This paper examines political social media interaction between Members of the United States Congress and the general public on Twitter. Specifically it attempts to gain a better understanding of what motivates a Member of Congress to reply to a tweet by building a model to predict which tweets Members of Congress will reply to. Predicting social media interaction of elected Members of Congress is a challenging machine learning task. MOCs reply more often to positive tweets based on personal interactions they have had and positive feedback. The distribution of reply to non-reply tweets makes predicting responses very error prone. In this process a several methods of predicting rare events in text were attempted with inconclusive results.

Headings:

Text Mining

Machine Learning

Microblogs
TALKING BACK: HOW CONGRESS ENGAGES WITH THE PUBLIC ON TWITTER

by
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A Master’s paper submitted to the faculty of the School of Information and Library Science of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Master of Science in Information Science.

Chapel Hill, North Carolina
April 2015

Approved by

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Jaime Arguello
Table of Contents

1. Introduction ........................................................................................................................................... 2
2. Literature Review .................................................................................................................................. 5
   2.1 Citizen Government Communications in the Internet Era .............................................................. 6
   2.2 Evaluating Twitter Interaction ........................................................................................................... 8
   2.3 Congress on Twitter .......................................................................................................................... 10
   2.4 Predictive Features ............................................................................................................................ 12
   2.5 The Question ...................................................................................................................................... 14
3. Methodology ........................................................................................................................................... 15
   3.1 Data Collection .................................................................................................................................. 15
   3.2 Data Analysis & Results ...................................................................................................................... 15
4. Discussion ............................................................................................................................................... 18
5. Conclusion ............................................................................................................................................. 20

References .................................................................................................................................................. 22
1. Introduction

The United States Congress spends a lot of time and effort attempting to communicate with constituents (Hickey, 2010). Twitter has also exploded in popularity and use by Members of Congress (MOCs). Of the 542 members of Congress (including non-voting members), 517 have official Twitter accounts (Hickey, 2010).

Twitter is a social microblogging website, often classified as social media, that allows public and private sharing of messages up to 140 characters. At its simplest level Twitter is a microblog, allowing users to share their thoughts in a limited, short form. Twitter also allows social interaction, messaging, and endorsements of others tweets. As part of the constraint of twitter, special characters and unique terminology are used to describe the communication tools built into Twitter. Twitter allows users to participate in conversations using #hashtags, a single term which links all tweets on a topic together. Users can @mention or @reply to other users, allowing one-to-one or one-to-many engagement.

Compared to 2008 when a MOC maintaining a Twitter or social media presence was the exception, Twitter has become a fundamental aspect of how Congress communicates with constituents and the public. Twitter has become so ubiquitous that in 2010 and 2012 every single newly elected member of the House had an official Twitter account before taking office (Chi and Yang, 2010). Media reports have cited Twitter as a key component of a shift in congressional and political communication which contributed to Obama’s 2008 electoral victory and the Republican House takeover of 2010 to skillful
use of social media platforms (Lomberg, 2012; Hendricks and (Jr.), 2010; Staff, Staff; Harfoush, 2009).

Given all the fuss around Twitter one would think that MOCs value the novel, rapid input from constituents and the general public Twitter presents. However, this does not appear to be true (Hemphill et al., 2013). Congressional engagement with Twitter as anything other than a broadcast platform would appear to be minimal (Mergel, 2012). Twitter seems to be treated as something of a second tier medium of interaction, warranting less focus and attention than phone calls or even emails. Many MOCs’ Twitter accounts are often managed by a low ranking staffer or intern (Englin and Hankin, 2012).

Part of the reason Twitter interaction may be relegated to low ranking staffers, is the sheer volume of tweets directed at some MOCs. Initial data collection suggests that high profile MOCs receive thousands of tweets per week. MOCs only respond to a small portion of tweets to them (roughly 1%, see results). Given the rarity of responses and the stated desire of both MOCs and constituents to interact, predicting which tweets will receive a response is rather challenging. It is quite probable that MOCs (and their staff) only view a small portion of incoming Tweets. However, there is no research regarding this claim.

