Buzzer Detection and Sentiment Analysis for Predicting Presidential Election Results in A Twitter Nation

Mochamad Ibrahim, Omar Abdillah, Alfan F. Wicaksono, Mirna Adriani
Information Retrieval Lab.
Faculty of Computer Science
Universitas Indonesia
Depok, Republic of Indonesia
{mochamad.ibrahim, omar.abdillah31}@ui.ac.id, {alfan, mirna}@cs.ui.ac.id

***Abstract*—In this paper, we present our approach for predicting the results of Indonesian Presidential Election using Twitter as our main resource. We explore the possibility of easy-to-gather Twitter data to be utilized as a survey supporting tool to understand public opinion. First, we collected Twitter data during the campaign period. Second, we performed automatic *buzzer* detection on our Twitter data to remove those tweets generated by computer bots, paid users, and fanatic users that usually become noise in our data. Third, we performed a fine-grained political sentiment analysis to partition each tweet into several sub-tweets and subsequently assigned each sub-tweet with one of the candidates and its sentiment polarity. Finally, to predict the election results, we leveraged the number of positive sub-tweets for each candidate. Our experiment shows that the mean absolute error (MAE) of our Twitter-based prediction is 0.61%, which is surprisingly better than the prediction results published by several independent survey institutions (offline polls). Our study suggests that Twitter can serve as an important resource for any political activity, specifically for predicting the final outcomes of the election itself.**

I. Introduction

The role of social media, such as Twitter and Facebook, has currently become a critical tool for political activities. In 2008, all of the US presidential candidates used social media like Facebook to grab a number of supporters. According to Cornfield [1], the great success of Barack Obama was attributed to the ”online politics” strategy accomplished by his campaign team. Regarding direct election prediction, interesting results were reported by Tumasjan et al. [2], who conducted research to find out if Twitter messages reflect the results of parliamentary election in Germany. They found that the number of messages in Twitter (i.e. ”tweets”) mentioning a political party surprisingly reflects the election result of that party, with only small differences to the actual election results. Moreover, the number of messages that contain joint mentions between two parties also reflects the real world political coalitions. Following their work, Bermingham and Smeaton [3] extended the work conducted by Tumasjan et al. [2] with respect to the Irish General Election. They concluded that sentiment analysis and volumed-based measures are predictive enough for the outcomes of the election. For presidential election, Beauchamp [4] showed that an extensive analysis of political tweets can predict fully state-level polling variation for presidential election in the US. Eventhough it is still difficult to draw a general conclusion by merely looking at these previous results, but these suggest that Twitter somehow can be used as an indicator of political sentiments and actual issues.

The aforementioned previous studies have shown that Twitter can really reflects, even predicts the outcomes of election. In this paper, we address similar issue with respect to the Indonesian Presidential Election in 2014. Indonesia itself is the world’s third-largest democratic country after India and the US, and one of the emerging economic countries in Asia-Pacific [5]. In 2014, Indonesia held legislative as well as presidential election. For presidential election, Indonesia had two president-vice president candidates: Mr. Prabowo Subianto-Mr. Hatta Rajasa and Mr. Joko Widodo (Jokowi)-Mr. Jusuf Kalla. Both candidates actively used Twitter for political engagement and campaign. Mr. Joko Widodo had the most followers at that time (1.6 million followers), followed by Mr. Prabowo Subianto (950 K followers), Mr. Jusuf Kalla (929 K followers), and Mr. Hatta Rajasa (636 K followers) [6].

As the microblogging online service, Twitter itself has became one of the most popular social media in the world with more than 200 million of active users[1] and 10.6 billion of tweets world-wide[2]. Every user easily shares their personal feeling, opinion, expression, news, or hot topic through Twitter. Indonesia, as one of the largest countries in the world with more than 220 million of people, is also becoming a country which has a huge number of Twitter’s active users. According to *Semiocast*, there are around 29.4 million Twitter users in Indonesia and Jakarta (the capital city of Indonesia) is the most active Twitter city in the world [7].

