Literature Review Presentation

Seattle Needles
Friday, November 20th

Presentation Roadmap

- Introduction
- Election Prediction
- Sentiment Analysis
- User and Tweet Filtering
- User Profiling
- Conclusion

Presentation Roadmap

- **Introduction**
- Election Prediction
- Sentiment Analysis
- User and Tweet Filtering
- User Profiling
- Conclusion

Our Question:

How has social media been used to predict previous election results?

Related Questions:

- Which social media's data was collected?
- How was the data collected and cleaned?
- Which features were used as predictors?
- Which methods of prediction were successful?
- How were results evaluated?
- How were users profiled or filtered?
- Is the pool of Twitter users who tweet about politics biased?

Why Answer this Question?

- Our project is: to what extent can social media predict the 2020 election?
- It is **cool** and **interesting**!
  - We can examine our own social media use/voting behaviors
    - Do I share my political views on social media?
    - Am I honest on social media?
- Answering this question brings us closer to answering our overarching question - **how can we exploit social media to understand the real world?**

Presentation Roadmap

- Introduction
- **Election Prediction**
- Sentiment Analysis
- User and Tweet Filtering
- User Profiling

Timeline of Election Prediction by Social Media

- 2005: political blogosphere and 2004 US election [19]
- 2009: Bayesian prediction model [20]
- 2010: 2010 UK general election [21]. Raw mentions count & basic sentiment analysis [42, 43]
- 2012: US presidential election & primaries [15, 22]
- 2014: Sentiment analysis in US and Italy [23]
- 2015: Text and image analysis of 2012 and 2014 US elections [24]
- 2016: Sentiment analysis on US election [25, 26]
- 2017: Inclusion of Google trends and online polls for US election [17, 27]
- 2018: Predicting changes in voter preference [28]
- 2019: Data mining approach [29]
- 2020: More sentiment analysis [30, 31]

Facebook vs Twitter for Election Prediction

Election Prediction with Facebook

- **Facebook** is used in hundreds of election prediction papers, though they are **not as well-cited** as those using Twitter
- **Election prediction approaches using Facebook** are generally based on likes and positive or negative sentiment responses on pages and posts of a political candidate [40]
- **Facebook uses a Graph API**, so you cannot directly query posts for location
- Since we are interested in locations of users (because we want to predict states in our project), **we focused our analysis and survey to how Twitter is used for predicting elections**

Election Prediction with Twitter

- **Twitter** is the primary social media website used for election prediction based on paper citations
- **Twitter API** can query tweets from relevant locations with geocoded tweets and profile location
- **Election prediction approaches using Twitter** are generally based on the total number of positive or negative sentiment tweets about a candidate [41]

User Merging

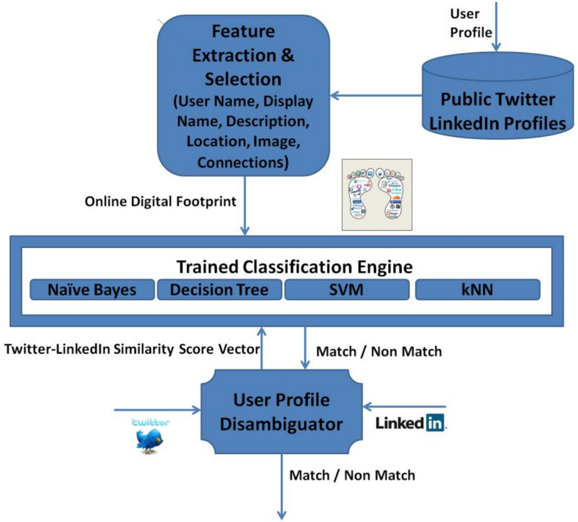
To identify the same user cross-platform, we can track the digital footprints of users [5].

- Use selected features based on user profile(N-dimensional vector)

Assess usefulness of features and different classifiers:

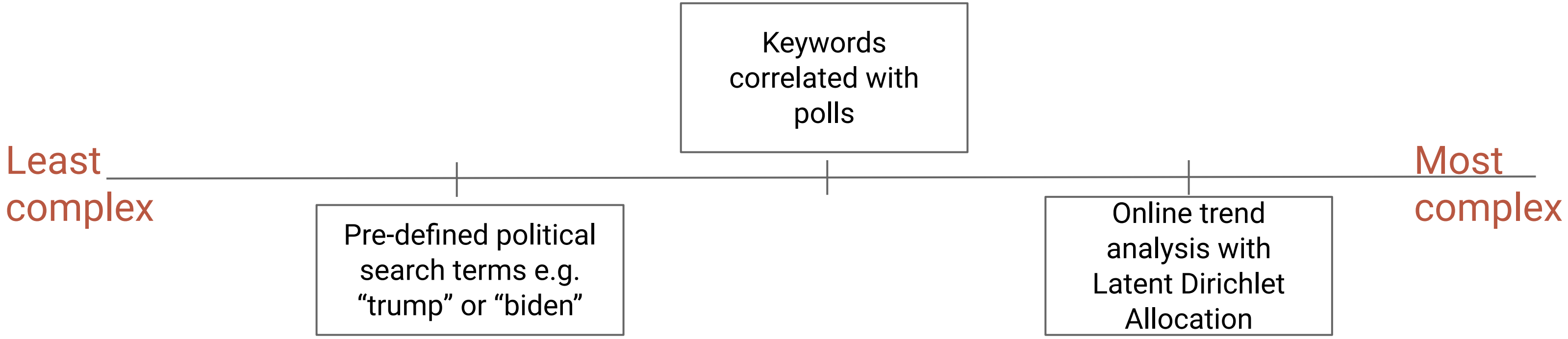
- **Naive Bayes**, Decision tree, SVM, KNN
- Feature set: <**name, userId, location, description, image**, # of connections, ...>
- Match users with 98% accuracy

……



Twitter Queries

- **Pre-defined list** of search terms [42]. For example: obama, romney, pelosi, reid, biden, mcconnell, cantor, boehner, liberal, liberals, conservative, conservatives, republican, republicans, democrat,
  - Critique: how do we discover new and emerging keywords related to political trends?
- Some papers use a similar approach to the Flu paper we read for class to **find keywords and hashtags that are highly correlated with political polls**, then filter out non political ones [43]
  - Critiques: polls may be unreliable + how do we filter out non-political terms for emerging trends?
- **Online Trend Analysis with Topic Models** which uses an online **Latent Dirichlet allocation (LDA)** system [44]
  - Explained this last Tuesday in a presentation, see Blei et al. (2003)
  - Critique of literature: Not implemented in any election prediction paper yet



