In-depth Analysis of "Fake News" on Indonesian Elections

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Abstract

The past few years, “fake news” has created a large amount of debate amongst a multitude of communities over its effect in politics and other aspects of society. The reach of fake news was best highlighted during the critical months of the 2016 U.S. presidential election campaign, where the top twenty frequently-discussed false election stories generated 8,711,000 shares, reactions, and comments on Facebook. Furthermore, fake news strikes other communities beyond just politics like the medical sciences with the anti-vaxxer movement and also the environmental sciences with climate change deniers.

This paper strives to further investigate the impact of this phenomenon and conducts an analysis of the spread of “fake news” in the Indonesian Election of 2019 and uses data from Twitter starting on April 20th 2019 over a period of two weeks. The analysis performed involved two aspects. The first aspect is a multivariate analysis to help determine the best factors that should be used to determine the influence of an individual user. The second study observes the subjectivity of tweets and conducts a Sentiment analysis in order to properly assess and evaluate the effects of these opinions. Results ultimately showed that the dissemination of fake news may come from the nature of the topic being discussed and also that the size of the user’s network may not matter as much as the “tightness” of it. These findings also contain limitations involving the length of time with which the data set was compiled over and also are purely confined to Twitter.
Introduction

Fake news is now seen as one of the greatest threats to democracy, journalism, and freedom of expression. It has weakened public trust in governments and its potential impact on the contentious “Brexit” referendum and the equally divisive 2016 U.S. presidential election – which it is reported to have affected– is yet to be realized. The reach of fake news was best highlighted during the critical months of the 2016 U.S. presidential election campaign, where the top twenty frequently-discussed false election stories generated 8,711,000 shares, reactions, and comments on Facebook. This is, ironically, larger than the total of 7,367,000 for the top twenty most-discussed election stories posted by 19 major news websites. Economies are not immune to the spread of fake news either, with fake news being connected to stock market fluctuations and massive trades. For example, fake news claiming that Barack Obama was injured in an explosion wiped out $130 billion in stock value. These events and losses have motivated fake news research and sparked the discussion around fake news.

In Indonesia, fake news has gripped the election cycle and caused public outrage at what many consider and contend to be corruption and meddling with the actual results of elections. This resulted in protests arising on the streets and unrest in many cities throughout the country. And even more importantly, a variety of fake websites and domains were created that drew in Indonesian citizens to vote, only to use their information to falsely vote for the candidate that those behind the website want to back.

The proliferation of social media platforms and the internet have allowed for much of this new information war to come into play. The introduction of these platforms have
significantly cut the costs that were necessary in order for information to be spread, as they can now be done with a simple tweet or shared news article. “Fake news” can instigate online discontent or even real public movements very quickly and it can do so with very little consequence due to the difficulty of policing online activity with resources like VPNs and fake accounts available for all parties involved. Platforms like Twitter and Facebook also serve as central places to spread news or opinions. Communities are constantly forming and while much of the activity can occur in decentralized and small groups, it is extremely effective in organizing and bringing together groups of people with a variety of interests.

Platforms like Twitter and Facebook offer new insight into how social networks have changed and have allowed researchers to look deeply into how society has evolved with it. Researchers have highlighted the flow of information on Twitter and also how news and other information can “cascade” up to two to four degrees of distance from the original source and essentially acts like a “directed social graph” that chronologically links users and the activity of those that they follow (Fabrega, Jorge & Paredes Navarro, Pablo. 2013).

Furthermore, the opinions and emotions of users participating in the social activity plays a great role in the spread of information. Social media platforms, with their lack of strong censorship in many parts of the world, serve as relatively risk-free way to express their ideas without expending much effort. In fact, social media is slowly becoming the predominant way in which we share not just personal but impersonal pieces of information like the daily news (Wong, L.Y.C., and Jacquelyn Burkell, 2017).
Inquiries and Hypothesis

When going into the work, I wanted to first ask several questions in regards to the topic of fake news, specifically what constitutes fake news and how I might be able to identify it.

To start, I wanted to investigate the actors involved in the Indonesian political process like voters, politicians, social media, and news outlets which cover the elections. Which of these groups are influential and capable of disseminating such information? What characteristics do they contain and how do they work to spread this information? This project aims to analyze data on such groups and places particular emphasis on its prevalence on the social media platform: Twitter.

