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Identifying misinformation on Twitter with a support vector machine

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Abstract

There is a large amount of information from disparate sources around the world. Due to the recent growth of online social media and its impact on society, identifying misinformation is an important activity. Twitter is one of the most popular applications that can deliver engaging data in a timely manner. Developing techniques that can detect misinformation from Twitter has become a challenging yet necessary task. This article proposes a machine learning method that can identify misinformation from Twitter data. The experiment was carried out with three widely used machine learning methods, naïve Bayes, a neural network and a support vector machine, using Twitter data collected from October to November 2017 in Thailand. The results show that all three methods can detect misinformation accurately. The accuracy of the naïve Bayes method was 95.55%, that of the neural network was 97.09%, and that of the support vector machine 98.15%. Furthermore, we analyzed the misinformation and noted some of its characteristics.

Keywords: Misinformation, Identifying misinformation, Online social network, Support vector machine

1. Introduction

In the past, news spread by word of mouth from person to person. When messages are spread in this way, there are many sources of inaccuracies, such as messages being delivered to the wrong recipients, misinterpretation of the messages, and miscommunication of the messages. Personal biases may be included in the messages as subjective comments before the news is shared. The content of the news may be distorted when a message is sent after a long period of time.

News in an electronic format can spread quickly. Social media has become the dominant source of news. Content from many sources can be absorbed by a reader. However, misinformation can also spread through social media [1].

From Digital 2020 [2], Twitter is one of the most used social platforms. Twitter has 339.6 million users. Many users access published information through this platform on a daily basis. Additionally, data transmission via Twitter is efficient and cost effective. In fact, Twitter messages are limited to a specific number of characters. Data control on this platform is also very liberal, as users are free to publish content. Over the years, Twitter users with malicious intent have spread malevolent information that affects the peace and security of society [3]. There is a pernicious impact of misinformation on individuals and society. Hence, rumors that have spread in social networks have had a negative effect on people [4], and some people who were affected by misinformation have died [5].

Misinformation also occurs through other social media such as WhatsApp. Five Indian victims were beaten to death because the attackers believed that the victims were involved in a kidnapping of children, and this belief was based on information shared through WhatsApp [6-7]. In India, WhatsApp has approximately more than 200 million users [8]. The effect of chain message hoaxes or fact distorted messages shared via WhatsApp is very serious. This situation occurs in many other countries as well. For example, in Thailand, the rumors of free gasoline in October 2017 were widely spread on all social media, including Facebook and Twitter [9].

Another example of an unexpected tragic effect based on social media was the suicide of the director of the Taipei Economic and Cultural Office in Osaka, Japan. The acting Taiwanese Consulate General in Osaka decided to commit suicide in the official residence because of rumors that started during a typhoon in the Kansai area of Japan. These rumors accused him of not providing adequate help to thousands of stranded Taiwanese people [10-11].

In 2017, it was reported that two-thirds of Americans use online social media to receive news and information [12]. The spread of news online has affected society at large. For instance, a few months before the election for the US president in 2016, there were many stories containing misinformation in social media. In particular, a particular bit of misinformation was shared more than 37 million times on Facebook [13]. Most of the misinformation came from obscure websites [14].

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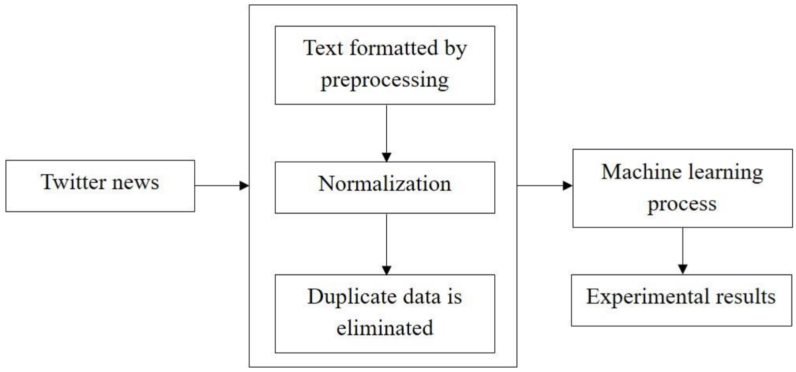

Figure 1 The proposed system to identify misinformation

Many people encourage the spread of fake news rather than endeavor to inhibit it [5]. How can one decide whether the content of the information received is accurate or it has been altered and is inaccurate? The assessment of fake news is related to not only the reliability of the news content, but also the trustworthiness of the social media sources [15]. Misinformation is limited when the truth proliferates. When the truth is presented, most misinformation will stop.

