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Marko Skoric,

Jing Liu,

Kokil Jaidka,

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MARKO SKORIC, JING LIU & KOKIL JAIDKA

Abstract Can social media data be used to make reasonably accurate estimates of electoral outcomes? We conducted a meta-analytic review to examine the predictive performance of different features of social media posts and different methods in predicting political elections: (1) content features; and (2) structural features. Across 45 published studies, we find significant variance in the quality of predictions, which on average still lag behind those in traditional survey research. More specifically, our findings that machine learning-based approaches generally outperform lexicon-based analyses, while combining structural and content features yields most accurate predictions.

Keywords: • Social Media • Election Prediction • Network Feature • Content Feature • Meta-Analytic Review •

CORRESPONDENCE ADDRESS: Marko Skoric, PhD, Associate Professor, City University of Hong Kong, Department of Media and Communication, Hong Kong, e-mail: mskoric@cityu.edu.hk. Jing Liu, PhD, Assistant Director, Hong Kong University of Science and Technology, School of Business and Management, Hong Kong, e-mail: echoliu@ust.hk. Kokil Jaidka, PhD, Nanyang Technological University, Presidential Postdoctoral Fellow, Singapore, e-mail: jaidka@ntu.edu.sg.

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1 Introduction

In recent years, the use of social media as a "social sensor" has been observed in many recent studies for predicting public opinion and election results. A rising proportion of everyday social interactions are happening in a digitally mediated context, making it easy to capture, store, process and analyze such data and use it as an always-on, unobtrusive spatiotemporal monitor of human thought and behavior. As compared to traditional methods of user data collection, social media analytics potentially offer a new kind of insight, through the ability to "listen in" to casual conversations, understand networks of friendship and influence, and assess their impact on public opinion.

This study presents a meta-analysis aimed at assessing the potential of different social media signals to correctly predict election results. It supports a fact-based understanding of the importance of social media to understanding public opinion by synthesizing the results from 45 published, peer-reviewed studies. We anticipate that our findings will address many of the concerns raised in recent work decrying the use of social media for electoral prediction. For instance, Jungherr et al. (2017) have raised the concern that measurement of political support through Twitter could instead be measuring "attention towards politics", and as such its relationship with political support is correlational but in need of further validation. Furthermore, Beauchamp (2017) suggests that many studies using social media to predict elections lack rigorous statistical testing, comparison against reasonable benchmarks and out-sample evaluations. Indeed, instead of predicting the future, many studies have usually predicted known outcomes in the present (Varian and Choi 2009) or the past (e.g., post-hoc predictions) and have rarely assessed the validity of their predictions through comparisons against other sources of data.

2 Background: Social Media and Public Opinion

The advent of social media-based opinion mining has challenged the two fundamental assumptions of survey research—namely, probability-based sampling and structured, solicited participant responses. First, probability-based sampling — employed by most quality surveys — assumes that all opinions have the same value and should be equally weighted (Bourdieu 1979), and can, therefore, be understood as "a possible compromise to measure the climate of public opinion" (Lazarsfeld 1957, p. 45). However, this approach ignores the dynamics of individual influence in forming public opinion (Katz 1957; Katz and Lazarsfeld 1955). Second, the survey-interview situation might produce a biased measure of public opinion skewed toward social desirability (Espeland and Sauder 2007).

Social media data differs from the structured, self-reported survey data in three main ways. First, it provides a large volume of user-generated content from organic, non-reactive expressions, generally avoiding social desirability biases and non-opinions, although self-censorship of political expressions has also been noted (Kwan, Moon, and Stefanone 2015). Second, social media data can be used to profile not only the active users but also "lurkers" who may not openly volunteer an opinion, by examining the interactional connections and network attributes of their accounts. Third, by looking at social media posts over time, we can examine opinion dynamics, public sentiment and information diffusion within a population (Jaidka, Ahmed, Skoric, & Hilbert 2018).

Still, social media data is criticized for not being representative of the general population, as it typically comes from the ranks of early adopters, teens, and better-educated citizens (e.g., Fox 2010; Wei and Hindman 2011). Political discussions on social media tend to be dominated by a small number of frequent users (Tumasjan et al. 2010). However, dismissing social media data as being invalid due to its inability to represent a population misses capturing the dynamics of opinion formation. As opinions held and debates conducted by certain politically active groups pre-empt those that develop in broader society (Zaller 1992) it is likely that social media conversations by active users play a stronger role in shaping public opinion.