Next, I looked towards investigating how these groups may disseminate fake news and what would make them likely to propagate this type of information. Previous research has shown that if the account, platform, or individual has previously shared or published some type of false story or account, then that group will likely do so once again. Furthermore, there is also evidence that groups, individuals, or platforms with large followings and many references by others are usually the most successful at disseminating information and causing a cascade online. This leads me to hypothesize that groups and institutions with large followings and readers will be most successful at fraudulently influencing the electoral process.

Furthermore, I hypothesize that previous success at generating views and shares by an entity will likely lead to future success at convincing viewers on a specific topic or idea. Data on views and shares generated by entities can be examined for correlation to how influential
that entity is in convincing others to react or share the news items being published. This allows me to identify the most influential nodes in the network and also whether they are official accounts by those involved in the electoral process, self-identified political activists, or those with no connection to these entities and possibly fake accounts used to support certain interests.

I will then proceed to analyze the network dynamics in order to assess how the dissemination of material has influenced public sentiment throughout the country specifically towards the presidential candidates. In order to do so, I will be using some NLP techniques in order to do so, specifically Sentiment analysis. This will help with determining how opinionated the information is and whether or not it will be considered “fake” news. Sentimental analysis proves to be useful in this case because it aptly measures the emotions and context of the users (Hamid Bagheri, Md Johirul Islam, 2017).

**Data Collection and Research Methodology**

Much of the fake news being propagated in the time leading up to the elections was shared on large social media networks like WhatsApp(11.92%), Twitter(12.84%), and Facebook(49.54%) according to Indonesian watchdog organization Mafindo (Sasmito, Aribowo, and Bentang Febrylian, March 2019).

To begin my data collection, I first looked up hashtags that were prominent in the protest and also communicated information about a politician running for office or a political group related to the election. These hashtags could be linked or attached to articles, posts, videos, or anything that communicates some information about the candidates or political process. I proceeded to use Twython, a python wrapper for the Twitter API in order to collect
the data necessary through the Tweepy API (Twitter’s python API). In total I collected 18,650
tweets from 8,300 users over a period of two weeks starting from April 20th, 2019.

Next, I continue my data collection and configuration by creating a follower graph to
map the “directed social graph” of the platform. I construct this graph using directed edges to
link followers and those being followed, or influencers. Accounts can be labeled as
influencers if they are being both followed and following.

Finally I set out to create an outline for user profiles of influence. Twitter contains
valuable information and history from its API on types of activity with metrics by users,
which allowed me to create a profile of each major identified account user or hash tag that
generated significant activity. This profile contains:

1) **Number of Relevant Tweets**: this is the number of relevant tweets that were posted
   about the election in Indonesia

2) **Number of Mentions**: this signifies the amount of times a user was mentioned in
   relation to fake news (whether it is being attacked for posting it or being “assumed” as a
   proponent of such information)

3) **Threshold Inception point**: amount of accounts or tweets followed/posted by user that
   then retweeted or followed an account once the tweet went viral.

4) **Number of Followers**: the number of followers of the account when analyzing users

5) **Initiation time**: Measurement of time from start of post or hashtag until the time the
   account interacts with it.
6) **Eigenvector centrality**: Measurement that approximates influence of node’s activity within a graph based on its placement within it (i.e. when it starts to when it ends and how much activity is generated).

To analyze the dynamics of fake news activity, I built an “influencer graph” through adding an edge from Node Y to Node Z if 1. Y has an Initiation time before Z and 2. if Y follows Z. This design assumes that Y sees some post or news that Z is attempting to share with Z’s followers and that Y then joins in reacting to this activity through a share, like, or even click. One can see visually how this works and also see how it can translate to multiple nodes beyond just Y and Z in the Figure A. The eigenvector centrality of each node contained in the influence graph is a measure of the amount of influence that individual user has in disseminating fake news. Let us consider the situation where Node Y influences only 2 nodes, Node Z and Node K, but Node Z goes on to influence 35 nodes and Node K influences 5 nodes. Node Y has only directly influenced 2 nodes but it has indirectly influenced 40 nodes. This means that Node Y will have a low in-degree of merely 2, but its eigenvector centrality value will be comparatively high.