This work proposes methods to identify misinformation on Twitter with a support vector machine to isolate untrustworthy news from Twitter to prevent its dissemination.

2. Misinformation

Credibility verification of online social media content is increasingly complex due to the growth of social media platforms. The credibility of information found in the news is usually presented as a correlation between word usage and content. Additionally, the trustworthiness of the news requires consideration of the relevant elements of credibility of the news source and reliability of the news content.

2.1 Analysis of misinformation

The misinformation analyses have been done including the following:

• News content analysis: This analyzes of semantics of words and understanding of the content [16-17], which includes the analysis of the syntax and structural context as well as development of knowledge (a corpus) [18] based on technical words and jargon. Another aspect is the analysis of the emotional tone from the context of the information [19-20] and the user's behavior [21].

• Analysis without content: This approach does not use the content of the news but rather other attributes, such as the analysis of the news proliferation or the source of the information. The attributes can be the profile of distributors and other relevant statistical data [3].

Numerous researchers have analyzed misinformation in other languages [22-24].

An important approach is automatic detection of misinformation. This approach is challenging because of the large amount of information and the specific domain of each content [25-27]. Machine learning has become one of the most popular approaches [28].

2.2 Machine learning

Machine learning has been applied in a wide variety of applications. A given learning process is appropriate for data in a specific format. Detecting misinformation can be considered a classification task. Many machine learning methods are suitable for this task. Naïve Bayes is commonly used for data classification [29]. It is a very simple and easily understandable classification method. The probability distribution of the variables in the data set are used, and the variable response values are predicted based on Bayes theorem.

Neural networks are effective for classification tasks. They have been extensively studied and have a wide range of applications.

Support vector machines are popular machine learning models that provide high accuracy in data classification tasks. Support vector machines are supervised learning models that are used for classification analyses [30]. A support vector machine model is a representation of input data that is mapped into separate categories, which are divided by the largest gap possible. This model can be used to classify new data.

The various techniques have been used for detecting fake news or misinformation on Twitter such as [31] and [32]. The accuracy of fake news classification in [31] is in the range of 49.9%-92.8%. The accuracy of detection classifies tweets as either hate speech, offensive speech or free speech in [32] with success in the range of 64.6%-80.3%.

3. Misinformation classification

There are three parts in our proposed system. They are to gather news from Twitter, preprocessing the text, and the machine learning process. The proposed system is illustrated in Figure 1.

Figure 1 shows the structure of the proposed system. The process starts by extracting data from Twitter by specific news topics. Next, the raw data is formatted. The unstructured data needs to be formatted so that it is suitable for the machine learning process. Preprocessing is done as follows. The messages and hashtags are stored as text. Then, the hashtags are used for subsequent labelling of the messages as true or false, however, the text message is not used in our method. The main context and data for machine learning are the attributes from Twitter messages. They are formatted in comma separated value (CSV) form. Then, the data is cleaned to eliminate incomplete data. After preprocessing, each attribute is converted into a range of numerical values to normalize the data. The normalization rules for each selected attribute are illustrated in Table 1. The last step is the elimination of duplicate data. After these steps are completed, the data is ready to be used to train a machine learning classification model.

