Analysis of Public Sentiment towards East Java Governor Election 2018 on Twitter using Text Mining

Fajar Darwis Dzikril Hakimi¹, Ahmad Zainul Hamdi², Nurissaidah Ulinnuha¹, Ahmad Hanif Asyhar¹, and Yuniar Farida¹

¹Department of Mathematics, State Islamic University Sunan Ampel Surabaya, Jl. Ahmad Yani 117, Surabaya ²Department of Religion Studies, State Islamic University Sunan Ampel Surabaya, Jl. Ahmad Yani 117, Surabaya

Keywords: Sentiment Analysis, East Java Governor Election, Naïve Bayes Classifier.

Abstract: Governor elections were held together in most of Indonesian regions in 2018, including East Java. In preimplementation of East Java Governor election, there were several public opinions which had positive and negative sentiment on Twitter. Those opinions can be used as parameter to evaluate the strength of each candidate. The purpose of this research is to know the tendency of public opinion about East Java Governor election on Twitter. In this research, there are several steps to do, i.e., crawling data, labelling data, removing data, pre-processing data, building classification system using Naïve Bayes, and applying the system on more Twitter data. The word weighting methods used are TF and TF-IDF. The result shows that TF word weighting method has better performance. This research has two results of system performance for each candidate. Based on data of the first candidate, the result of accuracy, precision, recall, and f-measure were respectively 98.99%, 93.44%, 97.78%, and 95.56%. Based on data of the second candidate, the result of accuracy, precision, recall, and f-measure were 98.95%, 97.78%, 98.55%, and 98.17% respectively. Based on data from Twitter, East Java citizens had tendency to choose the first candidate.

1 INTRODUCTION

Technological advancements in computer science make exchange of information become easier (Wongso, et al., 2017). Nowadays, the easiest way to exchange information is through social media. Social media, such as Facebook and Twitter, can facilitate users, not only to interact with one another, but also to read and share news, discuss important things, like politics and others (Yaqub, et al., 2017). This certainly leads to the abundance of information on social media. There are several types of social media that are often used as a tool to exchange information, one of which is Twitter. One way to transform abundant data into useful information is by classifying information. Therefore, it is necessary to create a system that can classify opinions automatically because manual classification takes a long time and it is not effective.

Some producers, service providers, and government agencies take advantages from the available information on social media to make improvements to the products or policies that have been made (Liu, 2012). In addition, social media also have become an important channel for political figure to address the public, making them accessible to their voters (Kusen & Strembeck, 2018). Information available on social media can also be used to find out the electability of a political figure. The most considered factor in influencing the electability of political figure is the movement of loyalists (Espinall, et al., 2017). One way to express the support of loyalists is through social media. Therefore, in the period before the election is held, the opinion on social media becomes very important.

In 2018, governor elections were held simultaneously in most regions of Indonesia, including East Java. In East Java, there were each two candidates for governor and vice governor. The first candidate was Khofifah Indar Parawansa and Emil Elestianto Dardak, while the second candidate was Saifullah Yusuf and Puti Guntur Soekarno. In pre-implementation of East Java governor elections, there were various kinds of public opinion which had positive and negative sentiments on Twitter. That public opinion can be used as a

262

Hakimi, F., Hamdi, A., Ulinnuha, N., Asyhar, A. and Farida, Y.

In Proceedings of the Built Environment, Science and Technology International Conference (BEST ICON 2018), pages 262-267 ISBN: 978-989-758-414-5

Copyright © 2022 by SCITEPRESS - Science and Technology Publications, Lda. All rights reserved

Analysis of Public Sentiment towards East Java Governor Election 2018 on Twitter using Text Mining. DOI: 10.5220/0008905900002481

parameter to evaluate the strength of each candidate. Therefore, by classifying opinions on Twitter relating to East Java governor election, information on the strength of each candidate will be obtained based on Twitter.

Problems will arise when opinions are classified manually. It takes a long time to classify opinion on Twitter and it is certainly not effective, considering that the evaluation of the campaign's performance must be carried out as quickly and effectively as possible. To solve this problem, a system that automatically classifying the opinion about East Java governor election on Twitter will be created. Algorithms that are often used to classify text documents and have good results are Naive Bayes classifier and support vector machine (Aggarwal & Zhai, 2013). In addition, the research conducted by Ghulam Asrofi Buntoro (Buntoro, 2016) analyzing sentiment analysis towards candidates of Jakarta governor 2017 on twitter showed that the highest accuracy values were obtained using Naïve Bayes classifier, with an average accuracy of 95%. This result shows that Naïve Bayes method has a high performance to classify Twitter documents. Therefore, this study will analyze public sentiment towards East Java Governor election 2018 on Twitter using Naïve Bayes classifier. The result of this study can be used to evaluate the strength of each candidate on Twitter. This strength on Twitter was one of factor that influence East Java Governor Election 2018.