2.1 Current Research

We identified several major methodological differences in how researchers approach the task of mining public support from social media data. The first important methodological choice made by researchers is which feature set – whether content features or network features – should be used to yield the most accurate predictions of election outcomes from social media. A similar "content vs. network" conceptualization is found in prior work by Livne (2011). Based on the Language Model of 687 candidates' tweets and documents cited and network features—i.e., number of retweets, replies, and hashtags, degree centrality, closeness centrality, HITS's Authority score (Kleinberg et al. 1999) and PageRank (Page et al. 1999) of candidates' "follow" networks, Livne (2011) built logistic regression models and correctly predicted the 49 out of 63 races' winner and loser during U.S. 2010 midterm elections.

Content features refer to the subjectivity and polarity convoyed in user-generated contents, i.e., social media users' direct expression of their attitude or opinion, which is often the form of texts, images or videos. There are many terms used to capture such automatic extraction of human attitude or sentiment from texts, among which sentiment analysis is the most widely used one. While apart from content features, political attitude/opinion could also be inferred from social media users' behaviors (e.g., follow, like, comment, share) with political candidates/parties, which constitutes a self-organizing and emergent network structure of the online communication flow. Within content features, sentiment analysis is further categorized into two sub-types: (1) lexicon-based, and (2) machine learning based. Prediction studies using lexicon-based sentiment analysis (González-Bailón et al. 2012; Ibrahim et al. 2015; Li, Ng, and Shiu 2013) adopt a given dictionary of words annotated with semantic orientation (polarity and strength) to classify the attitude/opinion conveyed by a piece of text toward a subject person or topic. The accuracy of such an automatic interpretation of semantic orientation is highly dependable on the quality and relevance of the lexical resources to the domain to which it is applied. Predictive studies using machine learning-based sentiment analysis (Contractor and Faruquie 2013a) learn from a set of (labeled or unlabeled) training data and then apply the learning model to classify the attitudes or opinions expressed in social media contents.

Studies using lexicon-based sentiment analysis yielded conflictive results in making political predictions. O'Connor et al. (2010) demonstrated that tweet sentiment correlated well with Obama's support rate during the 2008 presidential election and his job approval in surveys in 2009. While Chung and Mustafaraj (2011) and O'Connor et al. (2010) reported that sentiment analysis with lexica like Subjectivity Lexicon and SentiWordNet are not reliable for predictions due to the low coverage in their dataset. Studies which use machine-learning methods appear to have had better success (Beauchamp 2017; Dwi Prasetyo and Hauff 2015; González-Bailón et al. 2012; Kalampokis et al. 2017; Li et al. 2013; Monti et al. 2013; Sharma and Moh 2016; Huberty 2013; Xie et al. 2016). For instance, Contractor and Faruquie (2013) trained a regression model based on the bigram features from 37 million tweets to gauge Obama and Romney's approval rates in the 2012 U.S. Presidential election. Monti et al. (2013) trained a classification algorithm using Twitter Train Data and News Train Data and observed a strong correlation between offline inefficiency and online disaffection.

Network features encompass both centrality metrics (degree, betweenness, closeness, eigenvector centrality, etc.) used in social network analysis (Freeman 1979) and its non-normalized version—simple counts of edges of various network formed by social media users' interactions (mention, reply, retweet, share, follow, friend, etc.) with political candidates/parties. Network features are often interpreted as approval or support for a certain candidate or topic. For example, Mustafaraj et al. (2015) indicate that retweeting indicates not only interest in a message, but also trust in the message and the originator, and agreement with the message contents. Early studies focused mainly on simple counts of "mentions," e.g., the number of times political parties/candidate mentioned by social media users, as a proxy to predict political party/candidate's offline political support (Tumasjan et al. 2010). However, simple counts of "mentions" have largely been criticized because they fail robustness checks (Jungherr et al. 2012; Gayo-Avello et al. 2011a). Studies (Barclay et al. 2015; MacWilliams 2015; Vepsäläinen et al. 2017; Williams and Gulati 2008) have demonstrated that the "likes" recorded in candidates' Facebook Page/Fan pages could be used to predict electoral outcomes. MacWilliams (2015) use Facebook's PTAT ("People Talking About This") data to counting the interactions between the public and the candidates (e.g., liking a page, liking a post, commenting on a post, sharing a post, posting on the page's wall, etc.). Such "participation advantage" improved upon models that used only the Partisan Vote Index and incumbency as predictors. Cameron et al. (2016) found that the number of "friends" a candidate has in Facebook and number of "followers" they have on Twitter could be used the predict the candidates' vote share and the winner in 2011 New Zealand general election. Pimenta, Obradovic, and Den-gel (2013) predicted candidates' vote share in 2012 Republican primaries and opinion polls using the number of incoming links to blog posts, number of likes/repost a Facebook post received, number of retweet a tweet post received, the number of comments, likes/dislikes a YouTube video received and so on. Jaidka et al. (2018) used network features (counts of mentions, betweenness, PageRank of "mention" networks, etc.) and tweet sentiments to predict actual vote shares/opinion polls across three countries, finding that network features together with tweet sentiments are effective at predicting vote share, while machine learning based sentiment analysis yielded the most accurate predictors of election outcomes.

