619	0.02611	3.263708
Feb-16	0.729	0.094505	0.70204	0.216011881	0.850547	0.83704604	2.55164	0.094505	1.404077
Mar-16	0.8538	0.088702	0.43242	0.133052445	1.552279	0.76505156	8.559707	0.476771	2.006874
Apr-16	0.6101	0.097609	0.87848	0	0.414837	3.2454856	3.892143	0.122011	1.464129
May-16	0.6512	0.253256	0.20502	0.084418717	0.566811	0.4341534	2.062229	0.048239	1.724554
Jun-16	1.2278	0.58768	0.71361	0.020988561	1.647602	1.16486515	2.529122	0.640151	1.857488
Jul-16	0.8049	0.540605	0.38443	0.04805382	4.084575	4.43296492	1.790005	0.456511	1.477655
Aug-16	0.653	0.466418	0.37313	0.053304904	2.465352	1.23933902	1.319296	0.10661	2.038913
Sep-16	0.3957	0.48615	0.59921	0.056529112	3.02996	1.85415489	2.442058	0.282646	1.413228
Oct-16	0.4833	0.402779	0.60417	0.070486356	5.044809	2.94028799	4.762864	0.120834	1.500352
Nov-16	1.6881	0.633052	0.7219	0.422034651	7.418925	2.98756108	6.33052	0.077743	2.709907
Dec-16	2.3158	0.394737	0.65789	2.407894737	5.131579	0.46052632	1.565789	0.131579	1.973684
January 2017 (first 20 days)	0.823	0.240867	0.5821	0.421517463	6.403051	0.24086712	1.42513	0.240867	1.204336
Mean	0.896423077	0.331728462	0.545337	0.308663202	3.004168538	1.62496125	3.084009	0.217275	1.849146
Median	0.729	0.394737	0.599209	0.078328982	2.465352	1.16486515	2.442058	0.122011	1.724554