To measure the popularity of individuals, current market researchers, such as independent survey institutions, mostly employ an approach that includes human effort to collect the data accross the nation. In the case of Indonesia, survey activities usually involve face-to-face interviews, phone calls, and text messaging via short message service (SMS) [8]. These activities are time-consuming and expensive. Therefore, knowing that social media, like Twitter, is growing rapidly nowadays and also becoming a massive tool for political

[1] https://twitter.com/twitter/status/281051652235087872
[2] https://www.techinasia.com/indonesia-social-jakarta-infographic/

978-1-4673-8493-3/15 $31.00 © 2015 IEEE
DOI 10.1109/ICDMW.2015.113

activities, we then investigate whether or not analyzing massive Twitter messages can be used as an alternative to what current opinion polls and survey institutions do for presidential election. This is a challenging task since a Tweet is limited to only 140 characters, which is clearly much shorter than messages coming from other social media platforms, like weblogs and web forums. Moreover, previous studies conducted by Pear Analytics has suggested that 40% of all Tweets are just "mindless babbles" of people [9]. The other challenge is that how to detect *Buzzer* accounts from a huge Twitter corpora. We defined Buzzers as accounts that only talk about one of the candidates, while vilifying the other candidates. They most likely have been paid to deliberately mobilize users' opinion using false information. As a result, a special approach must be employed for this work.

In this paper, we present our system that we have developed for the Indonesian Presidential Election in July 2014. We employed lexicon and keyword based approaches to reveal the political sentiment of each candidate from Twitter messages crawled before the election. Moreover, we also employed *Buzzer* account detection and eliminated those messages generated by the Buzzers, which was never addressed in the previous work. We also examine if Indonesian political Twitter messages reflect the real world activities of Indonesian Presidential Election. Finally, we evaluate the result of our study by comparing it to the prediction outcome from survey institutions and Indonesian government. Our contributions in this research area are two-folds: (1) we employed Twitter user profiling approach to detect *Buzzer* from dataset and (2) we confirmed the study conducted by Prasetyo [10] which suggested that Twitter can be used as a survey resource for political activities.

II. Related Work

The studies regarding predicting election outcomes in several countries using Twitter data have been conducted in the past few years. One of the earliest extensive studies is the one conducted by Tumasjan et al. [2], which collected all tweets containing 6 parties in German and subsequently extracted the sentiment of those tweets using LIWC2007 [11]. In order to use LIWC, they automatically translated the crawled German tweets into English. To predict the election outcomes of a particular political party, they leveraged the number of tweets that mention the party. Following that, Jungherr et al. [12] then criticized the time period used by Tumasjan et al. [2] to collect the tweets and showed that including the data one week before the election harmed the prediction accuracy. In the US, O'Connor et al. [13] investigated the connection between the public opinion measured from polls and public sentiment measured from Twitter messages with respect to the US Presidential Election in 2008. They suggested that analyzing simple-to-gather Tweets would be an alternative to the expensive and time-intensive polling [13].

The following similar research then came up with different domain, several modifications, or extended methods. Sang and Bos [14] replicated the work of Tumasjan et al. [2] with respect to the Dutch Senate Election in 2011. Beauchamp [4] proposed a model to correlate the US state-level polls and the textual content of state-located Twitter messages using an approach, so called "time-series cross-sectional method plus bayesian shrinkage". Finally, Makazhanov and Rafiei [15] used "user-party interaction" to predict the political preference of users with respect to the Canadian Election. They also performed extensive data cleaning before analyzing the Twitter messages. Actually, before the aforementioned Twitter-based prediction studies, Kim and Hovy [16] have shown the promising results for predicting the outcomes of Canadian District Elections using information mined from a political prediction website.

In fact, Prasetyo [10] has conducted similar studies with respect to Indonesian Presidential Election in 2014. They did extensive works to correlate Twitter messages and presidential election outcomes, even from national level until provincial level. Proper data collection, spam removal, data normalization using demographic information, and sentiment analysis appeared to be very important for predicting the election results [10]. At the national level, his proposed approach successfully predicted the winner of the Presidential Election, with MAE around 0.6%. The difference is that we perform Buzzer detection, which is very important for removing fake or false information. Our work serves as an extension to what have been done by Prasetyo [10] as well as confirming his work. We used a different random Twitter data with the same time period to show that even though our data is different, but we can still produce the same outcomes with the one did by Prasetyo [10].