Since network features attempt to capture not only content but also the channels of opinion diffusion, it is hypothesized that:

H1: Studies using network features would outperform studies using content features in predicting public opinion and electoral outcomes.

H2: Studies using a combination of network and content features will outperform studies using any singular type of social media feature in predicting public opinion and electoral outcomes.

Given the relative sophistication of machine learning in extracting sentiment from texts, it is hypothesized that:

H3: Studies using machine learning-based sentiment analysis of social media contents would yield more accurate predictions of public opinion and electoral outcomes than studies using lexicon-based sentiment analysis.

3 Methods

3.1 Literature Search

The data collection was finalized in August 2018, using the following keywords—Twitter, Facebook, YouTube, microblog, blog, forum, social media, social networking site, online discussion or political sentiment, election, public opinion, protest, dissent or opinion mining, predict, measure, forecast, approximate—to search within the following databases: ACM Digital Library, IEEE Xplore, AAAI, ScienceDirect, Web of Science, EBSCO, JSTOR, SCOPUS, Taylor & Francis, Wiley Online Library, and ProQuest. After the initial search, a manual selection was performed to filter for relevance. Studies were included if they (a) utilized social media data to predict offline political behavior or opinion; and (b) measured one or more of the three criterion variables (i.e., political voting, protest, or public opinion) as a predicted variable. This resulted in a corpus of 61 articles published between 2007 and 2018, among which 45 studies predicted election results while 22 predicted opinion polls (6 predicted both). We only selected the studies which predicted election results directly and excluded those predicting opinion polls; the total number of studies included was 45, with the majority of studies analyzing Twitter data (above 75%).

3.2 Coding

Social media predictors are first categorized into two types: content features vs. net-work features. Content features are categorized into (1) lexicon-based and (2) machine learning-based sentiment analysis. While network features include (1) centrality metrics (degree, closeness, between-ness, etc.) which examines the individual nodes' (social accounts) position/importance in its social net-work, and (2) centrality metrics' non-normalized version —simple counts of the various type of edges, i.e., edges formed by the interactions among social media users and political candidates/parties. Such edges include social media users' interactions such as "follow"/"friend", "mention"/"tagging", "re-tweet"/"share", "reply", "comment", as well as "like" (a post or Fan page), which in the end constitute the network centrality. For blogs or forums, the edges are formed by incoming/outgoing links that a blog post has; for YouTube video, it includes setting videos as "favorites."

The present study focuses on electoral *results* alone, i.e.: (1) vote/seat share that political candi-dates or parties received during the election; (2) winning party or candidate in the election. This yielded 310 social media-based public opinion measures for our meta-analysis.

3.3 Results

Since each study may test more than one prediction, we ended up with 310 estimates in total, among which 161 estimates reported Mean Average Error (MAE) or other convertible forms (RMSE, Absolute Error, etc.) and 149 estimates reported R squared or coefficients.

As seen in Table 1, the best-performing feature set was a combination of content and network features, which yielded the lowest MAE (Mean=2.3, SD=4.17). Thus, Hypothesis 2 is supported. Studies which deployed structural features outperformed those with content features when measuring predictive power with R^2 (Mean=.60, SD=.32), but not with MAE (Mean=4.88, SD=4.55). Thus, Hypothesis 1 is partially supported.

Table 1 Predictive Power of Social Media Data with Different Predictors

	MAE (%)			R^2		
Predictors	Mean	SD	N	Mean	SD	N
Network features	4.88	4.55	83	.60	.33	96
Content features	4.27	3.83	69	.63	.26	33
Content & structural features	2.30	4.17	9	.58	.30	20
Total	4.47	4.17	161	.60	.31	149

To further assess whether machine learning produces better predictors of voting outcomes we compared (1) lexicon-based and (2) machine learning-based predictions, as shown in Table 2.