2 LITERATURE REVIEW

2.1 Twitter

Twitter is a social network that is quite popular among internet users (Zulfa & Winarko, 2017). Twitter limits its users to send a tweet with a length to 280 characters. Twitter has some similarities with other social networking sites like Facebook, which is useful for connecting internet users. Twitter was founded by Jack Dorsey and officially launched in March 2006. Twitter continues to grow rapidly in the number of users. This is evidenced by the number of users that reached 500 million users in January 2013 (Yulian, 2018). The advantage of Twitter, compared to Facebook, is the 'follow' feature that makes it easy for someone to connect with unlimited number of friends. This is certainly better than Facebook, which limits friendship to only 5000 people.

2.2 Text Classification

Classification is the process of building a model that will be used to predict a category (Juniawan, 2009). Classification has two processes that are learning process and classification process itself. In the first process, the classification algorithm creates a classification model by analyzing training data. This process is called supervised learning because each training data has its own class label. This process can be assumed as mapping of function y = f(x). It means that determining the class label y is based on data x by mapping function f. The second process is to determine the class label for testing data using classification model that has been created.

Classification of text documents is certainly different from the classification of numerical data. In the classification of text documents, the independent variables are the words in the text document. This causes the classification of text documents to have so many independent variables, depending on the number of words in the classified documents. Classification of text documents is included in text mining. The purpose of text mining is to get useful information from text documents (Nurhuda, et al., 2013).

2.3 Naïve Bayes Classifier

Naïve Bayes classifier is a machine learning method that uses probability calculation (Rini, et al., 2016). This method utilizes the probability theory found by British scientist Thomas Bayes. Naïve Bayes classifier is based on the Bayes theorem in Equations 1 and 2 below (Balagatabi, 2012):

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \tag{1}$$

$$P(A \cap B) = P(A|B) \cdot P(B)$$
(2)

Where:

- P(A|B) is the probability of A if B has happened
- $P(A \cap B)$ is probability of A that happens together with B
- P(A) is the probability of A
- *P*(*B*) is the probability of *B*

This method works by predicting the probability of future occurrences based on previous data. The main characteristic of Naïve Bayes classifier is the independence of each event that has a very strong assumption, where it is assumed that each data is independent (Rini, et al., 2016). Naïve Bayes classifier is a probability concept that can be used to determine class of text

documents and can process large amounts of data with high accuracy result (Lestari, et al., 2017).

In classifying text documents, there are several steps to do, that are:

- 1. Calculating the probability value of each document category.
- 2. Calculating the probability value of each word in each document category.
- 3. Determining the category of test documents based on calculations from the first step and the second step.

2.4 Text Pre-processing

Text pre-processing aims to prepare text documents to be ready for classification (Faradhillah, et al., 2016). This stage is important because the existing text documents usually do not have a definite structure so the information in the text cannot be processed directly. In addition, not all words in the text document reflect the contents contained in the document. This stage is done before the text document is classified with Naïve Bayes classifier method. The pre-processing stage of the text includes cleansing, case folding, stop word removal, tokenization, and word weighting.

1. Cleansing

Cleansing is included in pre-process text. Cleansing aims to delete all URL or web address that do not have meaning in documents classification (Mujilahwati, 2016). The URL and web address will interfere the classification process if it is not deleted.

2. Case Folding

In classifying documents, case folding is a must-do. The way to do case folding is by changing all letters to lowercase. The purpose of case folding is to make the word at the beginning of the sentence have the same meaning as the word in the middle or in the end of the sentence (Manning, et al., 2009). In addition, punctuation and number are replaced by the space character.

3. Stop word Removal

Usually, words that often appear in each document category are meaningless words in document categorization (Manning, et al., 2009). These words are called stop word. These words cannot be used as an identifier of a document, so the words should be deleted. Examples of stop words are conjunctions and pronouns.