This graph allows us to measure the variables:

1) **Indirect Influence Score**: this is from the eigenvector centrality of the specific account on the network

2) **Direct Influence Score**: this is measured by the in-degree of the specific accounts
Figure A shows graph between two Nodes Y and Z

Figure B shows graph between nodes and how indirect influence creates the network

**Data Cleaning and Extraction**

One thing to note with the data is that most of the tweets and hashtags are in the Indonesian Language. This means that in order for data to be thoroughly analyzed, it needs to be translated into English.

I will be using the TextBlob library in order to do this translation. TextBlob can access Google Translate’s API and create translation through this access.

```python
from textblob import TextBlob

def translate_english(text):
    try:
        blob = TextBlob(text)
        english_text = str(blob.translate(to='en'))
        print(english_text)
        return english_text
    except:
        return None

tweets['english_text'] = tweets.reset_index().text.apply(translate_english)
```
With this data in hand, I look towards analyzing tweets in which the two presidential candidates: Jokowi or Prabowo are mentioned.

Samples:

Tweet #2005: “Jokowi tidak berasal dari Jawa Tengah. Dia orang Cina!” (1 Jokowi Mention)

Tweet #10516: “Jokowi dan Prabowo selalu bertarung seperti siswa sekolah dasar” (1 mention for each candidate)

These counts can be paired and enumerated in order to see which post mentions which candidate. After that, I use the python pandas lambda function in order to pass through each Twitter entry and apply the method above to generate the number of mentions.

Figure C shows that Prabowo is mentioned far more than Jokowi by nearly 66%.
**Analysis of Results**

After data extraction, I move to analyze the network and devise multivariate analysis for the candidates and noted how influential mentions were in propagating the candidates and specific news topics regarding them.

**Table A: Network Statistics on Presidential Political Mentions.**

<table>
<thead>
<tr>
<th>Candidate</th>
<th>Number of Tweets</th>
<th>Clustering Coefficient</th>
<th>Network Diameter</th>
<th>Avg. Degree</th>
<th>Avg. Path Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prabowo</td>
<td>10519</td>
<td>0.39</td>
<td>8</td>
<td>20.5</td>
<td>3.03</td>
</tr>
<tr>
<td>Jokowi</td>
<td>6051</td>
<td>0.29</td>
<td>12</td>
<td>12.8</td>
<td>4.51</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>8285</strong></td>
<td><strong>0.34</strong></td>
<td><strong>10</strong></td>
<td><strong>16.65</strong></td>
<td><strong>3.77</strong></td>
</tr>
</tbody>
</table>

In order to predict the number of followers influenced by each user, I went on to use multiple linear regression and created a model based on number of Mentions (K1), number of Tweets regarding the election (K2), number of followers (K3), and eigenvector centrality(K4) to model the number of followers directly influenced.

*Followers Directly Influenced = K0 + K1X1 + K2X2 + K3X3 + K4X4 + error*

In order to model those indirectly influenced, I used the number of Mentions (J1), number of Tweets regarding the election (J2), and number of followers (J3).

*Indirect influence score = J0 + J1X1 + J2X2 + J3X3 + error*
The next table reports on these statistics:

Table B: Statistics on variables used in analysis (Values given are means)

<table>
<thead>
<tr>
<th>Number Of Mentions</th>
<th>Number of Tweets</th>
<th>Number of Followers</th>
<th>Eigencentrality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of times User was mentioned By others</td>
<td>Number of Tweets related to election</td>
<td>Total number of followers</td>
<td>Eigencentrality of user</td>
</tr>
<tr>
<td>12.12</td>
<td>14.13</td>
<td>514.3</td>
<td>0.061</td>
</tr>
</tbody>
</table>

As a result of this analysis I was able to come away with Average direct and indirect influence scores as follows:

Average followers directly influenced = 2.1

Indirect influence score = 0.011

Next, I proceed to perform sentiment analysis on the two candidates and attempt to identify and extract subjective information that can be classified as “Fake News” that is beneficial or detrimental to the candidate’s prospects. I run the text through the TextBlob library and use Sentiment analysis in order to detect polarity(positivity/negativity) and subjectivity(opinionated nature) of the statements that I processed. I then identify those statistics in relation to some popular tweets that I singled out and measure whether or not these statements could be true or false regarding one candidate or the other.
As one can see from the table, the tweets contain more favorable than negative for Prabowo relative to Jokowi, with both experiencing very subjective opinions.