Twitter Data Collection

- **Median length of data collection window is 2 months** before the election [41]
    - Critique of literature: no analysis done on what the best length for the collection window is
- **Current consensus on ending data collection to the day before the election**, Tumasjan et al. 2010 is the only widely cited (3000+) paper not following this consensus, which was later criticized by Jungherr et al. 2011. Nevertheless, no quantitative analysis on what the optimal time window is. [45, 46]
- **Location Filtering:**
    - Filter tweets by their **geocode or the location specified** on a Twitter profile (used by Gayo-Avello 2011 and Skoric et al. 2012)
    - Others (Tumasjan et al. 2010; Jungherr et al. 2011; Tjong Kim Sang & Bos 2012) make an **assumption about a user's location based on the language(s) used in their tweets** [45, 46, 47, 48, 49]

Election Prediction: Prediction Methods

- **Critique of literature:** many election prediction papers are written in hindsight using post-hoc analysis, so some authors do their analyses having already seen what they are trying to predict without simulating what data would be known at the time of making the prediction before the election [41]
- **Counting Raw Tweets Mentioning Candidate:** First paper to use this approach Tumasjan et al. 2010 just counted the tweets with the words “Obama” or “McCain” and assumed the more mentions one has, the more votes they have [41, 45]
  - Gayo-Avello 2011 showed that raw tweet counts perform *worse than a random classifier* [41]
  - We can see with 2020 hindsight that this approach isn’t good enough to deal with many complexities like many negative tweets about Trump, pro-Trump bots/trolls, and the “shy-Trump voter” phenomena
- **Volume of Positive Sentiment Tweets:** Currently, the most common method used in the literature advancing on raw tweet counts is to follow O’Connor et al (2010) in using the number of positive and negative sentiment tweets about a political candidate and either count the number of people who like the candidate or compute or a sentiment score for the candidate, then aggregate on national level [41, 50]
  - Critique: only uses the simplest of all sentiment analysis methods (positive / negative)
- **The literature is currently advancing by experimenting with new methods beyond these 2 basic methods**
- We give 3 examples of these new methods on the next 3 slides

New Election Prediction Method #1: Real-Time Analysis

- **Real-Time Analysis:** analyzing how the sentiment of tweets about the candidates change over time [51, 58]
- Analyzing which hashtag and keyword trends occurred before a shift in sentiment
- Not commonly used

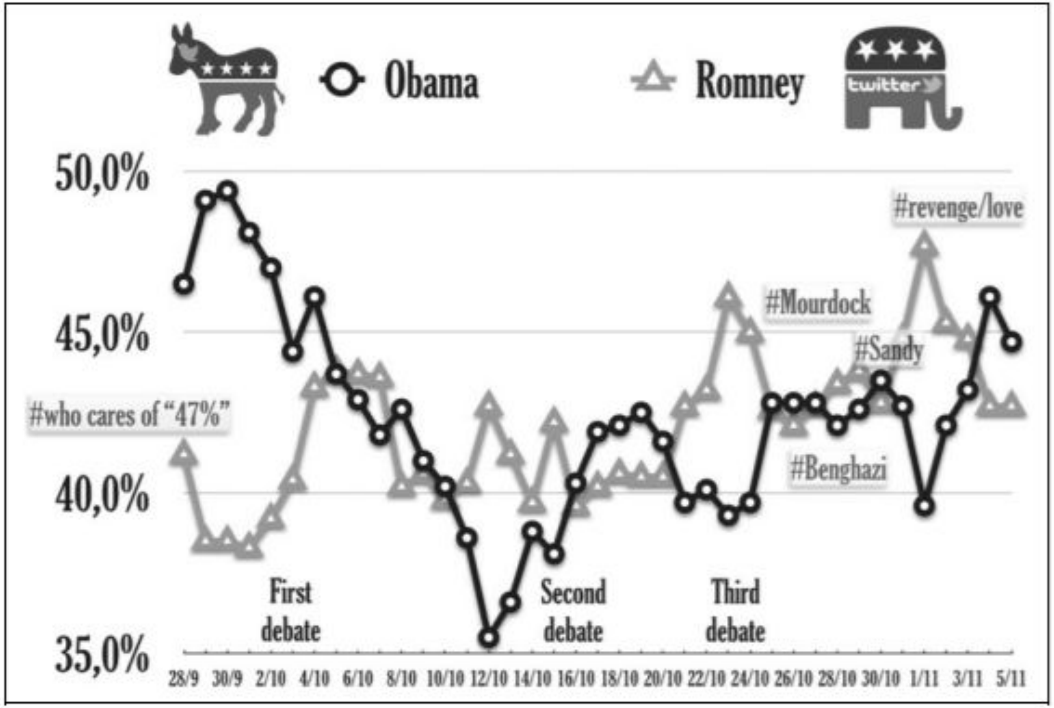


Figure 1. U.S. Presidential 2012: The trend of Twitter votes for Obama and Romney.

New Election Prediction Method #2: Distance Metric

- **Aggregated information** about parties and politicians and compared the resulting profiles with **anecdotal evidence from election programs and the press**
- **Analyzed the political sentiment of the tweets** using generated multi-dimensional profiles of the politicians using the **relative frequencies of category word counts**
- If $d_{i,p}$ is the value of the i-th dimension for politician p, then the following equation represents the **average distance from the mean profile per category of all politicians across the 12 dimensions**
- Prediction of party coalitions and election winners based on the **minimum distance** from the mean Twitter user to the political candidate across the 12 factors (money, future-oriented, etc) [45]
- **No evaluation of this method**, they called it a “plausible” reflection of political sentiment on Twitter
- Predicted election with a simple counting of the number of mentions of a candidate and MAE [45]

$$d = \sum_{d=1}^{n_d} \frac{\left| d_{i,p} - \left(\sum_{p=1}^{n_p} d_{i,p} \right) / n_p \right|}{n_d} / 12$$