The characteristics of tweets to MOCs that garner responses are not well studied. In studies of more general Twitter users, histories of having tweets replied to and larger social networks increases the likelihood of replies (Artzi et al., 2012). However, it would appear that MOCs treat Twitter as a broadcast platform (Golbeck et al., 2010).
The traits that inspire responses from Members’ official Twitter accounts are unclear. An initial, brief review of a small set of Twitter interactions with congress persons suggests that MOCs are more likely to respond to high profile tweets by other public figures, usually in line with existing policy goals. However, this is largely conjecture on the part of this author. A larger sample size will demonstrate just which features are actually influential in soliciting responses as well as elucidate any differences in behavior between MOCs’ Twitter responses.

It is important to explain that MOCs typically maintain two or more Twitter accounts. Strict Campaign finance regulations prohibit MOCs from using resources of their office to campaign. Given that more often than not Congressional Twitter accounts are maintained are run largely by Congressional staffers (Fitch and Goldschmidt, 2005), the use of an official Twitter account for campaign purposes (i.e. directly soliciting votes in an election) is forbidden. This means that MOCs will have second Twitter account for election purposes that may have very different patterns of interaction with the public. While examining the pattern of behavior of these campaign accounts may be useful and interesting, it is not the focus of this research. This paper is strictly focused on the utilization of Twitter as a means to deliver constituent services and constituent interaction by MOCs.

We do know MOCs place a very high value on constituent services and constituent interaction (Owen et al., 1999). Given the rising use of Twitter by MOCs and by the public, it would make sense that Twitter would become a platform for dialogue with MOCs. The rate of reply by MOCs is an excellent proxy for engagement by a MOCs office with the public. Additionally, the fundamental constraint of the limited bandwidth
of an MOC and their office to respond to a finite number of tweets suggests that Twitter responses may be a useful proxy for the features of constituent and public interaction a MOC and their office find valuable and useful.

Combined with the current second tier of congressional communications which to which Twitter seems to be relegated, those tweets which receive replies must be extraordinary in some way, or contain some features which differentiate them from the general flood of tweets to MOCS. Identifying the features of Tweets that receive replies vs those that do not allows some novel insight into the focus and priorities of an MOC and their staff. Understanding and taking advantage of these behaviors has the potential to significantly improve engagement on Twitter by citizens and advocacy groups.

Prior research suggests that MOCs’ interactions with twitter are fairly facile and self-aggrandizing Hemphill and Roback (2014), despite Twitter’s promotion as a platform for engagement. By documenting and exploring just how engagement on Twitter does, or does not, function, it may be possible to motivate better future interaction on the part of constituents and MOCS. Which brings us to the question: What features of tweets to congress members increase the likelihood of a reply?

2. Literature Review

The work presented in this paper is informed by four different areas of prior research: citizen government communications and their change in the Internet era, prior methods of evaluating Twitter (and other social media) interaction in the general population, Congressional Twitter use, and predictive features of text.
2.1 Citizen Government Communications in the Internet Era

Congressional communications is a well-studied topic. There is no shortage of literature exploring the importance, significance, and methodology of Congressional communication (Miller and Stokes, 1963; Grossman, 1995; Semiatin, 2012).

Historically, the primary methods of communication with congress were letters, phone calls, and in person visits (Hickey 2010). In the late 90s and early 2000s communication shifted from largely analog to mostly digital (Semiatin, 2012). Now, several decades into the digital revolution, the majority of communication with congress is done via digital mediums (Hickey, 2010).

All indications are that Congress has neatly integrated digital mediums into existing, analogous communication and media strategies. Grossman (1995) describes the early, idealistic, views of the future digital communication between government and the public. Grossman (1995) further articulates a vision of a more connected, more functional democracy. Enriched by the transparency created by free flowing communication to and from the halls of government. When the issue began to be studied a few years later, a number of studies evaluated the contrast between conventional means of communication and then emerging electronic modes.