III. Election Background

On 9th July 2014, a Presidential Election was held in Indonesia to elect one of the two president-vice president candidates: Mr. Prabowo Subianto-Mr. Hatta Rajasa and Mr. Joko Widodo (Jokowi)-Mr. Jusuf Kalla. The most interesting part is that both candidates intensively used well-known social media, such as Facebook and Twitter, as their campaign tool. Mr. Prabowo was the most popular candidate in Facebook, while Mr. Joko Widodo had the most followers in Twitter at that time [6]. Finally, General Elections Commission of Indonesia announced the official results on 22nd July 2014. The winner was Mr. Joko Widodo and Mr. Jusuf Kalla as they obtained 70,997,833 votes (53.15%), followed by Mr. Prabowo and Mr. Hatta Rajasa who obtained 62,576,444 votes (46.85%) [17].

IV. Methodology

A. Data Collection

We collected around 10 million political tweets during the campaign period (May 1st 2014 July 6th 2014) using Twitter Streaming API[3]. To collect those tweets, we used keywords mentioning the name or famous nickname of the two candidates. For example, people have been knowing Mr. Joko Widodo as "Jokowi", instead of his full name. Table I shows some keywords that we used to crawl the political tweets regarding the two candidates.

At the preprocessing stage, we removed "mention character" ("@") followed by the corresponding username, link of website ("http", "www", etc.), and retweet characters ("RT") for each tweet. We performed such preprocessing steps since

[3]https://dev.twitter.com/streaming/overview

TABLE I. THE CANDIDATE KEYWORDS

Candidate	Keywords
Mr. Joko Widodo - Mr. Jusuf Kalla	"jokowi", "jkw", "jokowi-jk", "jusuf kalla", "jk", "joko widodo", "m. jusuf kalla"
Mr. Prabowo Subianto - Mr. Hatta Rajasa	"prabowo", "hatta rajasa", "rajasa", "prabowo hatta", "prabowo subianto"

TABLE II. LIST OF PROPOSED FEATURES

No	Features
1	Average time period for the last 100 tweets from the user
2	Daily frequency of tweet produced by the user
3	The age of user account (from the creation date)
4	The number of URLs mentioned in the last 100 tweets
5	The number of retweets for the last 100 tweets
6	The number of followers
7	The number of following

we excluded the opinion messages produced by the manipulated Twitter users (i.e. computer bots or paid users), contained in a single Tweet.

B. Automatic Buzzer Detection

In our Twitter dataset, there exists kind of users who perform unusual activities that somehow dominate the distribution of the data. Based on our empirical observation, the messages produced by these users often do not reflect the real opinion from a Twitter users. Moreover, they are most likely computer bots, or paid users that work only to support one of the two candidates. We call them as Twitter Buzzers. As we mentioned previously, we found that there are two categories of buzzer. The first category is a computer bot, which is essentially a computer program that automatically performs based on some triggers. For example, if there are tweets that mention some keywords, like "*pemilu*" ("election"), this kind of bot will automatically re-post the tweet (i.e. retweeting). The second category of buzzer is a paid or fanatic user. This kind of user usually posts tweets with high frequency as well as quickly responds to some related tweets. Several local media also reported that every candidate most likely employed paid users in social media to help gaining their popularity[4]. We really need to remove those buzzers since we want our data manifests the real Twitter users.

To detect buzzers, we then performed observation on our data and subsequently found that Twitter buzzers usually produce high frequency of tweets as well as retweets since the buzzer accounts actively post tweets to mobilize other users' opinion. Moreover, we also found that they are usually users with short-term creation date since the accounts are merely created due to a special event, like Presidential Election. To recognize and differentiate buzzers among the normal users, we employ a machine learning approach to develop our computational model. Furthermore, we define a buzzer detection problem as a classification problem, which tries to classify whether or not a given Twitter user is a buzzer. Table II describes our features for this classification problem. All features were devised based on our observation on our data collection.

For the next step, we randomly selected Twitter users and subsequently manually labeled them as "buzzer" or "non-buzzer". Moreover, we asked three annotators to label our training data and we only used the label which was agreed by all annotators. Furthermore, to make our detection process more efficient, we did not applied our classifier to all Twitter users in our data. Instead, based on our preliminary observation, we only considered top 1000 users who have the most frequent number of tweets. We periodically performed this buzzer detection on our data and collected the buzzers in our repository. The performance of our buzzer detection method achieve 86% in terms of accuracy. Later, we will explain these results in the "Evaluations and Results" section.