Table 2 Predictive Power of Social Media Data with Different Predictors (recoded)

	MAE (%)			R2		
Predictors	Mean	SD	N	Mean	SD	N
Network features	4.88	4.55	83	.60	.33	96
Lexicon-based content features	5.36	4.65	23	.77	.24	7
ML-based content features	3.73	3.28	46	.60	.26	26
ML-based content & network features	2.09	1.70	8	.82	.14	3
Lexicon-based content & network features	4.00		1	.54	.30	17
Total	4.47	4.17	161	.60	.31	149

Hypothesis 3 is thus supported. As seen in row 5, studies with a combination of structural features and machine-learning based content features report the most accurate prediction across both MAE (Mean=3.08, SD=1.55) and R2 (Mean=.91, no SD), landing further support to H2 and H3.

4 Discussion and Conclusion

In this meta-analysis, we compared the predictive power of social media analytics across different approaches, platforms, and contexts. In many of the cases, the results reported using MAE-based estimates and R^2 estimates were in agreement with each other, which is an encouraging sign of the robustness of our findings. While R^2 based measures showed the most stability and can be interpreted as higher recall or explainability of the data, MAE-based estimates can be used in cases where errors are symmetrical, e.g., in sentiment analyses, or in two-party races, where precision is of importance. Machine learning-based sentiment analysis tends to produce predictions with higher precision than lexicon-based approaches; however, they typically explain less variance.

The first important insight from our findings is the theoretical importance of interactions in the formation of public opinion. Combinations of network features and machine learning-based sentiment analysis of content features provide the most accurate predictions as compared to all the approaches considered. This means that content features work best when they are combined with network features to model the diffusion of opinion in a social network, regarding the reach of the authors, their interaction patterns, and their importance as influencers within their communities of followers. Still, most studies have relied on a simple count of interactional edges, which can be gamed by astroturfing or by heavy users, spammers, and propagandists (Metaxas and Mustafaraj 2012). In addition, they may also show attention spikes because of news cycles. Instead, we recommend that more sophisticated measures of author importance, e.g., network centrality measures, should be adopted to provide more accurate measures of online communication structures. Network features can capture the density of online discussions. More decentralized networks have more active users and thus wider outreach to a larger potential voter base (Jaidka et al. 2018). Network features have been found to be useful to dampen the estimation effects associated with national parties that are over-represented on social media or regional parties which may be popular online.

The second important insight is regarding the limitations of applying generic sentiment tools to mine political opinions, and applying dictionaries developed in the 1980s to analyze the present-day language of social media, which can falsely detect positive sentiment where there is sarcasm and hence can lead to erroneous predictions (O'Connor et al. 2010). Also, lexica are designed for Standard English, but many messages on Twitter are written in informal versions of English, which include alternatively spelled words and emoticons. Informal language cues are potentially useful signals, which are usually ignored in traditional methods of sentiment analysis. On the other hand, a supervised learning approach, which trains sentiment models on a small set of hand-annotated political messages yields much better predictions by inferring sentiment from otherwise neutral words used in context. Furthermore, studies have suggested that discarding negative posts and instead focusing on the positive tweets can help to filter out a large part of the noise from election-related content on social media (Jaidka et al. 2018).

Although this study is one of the first systematic reviews of social media-based predictions, it is important to note several shortcomings. First, since social media-based predictions are still in the early stages, there insufficient data to produce reliable estimates across different analytical categories. Several studies did not report their data sizes (e.g., Franch 2013; Li et al. 2013), while the other studies reported a wide range of data sizes – ranging from thousands (e.g., Gayo-Avello et al. 2011b) to hundreds of millions (e.g., Gaurav et al. 2013), making examination of effect of data sizes on social media data's predictive power of public opinion difficult. Fourth, the predictive power is reported in a range of formats – MAE, RMSE, correlation coefficients, regression beta, R^2, offset error, race-based percentage, making a systematic comparison difficult. We thus need a more standardized way of reporting data collection methods and statistical estimates of predictive power. Lastly, we were unable to systematically explore the temporal dimension in opinion mining, which is one of the key advantages of social media data and has been shown to affect the quality of election forecasts (Jaidka et al. 2018).

Social media data has many potential advantages – most importantly, it can bring the temporal and interactive dimensions of public opinion formation and change back to the forefront of research. We are optimistic that social media-based computational research, with more refined data collection and analytical methods, will be able to provide improved insights into the dynamics of public opinion and political behavior. Understanding political contagion on social media is also the first step towards countering problems such as disinformation, filter bubbles and hate speech, which are of growing concern in an increasingly polarized online community. Policymakers would also need to understand the real world correlates of online discourse to order to determine the future availability of social media data in ways that satisfactorily address the concerns regarding the key issues of privacy, freedom of expression, and public safety.

Note: Studies marked with an asterisk in the reference section were included in the meta-analysis.

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