Carter (1999), Owen et al. (1999), and Bimber (1999) all made similar, parallel studies of electronic congressional communication. Owen et al. (1999) and Bimber (1999) found that congress was using email in a very similar manner to their existing communication strategies, treating email as a supplement for mass mailing and the Franking privilege\(^1\). Carter (1999) and Bimber (1999) examined the differences between

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\(^1\) The Franking Privilege allows Members of Congress to send official mail without paying postage.
the efficacies of these several methods, and found that while there were differences between electronic and traditional communication methods, the differences were quite small. Carter (1999) found that personalization of communication is important no matter the medium. Formulaic emails and form letters receive fewer replies than personalized communication. Carter (1999), Owen et al. (1999), and Bimber (1999) findings have been reproduced and reinforced; Hickey (2010), Semiatin (2012), Nielsen (2011a), and Christensen (2011) all found similar patterns of communication with congress. Thus, further supporting the idea that congress hasn’t changed the way it communicates in the past two decades; it has just changed mediums. Each of these authors have made novel additional findings about congressional communication.

Over the course of the 1990s, a meme entered popular discourse, framing internet activism as ‘slacktivism,’ a sort of minimal effort activism, less engaged than traditional modes of activism (Christensen, 2011). Christensen (2011) thoroughly disassembles this idea, demonstrating that online activists are also engaged offline, and that online activism improves offline activism. This supports Cohen (2006) who demonstrates that citizens who use the internet to contact government are more satisfied, as well as Goldschmidt and Ocheiter (2008) and Hickey (2010) who demonstrate that, regardless of modes of communication, citizens who contact government are more engaged. Additionally, Goldschmidt and Ocheiter (2008), Hickey (2010), and Cohen (2006) all show that citizens who receive contact back from government are more satisfied, regardless whether the feedback was negative or positive.

Nielsen (2011b) further frames the issue of internet interaction as falling into two differentiated modes, the more traditional communication which treats new media as a
means of one way communication, and a second mode of communication which encourages “coproductive citizenship,” increasing citizen investment in the process of government. Moore (2013), Semiatin (2012), and Hibbler (2009) expand the potentially positive repercussions of governmental engagement with citizens via the internet and social media. The consensus among these authors is that a more engaged citizenry are more receptive to the messaging of the elected officials and are good for the system as a whole.

2.2 Evaluating Twitter Interaction

Citizen interaction and engagement can be cultivated via engagement on social media. There have been many attempts to engage with citizens on a variety of scales, many unsuccessful (Semiatin, 2012). To evaluate what sorts of communications to and from MOCs are successful, we must consider the question of evaluating interaction and influence in social media. Of the immediately obvious approaches to quantifying and evaluating Twitter use, the first is to try to measure the influence of a single user on Twitter.

Bakshy et al. (2011) attempted to identify popular tweets and users. Their findings were that a user’s influence, and the propagation of an individual tweet, can best be predicted by looking at a user’s history of widely propagating tweets. Bakshy et al. (2011) built on Boyd et al. (2010) who describe how conversations form and flow on Twitter and how retweeting functions in a conversational context. Retweets can either serve as an endorsement of a tweet, or a simple form of passive response, mapping
closely to trends identified by Ye and Wu (2010) and Sousa et al. (2010), both of whom describe message propagation and the social aspect of Twitter interaction.

Sousa et al. (2010) describe two types of social networks forming on Twitter, those that are ego-centered (retweets happen because of @mentions) and social networks focused on the social aspect of interaction. This bears a close resemblance to the graphing of Twitter communications done by Cogan et al. (2012). Cogan et al. (2012) finds two distinct modes of social interaction on Twitter, which, when visualized, present as a star or a radial pattern. In a star pattern, interaction happens in a non-linear mode, while in a radial pattern, tweets flow from the interior out. This shared description of sharply bifurcating pattern of interaction suggests a potentially unified model of twitter social networks and interaction. It is not clear if these two dual models are finding the same relationship, or different pairs of distinct relationships.