[4]http://www.rmol.co/read/2014/04/23/152340/Pasukan-Nasi-Bungkus-Itu-Punya-Jokowi-atau-Prabowo-

C. Political Sentiment Analysis

Prasetyo [10] suggested that sentiment analysis serves as a good tool for predicting the election results. We then once again followed his suggestion to see the contribution of sentiment analysis for predicting the election results using our dataset. Moreover, our proposed method analyzes the polarity sentiment until the level of "sub-tweet", which is more fine-grained than the previous one. We consider that, in a single tweet, there might be more than one candidate being discussed. The following procedures describe our method on performing sentiment analysis:

1) We partition each Tweet into several sub-tweets. To do that, we use several delimiters, such as conjunction words, comma, point, question mark, and colons. We use conjuction words to partition a Tweet since they usually appear as border between two clauses (i.e. "sub-tweet"). For example, a tweet like "*jokowi is very close to people, **but** he is just manipulating his reputation*" is partitioned into two sub-tweets: "*jokowi is very close to people*" and "*he is just manipulating his reputation*".
2) We assign each sub-tweet with a candidate's name. To detect the candidates name in every sub-tweet, we simply check the existence of the predefined candidate-related keywords. If a sub-tweet does not contain any candidate's name, then we infer this information from the other sub-tweet within the same tweet. For example, in tweet "*jokowi sangat merakyat, **namun** itu hanya pencitraan*" ("jokowi is very close to people, **but** he is just manipulating his reputation"), there will be two sub-tweets after the first step. The first sub-tweet clearly contains the cadidate's name, i.e. "jokowi". On the other hand, the candidate's name of the second sub-tweet needs to be inferred. In this case, we look at the previous sub-tweet to determine its candidate's name.
3) We remove stopwords and punctuation-marks for every sub-tweet.
4) Finally, we compute the sentiment polarity score for each sub-tweet using Indonesian Sentiment Lexicon [18]

In conducting political sentiment analysis, we used some resources related to the sentiment lexicon. In our case, we used Indonesian sentiment lexicon that have been constructed by Vania et al. [18]. Unfortunately, some words are not suitable for political domain. Here, we modified some words, such as adding word ”*kampungan*” (”plebeian”) that has close relationship with ”Jokowi” (one of the candidates). To determine the sentiment score of each sub-tweet, we employed sentiment aggregation method proposed by [19]:

$$score(w, S) = \sum_{adj \in S} \frac{adj.so}{dist(adj, w)} \tag{1}$$

In this formula, S is a particular sub-tweet and w is a candidate's name of the sub-tweet. In addition, w can be represented as any candidate-related keyword contained in the sub-tweet. Moreover, $adj.so$ denotes the sentiment orientation of an adjective word contained in the sub-tweet and $dist(adj, w)$ denotes the distance between the candidate-related keyword and the adjective word. The sentiment orientation of a word is obtained from the aforementioned sentiment lexicon. If the score is less than zero, it means that the sub-tweet reveals negative sentiment towards the candidate, and vice versa.

D. Predicting Election Results

After we perform preprocessing and buzzer removal on our dataset, we are then ready to use our data for predicting the election results. Previously, Ceron [20] suggested that counting sentiment-bearing tweets towards each candidate gives better prediction results, instead of using basic counting of raw tweets. Prasetyo [10] also confirmed that suggestion by showing that using positive sentiment tweets really improved the prediction results with respect to Indonesian Presidential Election. By using positive tweets, Prasetyo [10] successfully reduced the mean average error (MAE) from 3.3% (using basic counting) to 0.83% (using positive tweets). Based on that suggestion, we also perform our political sentiment analysis tool for predicting the results. We aim at ensuring whether or not their method also works in our dataset with respect to Indonesian Presidential Election.

The difference is that, in our case, we leveraged the number of sentiment-bearing sub-tweets, which is more fine-grained than the previous work. Moreover, we only leveraged the number of positive sub-tweets towards candidates. To predict the election results, we used the dataset crawled during 60 days before 6th July 2015. We did not use the data on 7th and 8th July 2015 since that was ”cooling-off” period, which means that any form of campaign was forbidden.