4. Tokenization

Tokenization is the process of dividing text documents, that can be sentences or paragraphs, into tokens or certain parts (Manning, et al., 2009). The purpose of tokenization is to make words in the sentence of paragraph able to be weighted for each word.

5. Word Weighting

In text mining, word weighting is important step. It becomes features selection to classify document category. Word weighting methods that are often used are TF and TF-IDF. TF (Term Frequency) is word weighting method based on the appearance of a word on particular document. TF-IDF stands for Term Frequency–Inverse Document Frequency. So, TF-IDF is a combination of two weighting scheme namely TF and IDF (Juniawan, 2009). Equation 3 is TF-IDF calculation formula.

$$W_{ij} = \frac{TF_{ij}}{K_j} \cdot \log_2\left(\frac{D}{DF_i}\right) \tag{3}$$

Where:

Wij = term i weight for document j

Kj = number of all terms in document j

TFij =number of term *i* appearance in document *j* D = number of all documents in database

DFi = number of documents that contain term *i*

Weight of a word in TF method is calculated based only on the frequency of a word in a tweet. Meanwhile, weight of a word in TF-IDF method is calculated based on the frequency of a word in a tweet and also the number of tweet that contains that word in all database.

2.5 Evaluation of System Classification

A classification system is made with expectation that the system can classify all data correctly (Prasetyo, 2014). However, it cannot be denied that a system that has been built always has errors. Therefore, the classification system needs evaluation to find out how well a method is used to classify a particular data or how well the classification system has been made.

The most commonly used classification system evaluation is accuracy. Accuracy can be used to measure the performance of a classification system if the data used has balanced ratio of the number for each data category (Prasetyo, 2014). However, sometimes the accuracy value does not describe the actual performance of a classification system. This can happen if the ratio of the number of each data categories is very unbalanced (Prasetyo, 2014). Therefore, another type of classification system evaluation is used. The classification system is namely precision, *recall*, and *f-measure*, which are good enough to be used against proportionally unbalanced data (Hotta, et al., 2013).

Accuracy is ratio of correctly classified data to the total of data. It is the most simple performance evaluation. Precision is ratio of correctly classified positive data to the total of classified positive data. Recall is ratio of correctly classified positive data to all data that actually have positive class. Meanwhile, F-Measure is weighted average of precision and recall (Prasetyo, 2014).

3 RESEARCH METHOD

3.1 Data

The data used in this research is public opinion on Twitter about East Java Governor candidates for 2018-2022 period that obtained from crawling Twitter process in April 2018 until June 2018. In crawling process, the first thing to do is determining the keyword. For example, if the data searched is an opinion about the first governor candidate, then it can be crawled using the keyword "khofifah". If the data searched is an opinion about the second governor candidate, it can be *crawled* with the keyword "gus ipul".

3.2 Data Analysis

To solve the problem in this research, there are several steps to do such as in Figure 1.



Figure 1: Research Flow Chart.

In this research, there were seven processes to analyze data and get the results of sentiments classification. The first process is collecting data by crawling which is used to get opinion dataset on Twitter. The second process is labelling data into positive, negative, neutral, and outlier. The third process is eliminating neutral and outlier data. The fourth process is pre-text data processing. The purpose of pre-processing is to convert raw datasets into data that is ready to be classified. The fifth process is comparing two word weighting methods, TF and TF-IDF. Word weighting method with better performance is used in the sixth process. The sixth process is creating classification system using Naive Bayes classifier method. The seventh process is applying system to classify more data to obtain predictions of the results of East Java Governor election in 2018 based on public sentiment on Twitter.

4 RESULTS AND DISCUSSION

4.1 Comparison between TF and TF-IDF.

In this research, two word weighting methods were used. The first word weighting method was TF. The type of TF used was pure TF. Pure TF method is a simple word weighting method because the weight of each word is determined by the number of occurrences of the word in a document.

The second word weighting method was TF-IDF. TF-IDF is a development of TF method. After using normalized pure TF, the weight is multiplied by the IDF. The less often a word appears on set of documents, the greater the IDF value is.

In this research, the TF weighting method had a better performance than TF-IDF. For the first governor candidate, TF and TF-IDF had the same performance. The result of accuracy, precision, recall, and f-measure were 98.99%, 93.44%, 97.78%, and 95.56% respectively. Whereas for the second governor candidate, TF was slightly better with comparative performance as it is shown in Table 1:

Table 1: Comparison between TF and TF-IDF.