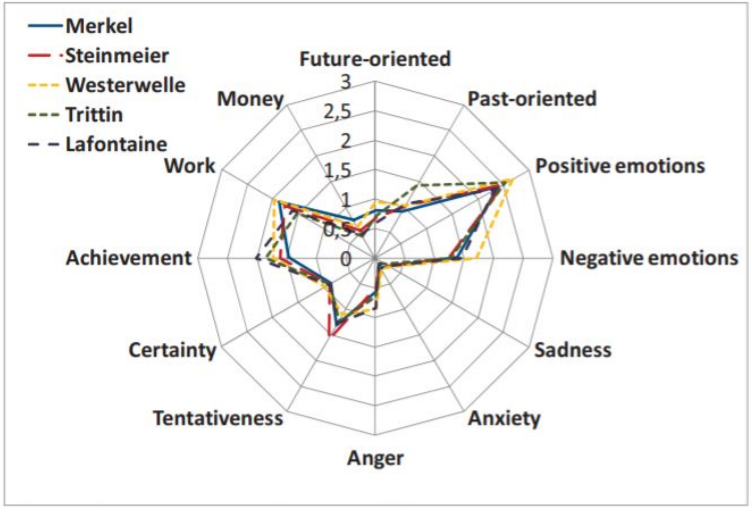


Figure 1: Profiles of leading candidates

New Election Prediction Method #3: Graph + Classifier

- **Logistic Regression model:** features of network structure in political communities [52]
- **Dependent variable**: candidate wins or loses election
- **Independent variables:**
  - Closeness-{in,out,all} (Freeman 1979) – measuring the centrality of a candidate in the graph.
  - HITS Authority score (Kleinberg et al. 1999) and PageRank (Page et al. 1998) – measuring the relative importance of a node in the graph.
  - In/Out-degree – number of edges to/from the node.
  - Incumbency – Boolean variable indicating whether the candidate was incumbent
  - KL-party/corpus – the KL-divergence between the LM of a user & the LM of his party
  - Party – indicating the political group a user belongs to (Democrat, Tea-Party or Republican).
  - Same-party – indicating whether the party of the candidate is the same as last to hold seat
  - Tweets, hashtags, replies and retweets – basic statistics of a candidate's Twitter activity
- **88% accuracy.** Does it generalize to elections in different years and countries?

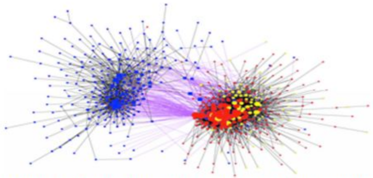


Figure 2. Plot of the candidate network (force-directed graph embedding layout modified to emphasize separation, nodes size proportional to indegree)

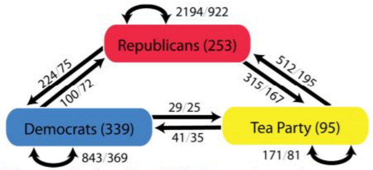
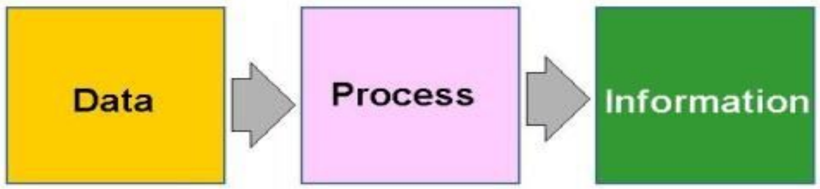


Figure 3. Number of explicit follower edges and unique @mention edges (follower / mention)

Post-Processing Tweets

- **Weakness of the literature:** Most papers do not consider or implement *any* of these filtering methods
- **Debiasing with Demographic Data:** Another filtering method is using demographic features (race/ethnicity, sex/gender, age, population on Twitter vs. Actual) to **undersample/oversample users or weight tweets differently** from demographics groups in particular locations
  - Reason used: Twitter users are a biased sample the general population
  - Goal: handle under/over-representation and biases from the sample of Twitter users
- **Debiasing with Assumption about Distribution of Political Beliefs:** Remove bias of Twitter users being more liberal than conservative in the US, and to address the “shy-Trump voter” phenomena [41, 49]
  - Results inconclusive because authors relied on polling data and no improvement in results [41]
- **Purifying with NLP:** filtering dataset by only considering prospective and potential voters [41]
  - Never implemented in the literature [41]
- **Denoising with Bot and Troll Detection:** filtering dataset by ensuring tweets are not spam from bots or misinformation from trolls. Considered by Metaxas et al. 2011 but not implemented [53]



Election Prediction: Evaluation

- **Important Note:** There are many ways to evaluate election predictions, with no one clear winner
- **Baseline:** Incumbent winning swing states and national election (9/10 times they win) [53]
- **Prediction Target**: Different levels of granularity e.g. national popular vote, state, district outcomes
- **Metric**: Mean absolute error (MAE) of one's prediction compared with either vote rates from the last election or from pre-election polls [45]

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|x_i - x|$$

- **MAE highly dependent on election and location,** so it is not obvious how to generalize MAE
- For example, MAE of 40% could give a correct prediction for Illinois, but a MAE of 5% could give a wrong prediction for Texas [54]
  - Critique of the literature: MAE does not generalize to all elections. It is too dependent on the specific election, country, etc to be interpretable. New evaluation metrics are needed.

Presentation Roadmap

- Introduction
- Election Prediction
- **Sentiment Analysis**
- User and Tweet Filtering
- User Profiling
- Conclusion

Tweets Sentiment Analysis

- The use of social media in last few decades have been helpful in determining people's attitude with respect to specific topics or events
- A wide research interest in natural language processing study the hypothesis based on the users' sentiment on social media.
- Sentiment analysis of the tweets can help determine the polarity and inclination of vast population towards specific topic, item or entity.
- Build sentiment classifier and classified the data basically as positive, negative and neutral. A two stage framework can be formed to create a training data from the mined Twitter data and to propose a scalable machine learning model to predict the election result.

Critique:

- But is it enough to only use positive, negative and neutral?

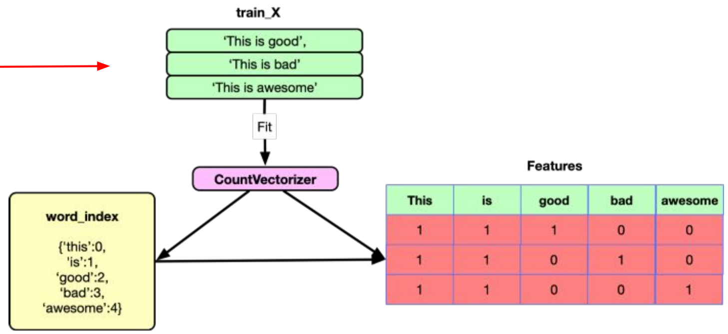
Tweets Sentiment Analysis methods (ML based)

Sentiment Analysis can be categorized into two approaches: **Machine Learning based approach** and **Lexicon based approach**.

- Machine Learning based approach classifies the text using classification algorithm. Popular text classification algorithms like **Naive Bayes** and **SVM** are Supervised Learning Algorithms that require **labeled training data**.
- To **numerically represent** the preprocessed data. The well-known techniques for vectorization of words in Natural Language Processing are: **CountVectorization** and **Tf-IDF transformation**.

CountVectorization generates a matrix representing all the words in the document

Tf-IDF transformation weight the words. So the normal or frequent words will not have much weight to influence the prediction.



Tweets Sentiment Analysis methods (Lexicon based)

- Lexicon based approach uses **sentiment dictionary** with opinion words and match them with data to determine polarity. Sentiment values are assigned to words that describe the positive, negative and neutral attitude of the speaker.

- A **score** of +1 is given to a positive word (like good, great etc) and -1 is given to a negative word (like bad, worse etc) and 0 for neutral words (like quite, average etc).

The **total polarity** of a tweet is then calculated by adding the scores of all the individual words. These counts are then used to determine the percentage of positive, negative and neutral tweets. The polarity will be normalized in ranges between [-1,+1].