Table 1 Normalization rules of the attributes

Attributes	Normalization Condition	
	Description	**Value**
Id	None	0
	9-10 digits	1
	18 digits	2
Name, Description	None	0
	All in Thai	1
	All in English	2
	Thai or English or Number	3
	Only symbols	4
	Otherwise	5
IsVerified	Null	0
	True	1
	False	2
ProfileImageUrl	No image	0
	.jpg	1
	.png	2
	otherwise	3
FollowersCount, FriendsCount, FavouritesCount, StatusesCount, RetweetCount,	None	0
	1-9	1
	10-99	2
	100-999	3
	1,000-9,999	4
	10,000-99,999	5
	100,000-999,999	6
	1,000,000-9,999,999	7
Location, TimeZone	None	0
	Thailand	1
	South East Asia (Not Thailand)	2
	Asia (Not South East Asia)	3
	Australia/New Zealand	4
	Europe/Russia	5
	US/Canada/Alaska/Hawaii	6
	Africa	7
	Otherwise	8
CreatedDate	None	0
	Less than 0.5 year	1
	Between 0.5 year and 1 year	2
	Between 1 years and 1.5 years	3
	…	…
	Maximum value	24
Status	None	0
	Valuable	1
Url, MessageImage, Mentions, HashTags, Number of Mentions, Number of HashTags	None	0
	a link / @ / #	1
	2 links / 2@ / 2#	2
	3 links / 3@ / 3#	3
	more than 3 links / @ / #	4
TweetCreatedDate	None	0
	06.01-12.00	1
	12.01-18.00	2
	18.01-24.00	3
	00.01-06.00	4
MessageText	Own message	1
	Retweet messages	2

The details of the data extraction process are described in Section 3.1. The attribute normalization process is explained in Section 3.2. The machine learning parameters used in the experiment are described at the end of the section.

3.1 Data set

The data for the experiment were extracted from the Twitter API between October 2017 and November 2017 in Thailand. There were 948,373 messages. The selected news topics were related to natural events, general issues in society and events related to the reign of King Rama IX.

Natural events affect the daily lives of villagers. Information on natural disaster alerts is a matter of great importance. People may be confused about how to prepare for a disaster when there is unreliable news, including misinformation, during a natural disaster.

Natural events were chosen for this study because they are factual, and hence, they can be easily verified. The keywords that were used to search for natural events included the following words and phrases: floods, Bangkok's floods, rainy, cracked dam, cracked dike, incoming storm, Kanhoon's storms, Long's typhoon, depression, Rangsit's water release, water release after the royal ceremony day,

Table 2 Details of the dataset extracted from Twitter

Topic	Number of messages	Quantity of news stories		Percentage	
		Valid news	Misinformation	Valid news	Misinformation
Natural events	361,751	254,777	106,974	70.43	29.57
General issues	222,983	214,811	8,172	96.34	3.66
Thai monarchy	363,639	357,485	6,154	98.31	1.69
Total	**948,373**	**827,073**	**121,300**	**87.21**	**12.79**

earthquake, into the winter, cold's disaster, decreasing temperatures, and climate change, among others.

The keywords used to search for general issues in society were as follows: one step at a time, Vegetarianism, Japanese elections, Accidents, Saudi Arabia's Prince, Mark Zuckerberg visiting Thailand, beer selling in convenience stores, tax deductions increasing social security contributions, and tax deductions.

The Thai monarchy has reigned in the country for a long period of time. Therefore, the monarchy is closely related to the people. In particular, King Rama IX has reigned for more than 70 years. His royal duties and accomplishments have been well recognized. Hence, Thai people adore and respect the king. Therefore, monarchy-related news, whether it is true or fake, has captivated more attention than other topics have.

The keywords that were used to search for data on the royal cremation ceremony event were the IXth reign, the royal ceremony, the flower for the father, Paklong's market, the exhibition of royal ceremony, to the heaven, forever in Thai's mind, to come to the heaven, free oil fuel, Bangchak's free oil, sandalwood's flower, and change the sandalwood's flowers stalks cover from black to white. The data extracted from Twitter are summarized in Table 2.

From the 948,373 raw messages, the preprocessing stage yielded 327,784 unique records that were used in the experiment. These data were labelled as valid news or misinformation. The labelling process is as follows. All messages are collected based on the selected hashtags without discrimination. The messages are labelled as misinformation when the announcements of events contradict the messages.