No	Evaluation Type	TF	TF-IDF
1.	Accuracy	98,.95%	98.25%
2.	Precision	97.78%	97.32%
3.	Recall	98.55%	96.57%
4.	F-Measure	98.17%	96.95%

The result shows that TF was slightly superior to TF-IDF, so the classification system was made using the TF word weighting method.

4.2 Creating Classification System

After all existing words were weighted by pure TF, the classification system was built using Naïve Bayes classifier. Naïve Bayes classifier's work method is based on the probability of the occurrence of words that have been given weight by the TF word weighting method.

Creating the classification system, the first step is distributing training data and testing data. This step cannot be done randomly because it will cause an imbalance in the proportion of training data and testing data. In addition, training data used must be data that represents most of the available data, so that the distribution of training and testing data cannot be done randomly. The proportion of data distribution that is often used is 80% for training data and 20% for testing data. In addition, there is also a proportion of 75% of training data and 25% of testing data. This system used the proportion of 80% training data and 20% testing data.

In the first system, the data used were 2497 data which were distributed into training data and testing data. Training data consisted of 2000 data which had 1906 positive-category data and 94 negativecategory data. Meanwhile, the testing data consisted of 497 data which had 469 positive-category data and 28 negative-category data.

In the second system, the data used were 1487 data which were distributed into training data and testing data. Training data consisted of 1200 data which had 1132 positive-category data and 68 negative-category data. Mean while, the data testing consisted of 287 data which had 238 positive-category data and 49 negative-category data.

No	Evaluation Type	The First System	The Second System
1.	Accuracy	98.99%	98.95%
2.	Precision	93.44%	97.78%
3.	Recall	97.78%	98.55%
4.	F-Measure	95.56%	98.17%

Table 2: Performance of Each Classification System.

Table 2 shows the performance of each classification system using TF word weighting method and proportion of 80% training data and 20% testing data. It can be concluded that each

classification system has high performance with values above 90%.

4.3 Results of System Application on More Twitter Data

The two systems had good values (more than 90%) of accuracy, precision, recall, and f-measure so that the next step was to apply on more Twitter data to know the tendency of public sentiment toward each governor candidate. Table 3 shows the results of system application for each data:

Table 3. Results of System Application.

No	Data	Positive	Negative	Total
1	First candidate (Khofifah and Emil)	18521	1423	19944
2	Second candidate (Ipul and Puti)	13714	2235	15949
	Total	32235	3658	35893
			ļ	

In Table 3, it can be seen that the data used in this study were 35893 data which were distributed into two kinds of data, namely the first data for the first governor candidate and the second data for the second governor candidate. This data was obtained from crawling Twitter data from April 2018 until June 2018. Data for the first candidate were 19944 data and data for the second governor candidate were 15949 data.

In data of the first governor candidate, there were 92.86% positive sentiments and 7.13% negative sentiments. While in data of the second governor candidate, there were 85.98% positive sentiments and 14.01% negative sentiments.

Based on the combination of the first data and the second data obtained from the Twitter crawling process, it can be concluded that the first governor candidate is superior to the second governor candidate. This conclusion can be taken based on the fact that the first governor candidate gets more attention from Twitter users. The number of tweet that mentioned the first governor candidate was 19944 tweets while the number of tweet that mentioned the second governor candidate was 15949. In addition, the first governor candidate had greater percentage of positive sentiments than the second governor candidate did and the first governor candidate had smaller percentage of negative sentiments than the second governor candidate did. This study contributes in creating classification sentiment model regarding to East Java governor election that can automatically and accurately classify tweets by using Naïve Bayes and TF word weighting method. The result of this study was based only on social media, especially Twitter. It will be even better if the result can be obtained from other social media like Facebook, Instagram, or other online media.

5 CONCLUSION

Based on the results of the classification system and system application, it can be concluded that Naïve Bayes classifier is a method that can be applied to classify sentiments on Twitter. This was indicated by the high performance of the system that was made. In the first system, the system performance obtained accuracy of 98.99%, precision of 93.44%, recall of 97.78%, and f-measure of 95.56%. Whereas in the second system, system performance obtained accuracy of 98.95%, precision of 97.78%, recall of 98.55%, and f-measure of 98,17%.