V. Evaluations and Results

A. Evaluation on Buzzer Detection

We evaluated the performance of our buzzer detection to see if our buzzer detection task is feasible to be applied in our election prediction system. To do that, we randomly selected 100 users that have been automatically labeled as ”buzzers” by our classifier. We then asked three independent participants to recognize the users and judge them into 3 predefined categories: ”computer bot”, ”paid/fanatic user”, and ”normal user” based on their profiles and the content of their tweets. Furthermore, ”computer bot” and ”paid user” labels correspond to ”buzzer” category, while ”normal user” label corresponds to ”non-buzzer” category. As can be seen in Table III, the evaluation shows that the three annotators mostly agreed with the results automatically yielded by our proposed method. The three annotators judged that the accuracy of our buzzer detection method achieves more than 86%, which is very promising and feasible enough for our prediction system.

TABLE III. The Evaluation Results of Our Buzzer Detection System

Evaluator	Accuracy (%)
1st Evaluator	93.3
2nd Evaluator	86.7
3rd Evaluator	86.7

TABLE IV. The Evaluation Results of Our Political Sentiment Analysis System

Evaluator	Accuracy (%)
1st Evaluator	87.2
2nd Evaluator	86.0
3rd Evaluator	76.7

B. Evaluation on Political Sentiment Analysis

We asked three different Indonesian native speakers to evaluate the performance of our proposed method for political sentiment analysis. First, we selected 50 tweets for each candidates randomly (total 100 tweets for both of the candidates). Next, we used our proposed method to determine the sentiment towards each candidate within its corresponding sub-tweets. Finally, we simply asked three evaluators to judge the decisions made by our computational model. Table IV summarizes the judgement results.

According to the evaluators, we see that the performance of our proposed method for political sentiment analysis is effective enough. The average accuracy between the three evaluators reaches 83.3%. In the next section, we show the results of using this sentiment analysis approach for predicting the election results.

C. Results on Election Prediction

To measure the performance of election prediction, we used Mean Absolute Error (MAE), which is defined as

$$MAE = \frac{\sum_{i=1}^{N} |e_i|}{N} \tag{2}$$

In the preceding equation, N is the number of candidates and e_i is the difference between the predicted result and the real result with respect to i-th candidate. In fact, MAE has also been widely used for evaluating political forecasts before [21].

When we used all positive sub-tweets, which was collected during 60 days before the ”cooling-off” period, we obtained 1,501,945 positive sub-tweets (53.93%) and 1,309,826 positive sub-tweets (46.07%) for Mr. Joko Widodo and Mr. Prabowo, repectively. As a result, if we only consider this data, the mean absolute error (MAE) of our prediction is 0.61%, which

TABLE V. THE RESULTS OF PRESIDENTIAL ELECTION PREDICTION. **JOK+** AND **PRA+** REPRESENT THE NUMBER OF POSITIVE SUB-TWEETS TOWARDS JOKOWI AND PRABOWO, RESPECTIVELY.

Duration	JOK+	PRA+	JOK+(%)	PRA+(%)	MAE(%)
5 days	112563	156255	41.87	58.13	11.28
10 days	253274	245736	50,76	49.24	2.39
15 days	409086	338268	54,74	45.26	1.59
20 days	540978	416521	56,50	43.50	3.35
25 days	651481	520620	55,58	44.42	2.43
30 days	705660	591465	54,40	45.60	1.25
35 days	849763	729679	53,80	46.20	0.65
40 days	1104850	868558	55,99	44.01	2.84
45 days	1286359	1052303	55,00	45.00	1.85
50 days	1383545	1189396	53,77	46.23	0.62
55 days	1465145	1263570	53,69	46.31	**0.54**
60 days	1501945	1291706	53,76	46.24	**0.61**

is surprisingly very close to the real official results. We also successfully predicted the winner of the election, i.e. Mr. Joko Widodo.

Prasetyo [10] reported that when he considered positive-bearing tweets for predicting the election result, he obtained 0.83% in terms of MAE, which means that our prediction result is slightly better than his result. But, in this case, we really cannot conclude which method is better since there are many factors that might involve. In fact, when he used the number of users (instead of the number of tweets) and incorporated negative sentiment information, his prediction result could achieve 0.62% in terms of MAE.

To see whether the duration of collecting data really matters in this case or not, we then tried to compute MAE when we used the data collected 5 days, 10 days, 15 days, ..., and 60 days before the cooling-off period. The results can be seen in Table V.