Both Budak and Agrawal (2013) and Bakshy et al. (2011) describe how Twitter interactions are largely the result of engaged, low profile users. These users are the focus of Romero et al. (2011), who, while attempting to identify influential Twitter users makes the valuable observation that the discerning feature between influential and non-influential Twitter users is simply overcoming the passive consumption most Twitter users engage in.

Rossi and Magnani (2012) describe how similarly newly engaged users can gain influence and followers by participating in large #hashtag discussions. Naturally, already popular users gain more followers, but less popular followers reliably gain followers by participating in the same discussions. Budak and Agrawal (2013) describes how users participating in a large #hashtag discussion may be made to feel welcome and included
in a conversation, specifically, which users will return and continue participating. Budak and Agrawal (2013) find that users participate in chats where they feel socially normative and included. Sharing linguistic traits with the broader group conversation makes users more likely to continue participating in a group discussion.

Possibly more relevant to the subject of congress on Twitter, is the behavior of business accounts. Popescu and Jain (2011) describe how businesses use Twitter for self-promotion, with most of their tweets falling into four narrow categories of tweets: announcements, brand awareness, engagement, and content endorsements.

2.3 Congress on Twitter
Social media has been credited as a critical factor in two presidential elections and has grown from a niche service to broad adoption (Chi and Yang, 2011; Lomberg, 2012). There have been attempts to turn Twitter towards predicting events and outcomes, however that idea has fallen out of popularity. Papers like Bravo-Marquez et al. (2012) demonstrated the dubious predictive powers of Twitter. Bravo-Marquez et al. (2012) attempted to predict the outcome of the 2012 US Presidential election using Twitter popularity and sentiment analysis. Finding that Twitter opinion mining is not a strong predictor of current or future events.

For the most part MOCs treat Twitter like broadcast media. Most Twitter use by MOCs is very unidirectional with low rates of response (Golbeck et al., 2010; Hemphill et al., 2013; Mergel, 2012; Otterbacher et al., 2012). Compared to other legislatures, the US Congress is much less likely to reply to tweets (Otterbacher et al., 2012; Lietz et al., 2014). In part, this approach to using Twitter may be a result of the long, contentious
history of Congressional communications and the very high demands of the office (Semiatin, 2012). Though in the earlier days of Twitter use MOCs were more likely to respond to tweets than they have been recently (Straus et al., 2013; Chi and Yang, 2011, 2010).

Twitter adoption approached its current peak in Congress very rapidly in a very narrow window of time around the 2009 Inauguration of President Barack Obama. Straus et al. (2013); Chi and Yang (2010, 2011) all attempted to account for the features of MOCs which drove or deterred adoption. Multiple studies found that in the period around Obama’s Inauguration, Republicans were more likely to adopt Twitter than Democrats were, and MOCs in more urban areas were more likely to adopt Twitter. The use of Twitter as a broadcast tool rather than a participatory tool is confusing given the findings of Hibbler (2009); Hickey (2010); Cohen (2006); Miller and Stokes (1963); Nielsen (2011b), emphasizing that any interaction with MOCs substantially improves the attitude of the public. The gain in sentiment is surely worth the time and effort needed to interact.

It is possible that US MOCs don’t interact as much as their counterparts in other countries because they view the public on Twitter as soap-boxing, pronouncing their beliefs and benefits for their own satisfaction, rather than soliciting meaningful engagement. However Hemphill and Roback (2014) and Roback and Hemphill (2013) both show this not to be the case. In both studies, members of the public are largely seeking to give input on specific issues and to build relationships with and lobby MOCs (Wigand, 2010).
The behavior and use of Twitter by MOCs is generally lackluster. It is rare to see a call to action by a MOC, more often than not Twitter use is simple self-promotion and publicizing actions a MOC has already taken (Hemphill et al., 2013). This contrasts quite sharply with the behavior of German politicians in Thamm and Bleier (2013) which show a distinct desire to both do their official duty communicating about their office and to interact with the public. This reality of Twitter adoption and use runs counter to the predictions of Grossman (1995) and similar who thought transparency would be a higher priority use of internet communication tools (Chi and Yang, 2010).