Based on data obtained from Twitter, Twitter users tend to choose the first governor candidate, Khofifah Indar Parawansa. This conclusion can be taken based on the fact that the first governor candidate gets more attention from Twitter users. In addition, the percentage of positive sentiments for the first governor candidate was greater than that for the second governor candidate and the percentage of negative sentiments for the first governor candidate was smaller than that for the second governor candidate.

REFERENCES

- Aggarwal, C. & Zhai, C., 2013. A Survey of Text Classification Algorithm. pp. 169-170.
- Balagatabi, Z. N., 2012. Comparison of Decision Tree and Naive Bayes Methods in Classification of Researcher's Cognitive Style in Academic Environment. *Journal of Advance in Computer Research*, 3(2), pp. 23-24.
- Buntoro, G. A., 2016. Analisis Sentimen Calon Gubernur DKI Jakarta 2017 di Twitter. *Integer Journal*, pp. 32-41.
- Espinall, E. et al., 2017. Vote Buying in Indonesia: Candidate Strategies, Market Logic and Effectiveness. *Journal of East Asian Studies*, Volume 17, pp. 1-27.
- Faradhillah, N. Y. A., Kusumawardani, R. P. & Hafidz, I., 2016. Eksperimen Sistem Klasifikasi Analisa Sentimen

Twitter pada Akun Resmi Pemerintah Kota Surabaya Berbasis Pembelajaran Mesin. Surabaya, SESINDO.

- Hotta, H. S., Shrivas, A. K. & Singhai, S. K., 2013. Artificial Neural Network, Decision Tree and Statistical Techniques Applied for Designing and Developing Email Classifier. *International Journal of Recent Technology and Engineering*, 1(6), pp. 164-169.
- Juniawan, I., 2009. Klasifikasi Dokumen Teks Berbahasa Indonesia Menggunakan Minor Component Analysis, Bogor: Institut Pertanian Bogor.
- Kusen, E. & Strembeck, M., 2018. Politics, sentiments, and misinformation: An analysis of the Twitter discussion on the 2016 Austrian Presidential Election. *Online Social Network and Media*, Volume 5, pp. 37-50.
- Lestari, A. R. T., Perdana, R. S. & Fauzi, M. A., 2017. Analisis Sentimen Tentang Opini Pilkada DKI 2017 Pada Dokumen Twitter Berbahasa Indonesia Menggunakan Naive Bayes dan Pembobotan Emoji. Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer, Desember, 1(12), pp. 1718-1724.
- Liu, B., 2012. Sentiment Analysis and Opinion Mining. 1st ed. s.l.:Morgan & Claypool Publishers.
- Manning, C. D., Raghavan, P. & Schutze, H., 2009. An Introduction to Information Retrieval. Cambridge: Cambridge University Press.
- Mujilahwati, S., 2016. Pre-processing Text Mining pada Data Twitter. Yogyakarta, SENTIKA.
- Nurhuda, F., Sihwi, S. W. & Doewes, A., 2013. Analisis Sentimen Masyarakat terhadap Calon Presiden Indonesia 2014 berdasarkan Opini dari Twitter Menggunakan Metode Naive Bayes Classifier. *JURNAL ITSMART*, 2(2), pp. 35-42.
- Prasetyo, E., 2014. DATA MINING Mengolah Data Menjadi Informasi Menggunakan Matlab. Yogyakarta: ANDI.
- Rini, D. C., Farida, Y. & Puspitasari, D., 2016. Klasifikasi Menggunakan Metode Hybrid Bayessian-Neural Network (Studi Kasus: Identifikasi Virus Komputer). JURNAL MATEMATIKA "MANTIK", 01(02), pp. 38-43.
- Wongso, R. et al., 2017. News Article Text Classification in Indonesian Language. *Proceedia Computer Science*, Issue 116, pp. 137-143.
- Yaqub, U., Chun, S. A., Atluri, V. & Vaidya, J., 2017. Analysis of political discourse on twitter in the context of the 2016 US presidential elections. *Governor Information Quarterly*, pp. 1-14.
- Yulian, E., 2018. Text Mining dengan K-Means Clustering pada Tema LGBT dalam Arsip Tweet Masyarakat Kota Bandung. JURNAL MATEMATIKA "MANTIK", pp. 53-58.
- Zulfa, I. & Winarko, E., 2017. Sentimen Analisis Tweet Berbahasa Indonesia dengan Deep Belief Network. *IJCCS*, 11(2), pp. 187-198.