Table V shows that when we used data collected 5 - 20 days before the "cooling off" period, the prediction error is quite high (3.35% - 11.28%). On the other hand, using the data collected during 50 - 60 days, the prediction error have a small value (0.54% - 0.61%). In the middle rows of the table (25 - 45 days), we cannot see the pattern between the duration of collecting data and MAE. This is actually in line with what Prasetyo [10] has mentioned in his thesis. As a result, at this time, we cannot conclude that the statement mentioning "the longer the duration of collecting data, the better the result will be". We need more evidences from the other Twitter dataset for further investigation.

During the campaign period, there were many independent survey institutions that published their works on predicting the presidential election results (offline polls) [10]. Most of them used multistage random sampling to collect the data as well as other time-consuming and expensive tasks, such as face-to-face interview, etc. Table VI shows the comparison between our method and their methods. The detail information of each institution can refer to Prasetyo's thesis [10]. For the survey institution, the best prediction was achieved by SSSG (Soegeng Sarjadi School of Government), with MAE around 0.9% [10].

Table VI shows that the performance of Twitter-based election prediction surprisingly outperforms any method used by several survey institutions. The results show that Twitter-based election prediction successfully predicted the winner of

TABLE VI. TWITTER-BASED ELECTION PREDICTION VS INDEPENDENT SURVEY INSTITUTIONS

Survey Institution/Method	MAE(%)
Twitter-based Method	
Our Method	**0.6**
Prasetyo [10] - using the number of users; positive and negative sentiments	**0.6**
Prasetyo [10] - using the number of positive tweets	**0.8**
Independent Survey Institutions	
SSSG	0.9
Pol Tracking	1.0
LSI Network	1.2
Kompas	1.4
LIPI	2.7
Cyrus Network	3.4
Puskaptis	4.2
IRC	5.6
LSN	7.0

the presidential election (i.e. Mr. Joko Widodo) as well as had lower MAE than the results obtained by several independent survey institutions. Despite the argumentation mentioning that polls conducted by survey institutions are actually political devices to mobilize public opinions [22], this result actually suggests that easy-to-collect Twitter data can really serve as a good resource for predicting the result of Presidential Election.

VI. CONCLUSION

In this paper, we have described our approach in predicting the results of election with respect to Indonesian Presidential Election in 2014. We performed our automatic buzzer detection on our Twitter dataset to remove buzzers, such as computer bot, paid users, and fanatic users that usually produce noise in our data distribution. Then, we used our fine-grained political sentiment analysis to partition each tweet into several sub-tweets and subsequently assigned each sub-tweet with one of the candidates and its sentiment polarity. Finally, to predict the election results, we leveraged the number of positive sub-tweets for each candidate. The mean absolute error (MAE) of our prediction is comparable to the results obtained by the other Twitter-based prediction approach conducted by Prasetyo [10]. Moreover, the most interesting part is that Twitter-based prediction successfully outperforms all prediction results published by several survey institutions. This would suggest that Twitter is a useful resource for predicting the outcomes of Presidential Election, at least in Indonesia.

Our work has several limitations. First, our dataset may not represent all Indonesian voters from all provinces since most Twitter users are concentrated in big cites, such as Jakarta and Bandung (all cities are located in Java island, which is the most populous island in Indonesia) [7], [10]. However, this fact could spark interesting research question on whether or not influential and massive Twitter users could frame opinion on other users, even all citizens in a particular country. This problem was also mentioned by Tumasjan et al. [2]. Moreover, it would be more interesting if our study takes into account the information regarding age, gender, occupation, and many other parameters that is commonly used by conventional survey institutions for selecting the target sample. Second, we cannot perform sentiment analysis on the candidate-related tweets that do not contain one of our keywords. Such case usually happens when there are some discussions regarding one of the candidates as well as replies to those discussions without any mention to the candidate.

To sum up, our result reveals that Indonesian Twitter dataset can serve as one of the important resources for automatically obtaining public opinion toward each candidate. By applying political sentiment analysis and giving consideration to the existence of buzzer account, our method can perform well with 0.61% in terms of MAE, which is better than the conventional prediction method conducted by several independent survey institutions.

Acknowledgment

The authors would like to thank to Amanah Ramadiah, Elsa Anggraini Darwin, and the other members of Information Retrieval Lab, Faculty of Computer Science UI as part of the team to build the system.