The US Congress further differs from other parliaments in its relative low level of interconnection with other MOCs. Lietz et al. (2014) showed that German political parties exhibited a high degree of interconnection and communication, while Mergel (2012) found that US MOCs are sparsely interconnected in their discourse (though Mergel’s sample size was small). Otterbacher et al. (2012) shows that in other democracies patterns of Twitter use by members of parliaments varies radically, with US MOCs being the least engaged and the most self-promoting of the studied populations.

Given that Congressional communication via Twitter is so stunted, replies by MOCs replying to tweets are rare. In a preliminary study, we found that roughly 1% of tweets receive replies. These tweets might either be outliers, distinct, or supremely lucky to receive a reply from a MOC’s account. Further study will determine the features that increase a likelihood of replies.

2.4 Predictive Features

Reply prediction from text features owes a great deal to prior research in predictive text analysis and general features of text and microblogs. First, and most relevant, is
Artzi et al. (2012). Artzi et al. (2012) attempt to predict which features of a tweet most strongly predict a reply. In addition, as with Bakshy et al. (2011) and Sousa et al. (2010), historic features are the strongest predictor of future results. Artzi et al. (2012) find that the strongest predictors of a reply are historic rates of reply and the strength of a user’s social network (i.e. more popular users are more likely to have a tweet replied to). This is quite similar to Hong et al. (2011) which find that the best predictors of retweets are a large follower base and a history of receiving many retweets.

Hong et al. (2011) is an interesting contrast with Bakshy et al. (2011) which finds that influential users have diminishing returns, from a publicity point of view, when compared with average users. While large users with large follower pools are more likely to receive retweets, the promotional cost of encouraging users with large followings to retweet is significantly higher than those with small followings, and the return on retweets by these users (re-retweets) is quite similar (Bakshy et al., 2011).

From a technical point of view, the most novel attempts to identify and predict responses and behaviors to specific facets of text are those constructing more complicated models than simple term frequency or user history. Users prefer information sharing and random thoughts to self-centered updates (something that may prove challenging for Congress) (Andre et al., 2012). Both Ritter et al. (2010) and Danescu-Niculescu-Mizil et al. (2011) suggest novel methods for predicting interesting features in the grand chaos of Twitter. Ritter et al. (2010) uses the idea of a ‘dialogue act’ to attempt to identify conversations within the Twitter stream. The idea of a dialogue act is closely related the ‘Tweet Acts’ coined by Hemphill and Roback (2014) to describe the patterns and sophisticated modes of speech that happen in human discourse.
Danescu-Niculescu-Mizil et al. (2011) demonstrate that humans engage in linguistic accommodation\(^2\) in Twitter, as they do in person. Danescu-Niculescu-Mizil et al. (2011) is a particularly interesting complement to Boyd et al. (2010) and Budak and Agrawal (2013). The contrast in modes patterns of engagement is enticing to explore further. Further exploration of patterns and uses of linguistic accommodation in large-scale discussions between strangers has the potential to reveal fascinating insights into very large group communication.

Zhang et al. (2013) and Wang et al. (2012) are another pair interesting to contrast and compare. Both attempt to discern some larger truth about some topic automatically. In Wang et al. (2012), the goal is to give some useful insight about the 2012 Presidential election, while Zhang et al. (2013) attempts to use the natural constraints of short, conversational Twitter discussions of hashtag topics to generate topic summaries. Though the results are largely unrelated, the underlying effort to discern some larger truth about some human state from an odd, constrained form of communication is shared.