Comparison of Methods

In paper [34], it compared the accuracy between these two methods in different conditions.

Research results show that machine learning methods, such as SVM and naive Bayes have the highest accuracy and can be regarded as the baseline learning methods, while lexicon-based methods are very effective in some cases, which require few effort in human-labeled document .

	Method	Data Set	Acc.	Author
Machine Learning	SVM	Movie reviews	86.40%	Pang, Lee[23]
	CoTraining SVM	Twitter	82.52%	Liu[14]
	Deep learning	Stanford Sentiment Treebank	80.70%	Richard[18]
Lexical based	Corpus	Product reviews	74.00%	Turkey
	Dictionary	Amazon's Mechanical Turk	---	Taboada[20]

Conclusions:

1. If we have clean labeled training data with a domain and context specific orientation, machine learning methods perform much better than lexicon-based methods.
2. But when we can't obtain the training data with label in a specific domain, lexicon-based methods perform better than machine learning methods.

Data preprocessing

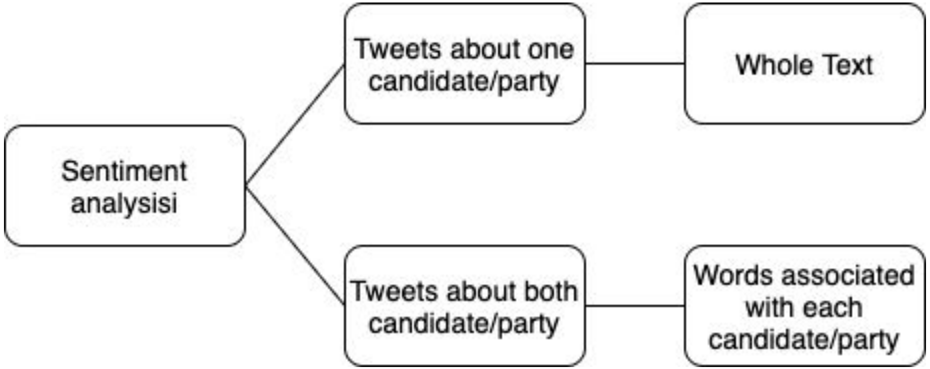
- ML based data preprocessing:
    - The text is tokenized
    - Correctly handles URLs, common emoticons, phone numbers, HTML tags, twitter mentions and hashtags, numbers with fractions and decimals, repetition of symbols and Unicode characters

- Lexicon based data preprocessing:
    - No need to train a model
    - No need to clean data
    - E.g. The past tense ‘hated’ is judged more negative than the present tense ‘hates’ in dictionary

Political alignment (Rep or Dem?)

The method used broadly for political alignment is context-dependent. Lots of research only consider tweets mentioning a single entity, i.e., tweets referring to more than one candidate are excluded, for example in [35].

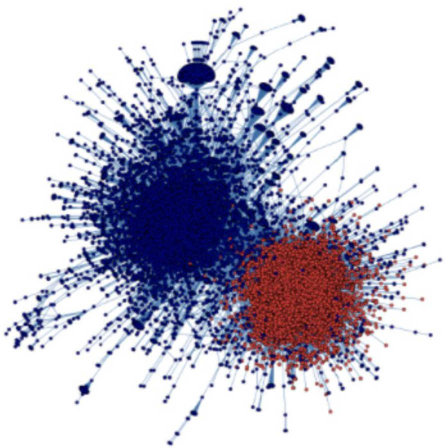
We instead also consider including the tweets mention more than one candidate respect to the following steps. Similar method in paper[36]



Digression: Political alignment without Sentiment analysis

In [57], instead of using sentiment analysis to classify the users, this paper use the communication network to cluster the users.

1. Construct two networks: one based on mention edges and one based on retweet edges. The edges are undirected with weighted count.
2. Manually label ⅕ random users in the network, then cluster the users based on a community detection algorithm using the label propagation method of Raghavan et al.

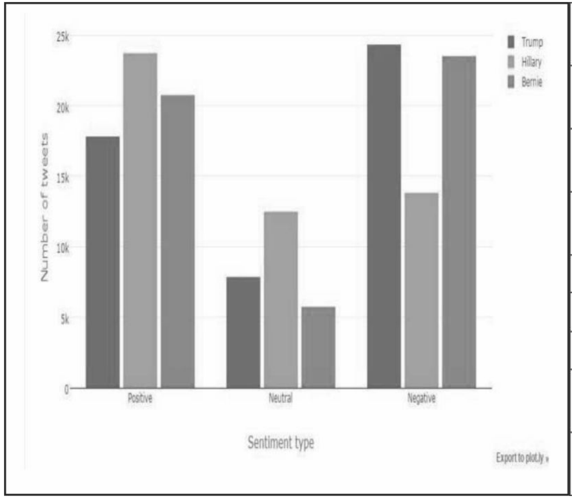


The result shows that techniques based on the statistical analysis of political communication networks provide the highest accuracy than text-content based approach. But this method needs human labeled users.

Lexicon based approach example

In [37], the author used lexicon method to classified the tweets about 2016 US election and generate word cloud, group bar graph and table to visualize the results.

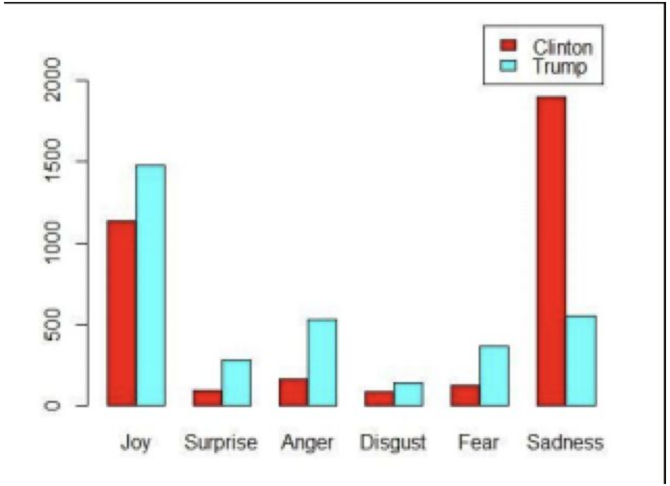
The experiment was completed before the official 2016 election result. **The paper predicts Clinton will win the election**, but it is incorrect and the results of the experiment did not explain the causal relationship between people’s attitudes and the results of the election. **It is difficult for us to make accurate predictions about the election simply by analyzing people’s attitudes directly.**



Name	Donald Trump	Hillary Clinton	Bernie Sanders
No. of positive comments	17812	23716	20748
No. of Neutral comments	7853	12475	5741
No. of Negative comments	24335	13809	23511
% Positive	35.624	47.432	41.496
% Negative	15.706	24.95	11.48
% Negative	48.67	27.618	47.022
Average Polarity	-0.0073	0.0482	0.0282
Average Subjectivity	0.278	0.2809	0.3138

Machine learning based approach example

In [38], the author used naive bayes method to classified the tweets about 2016 US election and generate word cloud, group bar graph and table to visualize the results. This time instead of using only three variable, it used 6 different variables for emotion analysis. Six different variable such as **joy**, **surprise**, **anger**, **disgust**, **fear** and **sadness**.