3.2 Data analysis

Indirect attributes of the news sources and the spread of the Twitter messages were used. There are hundreds of attributes in a Twitter message. Twenty-two attributes that were deemed relevant to the task were selected (Table 1). This selection method follows the method reported in a previous study [22], which demonstrates that the method is effective. In their work, Alrubaian et al. [22] achieved 90.3% accuracy using 22 Twitter attributes. These attributes are selected according to the analysis of their relative importance. They cited the study of 112 published papers on the credibility of web content and perform the analysis by pairwise comparison between attributes.

All attributes were transformed into a range of numerical values according to the normalization rules shown in Table 1. An explanation of the first two rules is as follows. The first attribute is the ID, which is the identification number of each Twitter account. When there was no ID, the numerical value was set to 0. A Twitter account that has been active for a long time was assigned an identification number of 9-10 digits, and it was given a numerical value of 1. A new Twitter account had 18 digits, and it was given a numerical value of 2.

The second attribute is Name. It is the name of each user, which can be any string. The normalization rules for Name are as follows: no name - value 0; all Thai characters - value 1; all English characters - value 2; a mix of Thai or English characters or Numeric values - value 3; special characters - value 4; and all others - value 5. The normalization rules of the remaining attributes are self-explanatory.

From the information collected, it was found that the date and time at which the news was posted (TweetCreatedDate) are significant factors. Twitter accounts that presented mostly valid news posted it between 0.01 and 12.00. The misinformation tended to be posted between 06.01 and 18.00. In terms of the number of messages, it was shown that 87.21% of the overall messages posted by Twitter accounts were valid news and 12.79% were misinformation. Many messages did not appear with a hashtag for the news. It is very surprising that news stories with headlines are more likely to display news content. Additionally, the URL found in both valid news and misinformation posted by Twitter accounts can be accessed by more than one link. Likewise, the mentions and the number of mentions of both valid news and misinformation also contain more than one link.

Three machine learning methods were chosen in the experiment. The first one is naïve Bayes. It is the simplest method. The second method is a neural network. It is among one of many popular methods in machine learning, for example, [33] and [34] used neural networks to detected fake news. The last method is a support vector machine. This method has very high accuracy for two-class (true/false) classification tasks. The tool that we used for the machine learning task is Weka, which includes all three methods. The parameters for each method were set as follows:

Naïve Bayes:
function naïveBayes,
batchSize = 100,
numDecimalPlaces = 2,
useKernelEstimator = False,
useSupervisedDiscretization = False.

Neural Network:
function MultilayerPerceptron,
batchSize = 100,
hiddenLayers = a, l
learningRate = 0.3,
momentum = 0.2,
nominalToBinaryFilter = True,
nomalizeAttribute = True,
nomalizeNumericalClass = True,
numDecimalPlaces = 2,
seed = 0,
trainingTime = 500,
validationSetSize = 0,
validationThreshold = 20.

Support Vector Machine:
function SGD,
batchSize = 100,

epochs = 500,
epsilon = 0.001,
lambda 1.0E-4,
learningRate = 0.01,
lossFunction = Hinge loss,
numDecimalPlaces = 2,
seed = 1.

4. Results

The following terms were defined for the measurements:

- True positives (TPs) refer to valid news stories that the model predicts to be valid news.
- False positives (FPs) are misinformation that the model predicts to be valid news.
- False negatives (FNs) are the valid news stories that the model predicts to be misinformation.
- True negatives (TNs) are the misinformation stories that the model predicts to be misinformation.

The F-measure is a metric of the overall efficiency of a model. It is calculated from the average of the precision and recall values. Precision is the measure of the predictive accuracy of the model. It is defined in Equation (1). Recall is defined in Equation (2). The rest of the measurements are defined in Equations (3-6).