### 2.5 The Question

When considered in its totality, the literature surround congressional communications, social media, and the internet suggests that increased engagement with citizens improves citizens views of MOCs, and that engaging on Twitter is not exceptionally difficult. But we find that MOCs do not use twitter anywhere near to its

\(^2\) Linguistic accommodation is an alteration of individual and group speech and linguistic models to allow individuals to enter a discourse or community. Danescu-Niculescu-Mizil et al. (2011)
full potential. At the moment replies, and meaningful engagement are sufficiently rare that the question of what encourages or changes how an MOC engages with Twitter is a novel question. Are there distinct features of tweets MOCs reply to? Is the content of these tweets differentiated in any substantial way from the general population of tweets MOCs receive? Put succinctly, knowing only the text of a tweet, and whether or not it received a reply, what features of tweets predict a response from an MOC?

3. Methodology

3.1 Data Collection

From August 18 to September 30, the period surrounding the September 2014 session of the 113th Congress, tweets to and from Congress were collected in cooperation with Mary Peterson and John Cluverius. These tweets were collected by using an R script written by John Cluverius to scrape all public tweets to and from MOCs. Approximately 159,000 tweets were collected from the Twitter API. Of these tweets, 41,000 were from MOCs and 118,000 were to MOCs.

3.2 Data Analysis & Results

The subset of tweets that received replies from MOCs were extracted and analyzed to find distinctive features from the broader pool of tweets. Specifically the tweets that received replies were analyzed for features distinct from the larger population.

Developing a robust model for predicting which tweets would receive replies proved quite challenging. The distribution of the positive class relative to the total sample set in the extreme; 175639 Negative instances and 2523 Positive instances. Presenting a ratio of 70 to 1 negative to positive instances.
The first method attempted was to train a simple logistic regression model on a unigram feature set, generated from a test subset containing an equal number of positive and negative instances. This method produced a model with an accuracy \(^3\) of 89.39\% and a Kappa of 0.787. Thus demonstrating that the positive and negative class are in fact differentiated. In this data sub-set, the strongest predictive features were @mentions of specific members of congress, such as Dana Orbacher. With these @mentions removed this model produced an accuracy of 70\% and a Kappa of 0.411.

However when this model was tested against a larger, more natural subset of the data it produced significantly poorer results. On a dataset with a 1:12 positive to negative distribution, the model produced an accuracy of 99\% and a Kappa of 0.201. Note that this statistic proved intensely variable across test and training sets.

LIWC features were generated for the complete dataset; these features did exhibit significant influence on the accuracy or Kappa scores of some models trained using said feature set. In some instances, LIWC features with Unigram features proved slightly worse than a simple unigram feature set. On some subsets LIWC improved Kappa scores, and on other subsets LIWC features had no or negative impact on Kappa scores. Results with LIWC features were sufficiently inconsistent that LIWC features were not included in later experiments.

<table>
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<tr>
<td>yes</td>
<td>2001</td>
<td>522</td>
</tr>
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</table>

\(^3\) Accuracy is fairly meaningless in this case
Next several models were trained on the complete natural distribution dataset in typical n-fold cross validation method. This dataset proved rather onerous to analyze because of its size, resulting in fewer training and testing experiments conducted on larger feature sets (tri-grams, Part of Speech). The full dataset was only tested a few times to verify that smaller subsets were in fact producing results that were representative of the larger dataset.

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The final method attempted was a modified 10-fold cross validation. A logistic regression-training algorithm emphasizes the dominant class. In this case, models trained on the natural distribution were prone to favoring the negative class, producing high accuracies, but quite poor Kappa scores.

To account for this over-fitting, a custom cross-validation very model was devised. For each training-fold, the training data was normalized to produce a 1:1 distribution of the positive and negative class, the positive class was increase to match the negative by duplicating all positive classes until an even ratio was achieved. This fold was then tested on the remaining folds, and the process was repeated for all folds. This method produced a model with 98.02% accuracy and 0.2748 Kappa. Almost identical results to
an unweighted model, which produced 98.64% Accuracy and 0.2955 Kappa on a simple unigram feature representation. The same model and feature set without @mentions produced 98.71% accuracy and 0.2563 Kappa. The model without @mentions had many fewer false negatives, but many more false positives (See Tables 1 and 2).