1. We observed that Sadness and joy were among most expressed emotions in our data. Hillary Clinton's had more tweets about sadness and trump has more expressing joy.
2. This suggests that in election **trump will get benefit of joyous tweets** and trump tweets has more tweets on all other emotions. It can be observed that **large part of Clinton tweets express sadness**.
3. This figure makes a little bit more sense for judgment on the results of the 2016 election, but it also shows that purely emotional judgments cannot be effectively judged. **We may need to apply this method to users level instead of tweets from all users about a candidate**

Sentiment analysis development

In [39], the author accurately predict the election outcome, infer the sentiment of the candidate photos shared in the social media communities, and account for the sentiment of viewer comments towards the candidates on the related images. VAR(Vector AutoRegression) for forecasting

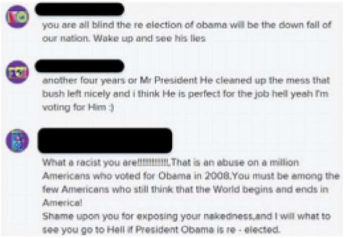


TABLE II
PREDICTION FOR THE SWING STATES ON ELECTION DAY

State	Official		AR		Flickr-AR		VAR		CVAR	
	Obama	Romney	Obama	Romney	Obama	Romney	Obama	Romney	Obama	Romney
CO	0.5239	0.4761	0.5073	0.4927	**0.5076**	**0.4924**	0.5059	0.4941	0.5049	0.4951
FL	0.5044	0.4956	0.4936	0.5064	0.4928	0.5072	0.4917	0.5083	**0.5018**	**0.4982**
IA	0.5287	0.4713	0.5139	0.4861	0.5132	0.4868	0.5153	0.4847	**0.5291**	**0.4709**
NC	0.4891	0.5109	0.4851	0.5149	0.4845	0.5155	**0.4866**	**0.5134**	0.4488	0.5512
NV	0.5335	0.4665	0.5144	0.4856	0.5144	0.4856	0.5165	0.4835	**0.5362**	**0.4638**
OH	0.5098	0.4902	0.5155	0.4845	0.5150	0.4850	**0.5105**	**0.4895**	0.5120	0.4880
VA	0.5157	0.4843	0.5022	0.4978	0.5019	0.4981	0.5013	0.4987	**0.5185**	**0.4815**
WI	0.5339	0.4661	0.5218	0.4782	0.5219	0.4781	**0.5285**	**0.4715**	0.5460	0.4540

- Therefore, sentiment analysis prediction still has a lot of room for development. By using a variety of emotion types and using different data sources, sentiment analysis can become more powerful

Presentation Roadmap

- Introduction
- Election Prediction
- Sentiment Analysis
- **User and Tweet Filtering**
- User Profiling
- Conclusion

Inference from Misinformation – Bots

Why bots?

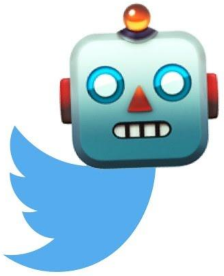
- An attempt for the politicians to make people believe in the favored and biased opinions [1].

How many?

- Among 30.7 million tweets, 25% links to fake news or extremely biased website, 8% are likely bots and responsible for 30-40% tweets [2].

What can they do?

- Make our dataset biased and result in wrong prediction.

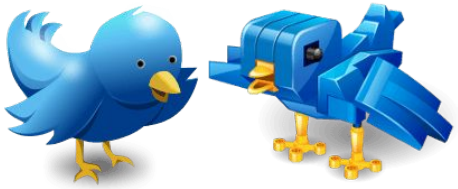


A twitter bot

Filtering Out Bots - Baseline

To improve our prediction results, we need to filter out bots to our election prediction.
Botometer (formerly BotOrNot) is a tool suggested [4].
Generate 1000 features which can be grouped into 6 classes:

1. Network(information diffusion pattern: retweet, mention, ...)
2. User(acc. creation time, location, …)
3. Friends(social statistics, …)
4. Temporal(timing patterns of content creation)
5. Content(linguistic cues)
6. Sentiment(emotion score).

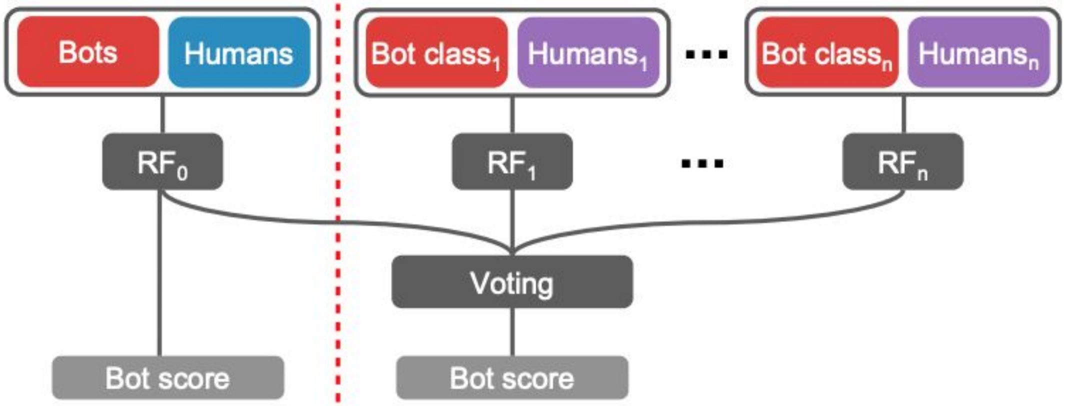


- Trained with >5.6 millions tweets
- Random Forest based algorithm to give bot score

Filtering Out Bots – Improved

Ensemble of Specialized Classifiers (ESC) [32]

- Better cross-domain performance
    - More generalized
- Easy to adapt model with novel cases
    - Add a new classifier RF[n+1] to be trained with the new data without retraining existing ones



Presentation Roadmap

- Introduction
- Election Prediction
- Sentiment Analysis
- User and Tweet Filtering
- **User Profiling**
- Conclusion