Accuracy is the ratio of the sum of the number of valid news stories that the model can predict as valid news and the number of stories that are correctly identified as misinformation to the total amount of data in the data set. Accuracy is defined in Equation (7).

$$Precision = \frac{TP}{(TP + FP)} \tag{1}$$

$$Recall = \frac{TP}{(TP + FN)} \tag{2}$$

$$F\text{-}measure = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{3}$$

$$True\ Negative\ Rate\ (TNR) = \frac{TN}{(TN + FP)} \tag{4}$$

$$False\ Positive\ Rate\ (FPR) = \frac{FP}{(TN + FP)} \tag{5}$$

$$False\ Negative\ Rate\ (FNR) = \frac{FN}{(TP + FN)} \tag{6}$$

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \tag{7}$$

The results of the experiment are shown in Table 3. The experimental results of all three methods are highly accurate in identifying misinformation. The neural network and support vector machine were better than the naïve Bayes model in terms of accuracy. The accuracy of the naïve Bayes method was 95.55%, while the neural network was 97.09% accurate, and that of the support vector machine was 98.15% accurate.

From the analysis of the data on misinformation, the characteristics of misinformation in this dataset are as follows.

Most misinformation (89.35%) is posted from Twitter accounts that have been active for a long period of time. The average age of these accounts is 4-4.5 years. These accounts are more likely to have names with special symbols. Almost half of the accounts that post misinformation (48.82%) have 100-999 followers, and they follow 1,000-9,999 other users. These accounts "like" 1,000-9,999 other users. The users of these accounts sent tweets 10,000-999,999 times. A total of 37.87% of these users sent 10,000-99,999 tweets, and 34.02% send 100,000-999,999 tweets. The descriptions of these accounts are mostly composed of special symbols. These accounts are more commonly located in Thailand and Southeast Asia than in other places. The users of these accounts do not usually specify the time zone. The misinformation was retweeted 10-99 times. The account users are more likely to post stories during the daytime than at night. They post an original message more frequently than they retweet a message posted by other users.

Misinformation found on Twitter mostly appears for only a short period of time. Based on the results of our experiment, there are significant differences between valid news and misinformation. The spreading time is the duration of time between the first post of a news story and the last post on a related topic. There was a difference between the spreading time of more than 20 topics on valid news, with an average spreading time of 7 days, 7 hours, 13 minutes. Ten topics containing misinformation had an average spreading time of 5 days, 1 hour and 19 minutes. The variance of the spreading times of valid news and misinformation were 7.34 days and 4.78 days, respectively. Misinformation has a shorter lifetime than valid news.

For news that is published very quickly on Twitter, some misinformation proliferates until the truth appears, then it quietly disappears. The problem is that misinformation will continue to be published when the truth is not revealed.

The results of our experiments suggest that misinformation has a shorter lifetime and that the amount of misinformation is much smaller than that of valid news, in accordance with the results of [17].

A neural network and support vector machine were the techniques used in this experiment. These methods have also been used in other studies [17, 29, 33, 35].

Table 3 The results of the experiment.

	F-Measure	**Precision**	**Recall (True Positive Rate)**	**True Negative Rate**	**False Positive Rate**	**False Negative Rate**	**Accuracy**
Naïve Bayes	0.9748	0.9900	0.9601	0.9157	0.0843	0.0399	95.55%
Neural Network	0.9836	0.9943	0.9732	0.9512	0.0488	0.0268	97.09%
Support Vector Machine	0.9896	0.9955	0.9838	0.9615	0.0385	0.0162	98.15%

The experiments in [34] shows that support vector machines have higher accuracy than other machine learning methods. Recently, deep learning has become very popular and there are several studies that used this method such as [36] and [37].

5. Conclusions

It is not difficult to identify misinformation with machine learning if the data used in the classification process have clear labels. All three machine learning methods, the naïve Bayes, neural network and support vector machine methods, had high accuracy in identify misinformation in this dataset. The limitation of this approach is that it works well only when the training data is labelled correctly. This approach did not use the content of the news in its analysis. To enlarge the scope of the news that can be verified, machine learning methods should be used in combination with a method that performs semantic word analysis.

A limitation of this research is that the model used to identify misinformation was created from data that was collected over a short period of time. Over time and the news issues change, this model may not be as accurate. Therefore, it is necessary to continuously retrain the model with contemporary data. To increase the scope of the news issues addressed, more diverse news must be collected.

Machine learning also has one important limitation. The model cannot perform correctly without a large amount of training data. Therefore, it is necessary to collect a vast amount of data to support the analysis of more diverse news.

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