**Discussion of Results**

This collection of data revealed many important results regarding my initial hypotheses in addition to producing new findings. The first important point to note is that the number of times a user is mentioned (through retweets or comments, etc) is the greatest predictor of influence in the network. This follows my original hypothesis that those with the largest followings are more likely to cause cascade effects. My results revealed that users with over 8 mentions were able to influence 1.3 more people.

Also, the eigenvector centrality can be seen to have correlation to higher levels of influence. Eigenvector centrality for tweets regarding Prabowo was higher in accordance to the greater amount of activity, and thus influence, that he endowed upon most individuals.
However, since we only have two candidates available, this conclusion cannot be fully drawn even though the correlation implies that it might be there.

We did not see, however, that the more followers a user has the more likely that account would be influential on its users. While there was a slight positive correlation that signaled that, many accounts with many followers (greater than 1000) did not generate a large amount of activity or sentiment when it came to political posts. This may be due to a weak tie between the large followings and the “friend” being followed. Prior research has indicated that although weak ties may help in spreading official information like the spread of disease and new technologies that have been developed, more personal and actionable beliefs are more easily influenced by stronger and closer ties that are well-known (Guilbeault, Douglas, Becker, Joshua, & Centola, Damon, 2018). This means that although a user is following an individual with many followers, the fact that the user probably does not know the other account user well means that they are less likely to take that individual’s word on something as personal as long-held political beliefs especially if they are different from the user’s own.

Strong ties and their relevance in the relationships between users of a social network could play a very strong part in determining how influential an individual within a network can be. Users who are more engaged with followers could signal that there is a stronger tie between the user and followers. While not investigated fully in this study, it could explain another aspect of higher influence in the network that can be accounted for.

Finally, when looking at our sentiment analysis, we see that public sentiment to both candidates is relatively similar, as both get subjective opinions and see stronger negative opinions than positive ones. This means that the sentiment amongst the public is relatively
consistent and could indicate a particular style with which information is generally dispersed on social media. Since we can see that there was significant emotion in many sample tweets, it could be that emotional accounts, and exaggerated claims to an extent, are simply extremely prevalent in social media. In fact, recent research supports that notion, as certain topics like politics draw many exaggerated and emotional claims that we classify here as “Fake News” due to the personal nature of these subjects (Patro, Jasabanta & Baruah, Sabyasachee & Gupta, Vivek & Choudhury, Monojit & Goyal, Pawan & Mukherjee, Animesh. 2018).

Conclusion

In all, our study details the profiles of those that are more influential in spreading news and how the dissemination of exaggerated information may simply stem from the nature of social networks and the subjects being discussed.

A variety of factors contribute to the influence of these individuals, namely the level of engagement between accounts. Surprisingly, the size of the network was not as important as initially hypothesized, which could possibly be due to the lack of strong ties in such a large network. Furthermore, our study views the sentiments felt towards the candidates as a measure of how objective information regarding the political process is spread. In this, we found consistency of generally polar statements and recognize that it could be due simply to the divisive nature of political beliefs where reason is but one of many determining factors as to how users will align themselves.

Although many discoveries have been made, there are also many limitations that put guards on how confident this study is in asserting its findings. Those will be discussed below.


Limitations

The research done has multiple drawbacks to consider with its findings. For one, the data collected was over an approximately two week time span, one week at a time due to limits set by Twitter, and had portions which could not be adequately translated. This small time frame could mean that one candidate simply had a significant amount of activity over another during this time and that there were a good number of news items regarding the other candidate that could swing it over during another week leading up to the election. Looking over the movement over a longer time frame would create a more robust analysis, as the sentiment analysis and network cluster would be larger and more diverse in types of information/news dispersed.

Also, doing more research in comparative analysis on the effectiveness of information dispersion across platforms could give a notion as to the characteristics of more favorable platforms for spreading fake news. A network like Twitter which works like a directed social graph is an ideal example in this case but platforms like Facebook and Instagram could offer other advantages that could be looked into.

These are but two of the potential examples that could be looked into when furthering the research done here.
References


Patro, Jasabanta & Baruah, Sabyasachee & Gupta, Vivek & Choudhury, Monojit & Goyal, Pawan & Mukherjee, Animesh. (2018). Characterizing the spread of exaggerated news content over social media

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