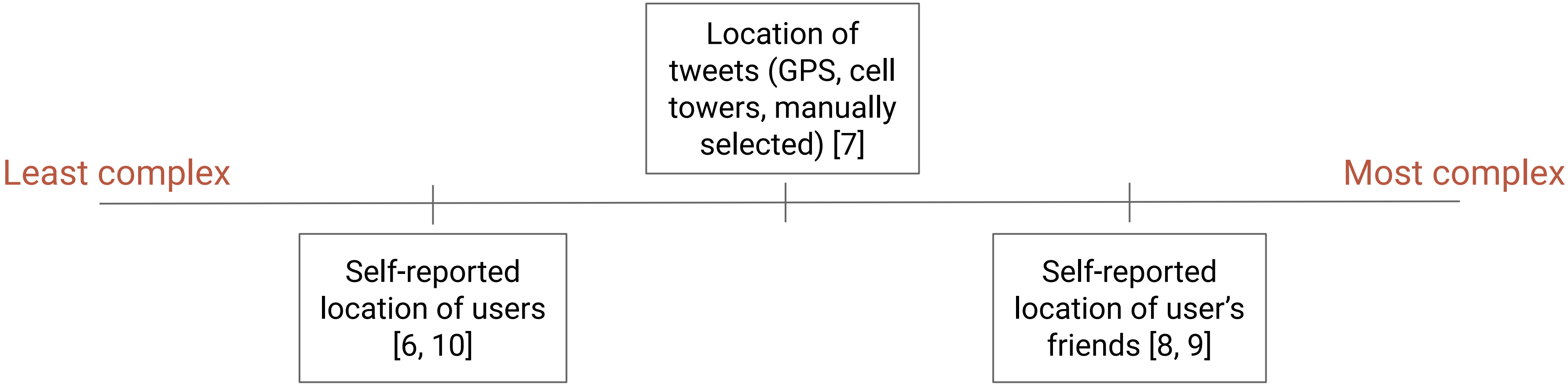
Profiling Users

Why profile users?

- If users on social media do not represent the diverse group of people who vote (in age, gender, race, etc.), we need to take this into account while considering if social media can be used to predict election results
- The general idea in literature is to exploit some aspect of Twitter users' profiles in order to learn something about them

What we want to know: a user's location, gender, race/ethnicity, age
How can we learn it?: a user's tweets, name, profile picture or other visual markers on their profile, self-reported information, following/follower network

Locating Users By...



Locating Users By...

Least complex

Most complex

Self-reported location of users [6, 10]

Pros:

- Simple
- ~75% of users are labeled [6]

Cons:

- Unknown accuracy
- Users may move, lie, or give non-specific responses (like Earth or USA)

Locating Users By...

Pros:

- Actual measurement of location (accurate!)

Cons:

- Only ~1% of tweets are geolocated - to use this method, you need a lot of tweets! [7]
- Location of tweets does imply location of user

Location of tweets (GPS, cell towers, manually selected) [7]

Most complex

Locating Users By...

Least complex

Pros:

- ~50% of users can be located using their friends' locations alone [8]

Cons:

- Same as first method, because of self-reported location, but less pronounced because of volume of data
- Need to collect much more data (entire network of each user)

Most complex

Self-reported location of user's friends [8, 9]

Profiling Users by Gender

From our review of the literature, we found that the most straightforward way to classify twitter users by gender is by looking at **first names** [6, 11]. In [6] there is a match for 64.2% of users (US), and in [11] only 14.7% (UK). This discrepancy makes it quite difficult to know how useful this method is.

No need for labeled data, but cannot calculate accuracy.

Other methods:

- Color-based classification [12]

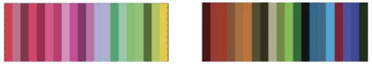


Figure 4. Spectrum of popular colors for female users (left-hand side) and male users (right-hand side).

- Text and image processing [13]

Need labeled data.

Self-Selection Bias of Twitter Users

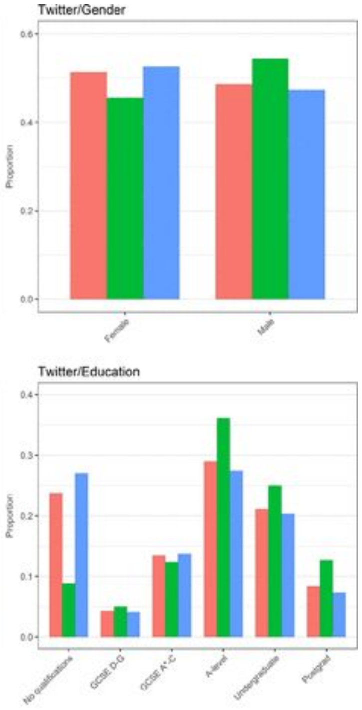
Why analyze self-selection bias?

- Since Twitter users who tweet about politics are self selected, many researchers hypothesize that Twitter is biased toward the very politically active
- We need to understand if this is an issue that needs to be corrected before answering our question
- We looked to the literature to understand selection bias of Twitter users

Note: some papers which predict elections do not take demographic data into account at all, yet claim to accurately predict elections. Some papers note that this is a deficiency in their own work [15]. Others [16, 17] observe that ignoring demographic data of users is an issue in current work.

Selection Bias Results

In the UK, Twitter and Facebook users differed from the general population on relevant dimensions like vote choice, turnout, age, gender, and education. However, the authors conclude that after controlling for age, gender, and education, there will be no statistically significant difference in political behavior between social media users and the general population [14].



More Selection Bias Results

In [33], the authors study demographic distribution differences between Twitter and real life in 6 cities in Brazil.

This data corroborates various other papers we read [6].

TABLE III. TWITTER SAMPLE VERSUS REAL USER DISTRIBUTIONS FOR ELECTIONS

Features	Value	MG	PR	RS	RJ	BA	SP
Twitter Distribution							
Gender	Male	75.31	73.57	75.90	69.08	77.61	74.58
	Female	24.69	26.42	24.10	30.92	22.39	25.41
Age	Up tp 25	28.19	42.37	27.77	48.80	16.50	35.28
	25 to 45	29.23	30.08	40.87	31.96	36.90	41.21
	Above 45	42.58	27.54	31.36	19.23	46.60	23.50
Social Cl.	Lower	2.03	2.24	2.43	2.58	11.62	3.02
	Medium	25.31	35.39	32.79	40.94	18.31	27.73
	Upper	72.66	62.36	64.78	56.48	70.07	69.24
Real Distribution							
Gender	Male	46.03	45.83	45.38	45.33	45.72	46.17
	Female	53.89	54.17	54.63	54.53	54.20	53.63
Age	Up tp 25	13.90	15.49	12.64	12.73	14.57	14.32
	25 to 45	42.95	44.09	39.36	38.59	47.80	43.38
	Above 45	43.15	40.42	48.00	48.68	37.63	42.29
Social Cl.	Lower	26.50	13.24	24.32	30.96	36.04	23.71
	Medium	52.54	58.20	49.00	48.84	48.29	54.63
	Upper	20.97	28.56	26.68	20.20	15.67	21.66