An additional, proper modified 10-fold cross validation method was attempted, using a 90% training fold, with an inflated number of positive instances to create a 1 to 1 ratio of the positive to the negative class, and a 10% test fold with a natural distribution. However, the size of the inflated dataset was sufficiently large that it could not be run in LightSide or Weka.

4. Discussion
A cursory examination of those tweets in the positive class, and those which where

<table>
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<th>Frequency</th>
<th>Feature Influence</th>
<th>Feature Weight</th>
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<td>1504</td>
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Table 3: Strongly Negative Features

scored as false positives by the strongest model reveals that many of the tweets which did not receive replies were quite similar to those (and in some cases identical to) those that did receive replies. Reliably identifying a tweet that will receive a reply is very
likely down impossible as MOCs receives such a volume of tweets. It is possible that MOCs only see a small portion of the tweets they receive and reply at a higher rate to those tweets they see, however there is no research on the subject available at time of writing.

We can learn some interesting things about what MOCs priorities are on Twitter by which tweets they elect to respond. Certain MOCs are much more engaged on Twitter and reply much more frequently than others reply. @danarohrabacher was the strongest or top three unigram feature in every model tested. Without @mentions, the robustness of any model falls appreciably, reflecting how much engagement is dependent on an individual MOC.

With @mentions removed the most solicitous topics were select items of public policy and social engagement campaigns. MOCs would appear to intentionally ignore certain topics as well. Among the features most strongly predictive of the negative class were several related to online poker, which has been the subject of vocal and focused social media campaign, which appears to have totally failed to gain focus of engagement by MOCs, as can be seen in Table 4. This would suggest that unless an MOC is already

<table>
<thead>
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<td>0.01234</td>
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</tr>
</tbody>
</table>

Table 4: Strongly Positive Features
predisposed to want to engage on a subject, it is not worth an issue advocates time to arrange to bombard them with tweets on the subject.

MOCs also are much more likely to ignore tweets about topics which are closer to realm of conspiracy theories or social media tempests in a teapot (Benghazi, or anti-vaccine campaigns for instance). Table 3 contains some of the most influential features in predicting the negative class. As the accuracy scores have suggested, it is much easier to predict the negative class than the positive class.

5. Conclusion
In conclusion, tweets, which received replies from Members of Congress (MOCs), were used to construct a model to attempt to predict with which tweets MOCs would engage. The principal findings were that this is a very challenging task. The distribution of tweets that do receive replies to those that don’t is on the order of 70:1 non-reply to reply generating tweets. As most MOC responses were from a few MOCs, we can make no meaningful conclusions about the general linguistic properties of tweets that receive responses from MOCs.

Features in addition to simple text features could potentially significantly improve reply prediction. Including social media influence metrics such as follower count and prior positive interactions with MOCs and geographic location. Additionally it is not known what percentage of tweets a MOC or their staff ever see. A survey or other evaluation of the simple proportion of the quantity of tweets to an MOC that are ever read by their office could greatly improve future research in this area.

Were these experiments to be continued or done over, this researcher would be much more careful of methodology and planning. As it stands a number of interesting methods
remain untried due to time constraints and quite a bit of useful and informative data was simply not recorded. These experiments relied on LightSIDE and Weka for feature extraction, model training, and evaluation. Weka and LightSIDE are better suited to smaller datasets and run into issues with large datasets (Multiple gigabytes). A purpose-built tool would be better suited to future explorations of this subject area. Particularly when exploring non-standard methods such as a weighted or inflated n-cross validation.

Further research into social media interactions with MOCs is warranted. Such research may prove useful in improving public interaction and social media advocacy campaigns. There is room for improvement in exploring other features, including social influence metrics and read rates.
6. References


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