References

[1] M. Cornfield, "Yes, it did make a difference," Media & Politics, June 2008. [Online]. Available: Retrieved July 16, 2015, from http://takingnote.tcf.org/2008/06/yes-it-did-make.html

[2] A. Tumasjan, T. Sprenger, P. Sandner, and I. Welpe, "Predicting elections with twitter: What 140 characters reveal about political sentiment," in *International AAAI Conference on Web and Social Media (ICWSM)*, 2010.

[3] A. Bermingham and A. F. Smeaton, "On using twitter to monitor political sentiment and predict election results," in *Proceedings of the Workshop on Sentiment Analysis where AI meets Psychology (SAAIP), IJCNLP 2011*, 2011.

[4] N. Beauchamp, "Predicting and interpolating state-level polling using twitter textual data," in *Meeting on automated text analysis, London School of Economics*, 2013.

[5] H. Clinton, "America's pacific century," *Foreign Policy*, vol. 189, pp. 56–63, 2011.

[6] L. A. Abdillah, "Indonesian's presidential social media campaigns," in *National Conference On Indonesian Information System*, 2014.

[7] Semiocast, "Twitter reaches half a billion accounts more than 140 millions in the us," July 2012. [Online]. Available: Retrieved July 16, 2015, from http://semiocast.com/en/publications/2012_07_30_Twitter_reaches_half _a_billion_accounts_140m_in_the_US

[8] A. Trihartono, "A vox populi reflector or public entertainer? mass media polling in contemporary indonesia," *Procedia Environmental Sciences 17*, pp. 928–937, 2013.

[9] Semiocast, "Twitter study," August 2009. [Online]. Available: Retrieved July 16, 2015, from http://www.pearanalytics.com/ wpcontent/ uploads/2009/08/Twitter-Study-August- 2009.pdf

[10] N. D. Prasetyo, "Tweet-based election prediction," M. Sc. thesis, Delft University of Technology, Delft, Netherland, December 2014.

[11] J. W. Pennebaker, C. K. Chung, M. E. Ireland, A. L. Gonzales, and R. J. Booth, "The development and psychometric properties of liwc2007," Austin, TX, 2007. [Online]. Available: LIWC.net

[12] A. Jungherr, P. Jurgens, and H. Schoen, "Why the pirate party won the german election of 2009 or the trouble with predictions: A response to tumasjan, a., sprenger, t. o., sander, p. g., & welpe, i. m. 'predicting elections with twitter: What 140 characters reveal about political sentiment'," *Social Science Computer Review*, vol. 30, pp. 229–234, 2012.

[13] B. B. O'Connor, "From tweets to polls: Linking text sentiment to public opinion time series," in *ICWSM*, 2010, pp. 122–129.

[14] E. T. K. Sang and J. Bos, "Predicting the 2011 dutch senate election results with twitter," in *Proceedings of SASN 2012, the EACL 2012Workshop on Semantic Analysis in Social Networks*, 2012.

[15] A. Makazhanov and D. Rafiei, "Predicting political preference of twitter users," in *Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, 2013, pp. 298–305.

[16] S.-M. Kim and E. Hovy, "Crystal: Analyzing predictive opinions on the web," in *Proceedings of the Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL)*, 2007.

[17] KPU, "Official election results," July 2014. [Online]. Available: Retrieved July 29, 2015, from http://kpu.go.id/koleksigambar/PPWP_-_Nasional_Rekapitulasi_2014_ -_New_-_Final_2014_07_22.pdf

[18] C. Vania, M. Ibrahim, and M. Adriani, "Sentiment lexicon generation for an under-resourced language," *International Journal of Computational Linguistics and Applications*, vol. 5, pp. 63–78, 2014.

[19] B. Liu, "Sentiment analysis and opinion mining," *Synthesis Lectures on Human Language Technolo-gies*, vol. 5, pp. 1–167, 2012.

[20] C. A. C., L. Curini, and I. S. M., "Using sentiment analysis to monitor electoral campaigns: Method mattersevidence from the united states and italy," *Social Science Computer Review*, 2014.

[21] J. Huber and F. Hauser, "Systematic mispricing in experimental markets evidence from political stock markets," in *In 10th Annual Workshop on Economic Heterogeneous Interacting Agents*, 2005.

[22] P. Hitchens, "The broken compass," *Bloomsbury Publishing*, pp. 56–63.