Even More Selection Bias Results

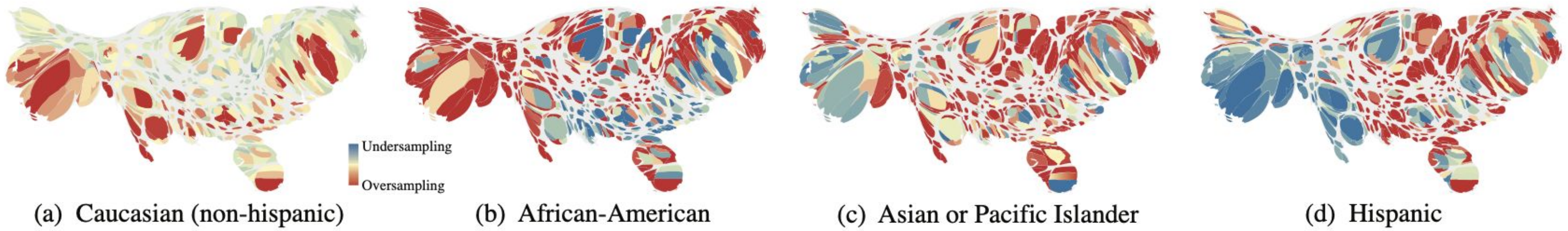


Figure 4: Per-county area cartograms of Twitter over- and undersampling rates of Caucasian, African-American, Asian, and Hispanic users, relative to the 2000 U.S. Census. Only counties with more than 500 Twitter users with inferred race/ethnicity are shown. Blue regions correspond to undersampling; red regions to oversampling.

From our study of this literature, it seems that Twitter is not representative of the general population due to some self-selection bias. However, few studies have been done that address how under/over sampling key groups could correct this bias. Above image from [6].

Presentation Roadmap

- Introduction
- Election Prediction
- Sentiment Analysis
- User and Tweet Filtering
- User Profiling
- **Conclusion**

“To what extent has social media been used to predict elections?”

- This literature has a 15 year long history that will likely continue (top papers have 3000+ citations)
- Simple raw counts of tweets → real-time analysis, graph structures, distance metrics, and statistical models
- Demographic & self-selection biases of Twitter users is often not addressed
- Filtering tweets to address bots, spam, disinfo, potential voters (18+) is beginning to be considered
    - Use of multiple Random Forest classifiers is more generalizable and performs better in cross-domain cases
- Basic methods for sentiment analysis (little thought given to emojis, humor, and sarcasm), user demographic profiling, and user political alignment profiling
    - Recent papers ([52, 57]) are using social network analysis and to advance these basic methods
    - Sentiment analysis improvements - inclusion of more emotions and non-textual features
- Theoretical improvements to election prediction methods are often unmeasurable or inconclusive
    - No generalizable evaluation metric for predicting elections
    - Most papers do post-hoc analysis
- Election prediction remains an open problem

Citations

1. Kahan DM. Ideology, motivated reasoning, and cognitive reflection: An experimental study. Judgment and Decision Making. 2013;8:407–424.
2. Bovet, Alexandre & Makse, Hernán. (2019). Influence of fake news in Twitter during the 2016 US presidential election. Nature Communications. 10. 10.1038/s41467-018-07761-2.
3. Shao, C., Ciampaglia, G., Varol, O., Flammini, A., & Menczer, F. (2017). The spread of misinformation by social bots.
4. C. A. Davis, O. Varol, E. Ferrara, A. Flammini, and F. Menczer. Botornot: A system to evaluate social bots. In Proceedings of the 25th International Conference Companion on World Wide Web, pages 273–274, 2016.
5. A. Malhotra, L. Totti, W. Meira Jr., P. Kumaraguru and V. Almeida, "Studying User Footprints in Different Online Social Networks," 2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, Istanbul, 2012, pp. 1065-1070, doi: 10.1109/ASONAM.2012.184.
6. Mislove, Alan, et al. "Understanding the demographics of twitter users." Icwsm 11.5th (2011): 25.
7. Li, Linna, Michael F. Goodchild, and Bo Xu. "Spatial, temporal, and socioeconomic patterns in the use of Twitter and Flickr." Cartography and geographic information science 40.2 (2013): 61-77.
8. Rout, Dominic, et al. "Where's@ wally? a classification approach to geolocating users based on their social ties." *Proceedings of the 24th ACM Conference on Hypertext and Social Media*. 2013.
9. Backstrom, Lars, Eric Sun, and Cameron Marlow. "Find me if you can: improving geographical prediction with social and spatial proximity." *Proceedings of the 19th international conference on World wide web*. 2010.
10. Java, Akshay, et al. "Why we twitter: understanding microblogging usage and communities." *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 workshop on Web mining and social network analysis*. 2007.

Citations cont.

11. Sloan, Luke. “Who Tweets in the United Kingdom? Profiling the Twitter Population Using the British Social Attitudes Survey 2015.” *Social Media + Society*, Jan. 2017, doi:10.1177/2056305117698981.
12. Alowibdi, Jalal S., Ugo A. Buy, and Philip Yu. "Language independent gender classification on Twitter." *Proceedings of the 2013 IEEE/ACM international conference on advances in social networks analysis and mining*. 2013.
13. Sakaki, Shigeyuki, et al. "Twitter user gender inference using combined analysis of text and image processing." *Proceedings of the Third Workshop on Vision and Language*. 2014.
14. Mellon, Jonathan, and Christopher Prosser. “Twitter and Facebook Are Not Representative of the General Population: Political Attitudes and Demographics of British Social Media Users.” *Research & Politics*, July 2017, doi:10.1177/2053168017720008.
15. Choy, Murphy, et al. "Us presidential election 2012 prediction using census corrected twitter model." *arXiv preprint arXiv:1211.0938* (2012).
16. Gayo-Avello, Daniel. "I Wanted to Predict Elections with Twitter and all I got was this Lousy Paper"--A Balanced Survey on Election Prediction using Twitter Data." *arXiv preprint arXiv:1204.6441* (2012).
17. Beauchamp, Nicholas. "Predicting and interpolating state-level polls using Twitter textual data." American Journal of Political Science 61.2 (2017): 490-503.
18. Mellon, Jonathan, and Christopher Prosser. “Twitter and Facebook Are Not Representative of the General Population: Political Attitudes and Demographics of British Social Media Users.” *Research & Politics*, July 2017, doi:10.1177/2053168017720008.
19. Adamic, Lada A., and Natalie Glance. "The political blogosphere and the 2004 US election: divided they blog." Proceedings of the 3rd international workshop on Link discovery. 2005.
20. Rigdon, Steven E., et al. "A Bayesian prediction model for the US presidential election." American Politics Research 37.4 (2009): 700-724.

Citations cont.

21. Anstead, Nick, and Ben O'Loughlin. "Social media analysis and public opinion: The 2010 UK general election." Journal of Computer-Mediated Communication 20.2 (2015): 204-220.
22. Shi, L.. “Predicting US Primary Elections with Twitter.” (2012).
23. Ceron, Andrea, Luigi Curini, and Stefano M. Iacus. "Using sentiment analysis to monitor electoral campaigns: Method matters—evidence from the United States and Italy." Social Science Computer Review 33.1 (2015): 3-20.
24. A multifaceted approach to social multimedia-based prediction of elections Q You, L Cao, Y Cong, X Zhang, J Luo IEEE Transactions on Multimedia 17 (12).
25. Tunggawan, Elvyna, and Yustinus Eko Soelistio. "And the winner is…: Bayesian Twitter-based prediction on 2016 US presidential election." 2016 International Conference on Computer, Control, Informatics and its Applications (IC3INA). IEEE, 2016.
26. Wicaksono, Andy Januar. "A proposed method for predicting US presidential election by analyzing sentiment in social media." *2016 2nd international conference on science in information technology (ICSITech)*. IEEE, 2016.
27. Kassraie, Parnian, Alireza Modirshanechi, and Hamid K. Aghajan. "Election Vote Share Prediction using a Sentiment-based Fusion of Twitter Data with Google Trends and Online Polls." *DATA*. 2017.
28. Grover, Purva, et al. "Polarization and acculturation in the 2016 US presidential election: Can Twitter analytics predict changes in voting preferences?." Technological Forecasting and Social Change (2018).
29. Ahammed, Md Sohel, Md Nahid Newaz, and Arunavo Dey. "Analyzing Political Opinions and Prediction of Voting Patterns in the US Election with Data Mining Approaches." Global Journal of Computer Science and Technology (2019).
30. Sanders, Eric, and Antal van den Bosch. "Optimising Twitter-based Political Election Prediction with Relevance andSentiment Filters." Proceedings of The 12th Language Resources and Evaluation Conference. 2020.

Citations cont.

31. Shirodkar, Madhura et al. “Election result prediction using Sentiment Analysis.” (2020).
32. Mohsen Sayyadiharikandeh, Onur Varol, Kai-Cheng Yang, Alessandro Flammini, and Filippo Menczer. 2020. Detection of Novel Social Bots by Ensembles of Specialized Classifiers.
33. Miranda Filho, Renato, Jussara M. Almeida, and Gisele L. Pappa. "Twitter population sample bias and its impact on predictive outcomes: a case study on elections." *2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*. IEEE, 2015.
34. Sentiment Analysis of Twitter Data: A Survey of Techniques. *International Journal of Computer Applications* 139(11):5-15, April 2016
35. Twitter Population Sample Bias and its impact on predictive outcomes: a case study on elections
36. Using sentiment analysis to define twitter political users’ classes and their homophily during the 2016 American presidential election
37. Ms. Farha Nausheen et al., “Sentiment Analysis to Predict Election Results Using Python”, Proceedings of the Second International Conference on Inventive Systems and Control (ICISC 2018).
38. Ms. Farha Nausheen et al., “Sentiment Analysis to Predict Election Results Using Python”, Proceedings of the Second International Conference on Inventive Systems and Control (ICISC 2018)
39. A multifaceted approach to social multimedia-based prediction of elections Q You, L Cao, Y Cong, X Zhang, J Luo IEEE Transactions on Multimedia 17 (12)
40. Vepsäläinen, Tapio, Hongxiu Li, and Reima Suomi. "Facebook likes and public opinion: Predicting the 2015 Finnish parliamentary elections." *Government Information Quarterly* 34.3 (2017): 524-532.

Citations cont.

41. Gayo-Avello, Daniel. "A meta-analysis of state-of-the-art electoral prediction from Twitter data." *Social Science Computer Review* 31.6 (2013): 649-679
42. Beauchamp, Nicholas. "Predicting and interpolating state-level polls using Twitter textual data." *American Journal of Political Science* 61.2 (2017): 490-503.
43. Ginsberg, Jeremy, et al. "Detecting influenza epidemics using search engine query data." *Nature* 457.7232 (2009): 1012-1014.
44. Lau, Jey Han, Nigel Collier, and Timothy Baldwin. "On-line trend analysis with topic models:# twitter trends detection topic model online." *Proceedings of COLING 2012*. 2012.
45. Tumasjan, Andranik, et al. "Predicting elections with twitter: What 140 characters reveal about political sentiment." *Fourth international AAAI conference on weblogs and social media*. 2010.
46. Jürgens, Pascal, Andreas Jungherr, and Harald Schoen. "Small worlds with a difference: New gatekeepers and the filtering of political information on Twitter." *Proceedings of the 3rd international web science conference*. 2011.
47. Gayo Avello, Daniel, Panagiotis T. Metaxas, and Eni Mustafaraj. "Limits of electoral predictions using twitter." *Proceedings of the fifth international AAAI conference on weblogs and social media*. Association for the Advancement of Artificial Intelligence, 2011.
48. Skoric, Marko, et al. "Tweets and votes: A study of the 2011 singapore general election." *2012 45th hawaii international conference on system sciences*. IEEE, 2012.
49. Sang, Erik Tjong Kim, and Johan Bos. "Predicting the 2011 dutch senate election results with twitter." *Proceedings of the workshop on semantic analysis in social media*. 2012.
50 O'Connor, Brendan, et al. "From tweets to polls: Linking text sentiment to public opinion time series." *Tepper School of Business* (2010): 559.

Citations cont.

51. Ceron, Andrea, Luigi Curini, and Stefano M. Iacus. "Using sentiment analysis to monitor electoral campaigns: Method matters—evidence from the United States and Italy." Social Science Computer Review 33.1 (2015): 3-20.
52. Livne, Avishay, et al. "The party is over here: Structure and content in the 2010 election." *ICWSM* 11.2011 (2011): 17-21.
53. Metaxas, Panagiotis T., Eni Mustafaraj, and Dani Gayo-Avello. "How (not) to predict elections." *2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing*. IEEE, 2011.
54. Gayo Avello, Daniel, Panagiotis T. Metaxas, and Eni Mustafaraj. "Limits of electoral predictions using twitter." *Proceedings of the fifth international AAAI conference on weblogs and social media*. Association for the Advancement of Artificial Intelligence, 2011.
55. Mellon, Jonathan, and Christopher Prosser. "Twitter and Facebook are not representative of the general population: Political attitudes and demographics of British social media users." *Research & Politics* 4.3 (2017): 2053168017720008.
56. Huang, Yuan, et al. "Understanding US regional linguistic variation with Twitter data analysis." *Computers, environment and urban systems* 59 (2016): 244-255.
57. Conover, Michael D., et al. "Predicting the political alignment of twitter users." *2011 IEEE third international conference on privacy, security, risk and trust and 2011 IEEE third international conference on social computing*. IEEE, 2011.
58. Wang, Hao, et al. "A system for real-time twitter sentiment analysis of 2012 us presidential election cycle." *Proceedings of the ACL 2012 system demonstrations*. 2012.