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Philippine Twitter Sentiments during Covid-19 Pandemic using Multinomial Naïve-Bayes

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ABSTRACT

News of the novel coronavirus (COVID-19) started circulating in the Philippines by the end of January 2020. Like any calamity or relevant news, people used social media platforms such as Twitter to voice their options. This paper examines the polarity of COVID -19 related opinions on Twitter from January to March 2020 by applying natural language processing. A total of 29,514 tweets were collected throughout the said dates, where 10% of which was manually labeled to train a Multinomial Naive Bayes classification model that achieved 72% accuracy. Results showed that 52% of the remaining tweets are positive, and 48% have negative sentiments.

Key words: COVID-19, Naïve Bayes, Natural Language Processing, Pandemic, Sentiment Analysis, Twitter, Tweets.

1. INTRODUCTION

Twitter users started posting messages called tweets as major news outlets covered the COVID-19 pandemic in the Philippines [1]. With almost 7.15 million users in the Philippines as of April 2020 [2], Twitter as a microblogging platform is a good source of sentiment polarization. A tweet could be about self-documentation, sharing of information, or as a medium to express an appeal [3], which is related to a particular topic domain. Hashtags allow tweets to be searchable, traceable and make coordinated conversations around a topic [4]. This paper aims to perform sentiment analysis in the Philippine setting for the Covid-19 while using accessible hashtags as a topic filter.

2. REVIEW OF RELATED LITERATURE

Sentiment analysis described as a computational treatment of opinions, sentiments, and subjectivity of texts [5]. Also known as opinion mining or subjectivity analysis, whose applications and approaches were extensively surveyed in detail by several studies [5][6][7]. The same work by Pang and Lee also explained the variation of vocabularies across other domains. One reason for this is that the same phrase can have a different emotion on another topic.

The extensive amount of text data or phrases that are accumulating on Twitter makes it an attractive data source for opinion mining and analysis of sentiments [8]. The same work by A. Pak and P. Paroubek also used Twitter to collect the corpus needed to produce a similar sentiment classifier.

The hashtag is a viable means to apply a topic filter to the massive amount of accumulated data on Twitter. J Huang et al. [9] studied the tagging phenomenon on Twitter. They concluded that hashtags are added to tweets to join discussions on existing topics. Also demonstrated in a paper by A. Bruns and J. Burgess [10], where hashtags grouped the topic interests and used to coordinate information since hashtags allowed Twitter users to search for a particular topic and contribute to the discussion

Sentiment analysis is one of the fastest-growing fields of research since the beginning of the 20th century. In recent years beginning with 2014 to 2016, Twitter and other social media are wildly popular in the field of sentiment analysis [11]. In 2019, J. Hartman et al. [12] published a paper that identified and compared ten approaches for conducting sentiment analysis. Such as includes Artificial Neural Networks (ANN), k-Nearest Neighbors (kNN), Naïve Bayes (NB), and Random Forest (RF), as well as four additional lexicon-based methods. It concluded that there are not many trade-offs required by NB or RF and is appealing because of its less training time and prediction performance.

Naïve Bayes (NB) is an algorithm often utilized to solve text classification problems. Multiple studies concluded that NB is computationally very efficient, easy to implement, high accuracy, and insensitive to unbalanced data. A. M. Kibriya et al. also summarized the two event models for NB, which are the Bernoulli event model (BNB) and the Multinomial event model (MNB). Existing literature considers that MNB is the more dominant approach [13][14][15].

In 2017, Sindhu C. et al. [16] published a paper that includes a description of Feature Extraction and its importance on classification models, especially for Naïve Bayes. The extracted features were then re-weighted using the term frequency–inverse document frequency method or TF-IDF. In TF-IDF, a particular word that occurred in many documents is not a reliable basis for its weight (or importance). The frequency of its occurrence negates the weight of a word in the whole collection [17].

To date, various studies were developed and introduced that performs sentiment analysis using tweets as the dataset in the Philippine setting. There are broad studies such as that conducted by M. M. Pippin et al. [18] in 2015 on Classifications of Emotion Expressed by Filipinos through Tweets. Their study used the Naïve Bayes algorithm and produced 70% accuracy on their model. Similarly, M. J. C. Samonte et al. [19] in 2018 also utilized a Naïve Bayes model. Their experiments utilized WEKA and RapidMiner for the detection of sarcasm in Filipino Tweets. Their results show that applying TF-IDF on RapidMiner shows better results on Training, Testing, and Validation for both Filipino and English datasets.

Several studies thus far have utilized Twitter sentiment analysis in the Philippine setting with business-related problem statements. In 2015, F. F. Patacsil et al. [20] published a paper in which Naïve Bayes, with 60.27% accuracy, is used to estimating ISP customer satisfaction of Filipinos. This study also suggests that low performance is due to several factors such as translations, synonyms, and antonyms, as well as the use of colloquial language and textspeak. In another study, A. R. Caliñgo et al. [21] also used Naïve Bayes. The results presented a predictive model with 73% accuracy, with 66% and 63% result accuracy on predicting the PSEi. This 2016 study also used public tweets from individuals and a variety of local Philippine news outlets such as GMA News and ABS-CBN. In a 2017 study by M. J. C. Samonte et al. [22], a Naïve Bayes classifier, is also used for local airlines with 66.67% accuracy.

There were also numerous studies in the Philippine context that used sentiment analysis on tweets for use in disasters and events. In 2010, a pandemic related study by C. Chew et al. [23] for sentiment analysis on tweets during the 2009 H1N1 outbreak used hashtags and statistical software. J. Lee Boaz et al. [24] studied the behavior of Filipino twitter users during a disaster in 2013. They used harvested keywords about the 2012 flooding caused by Habagat. Although using a walk trap algorithm, they also utilized TF-IDF on their work that classifies participants vs. observers. Naïve Bayes algorithm was again utilized on a similar paper by K. Espina et al. [25] that classifies health-related Filipino tweets. The classifier that is produced by their work recorded 79.81% accuracy and classified tweets as infodemiological or non-infodemiological. Yolanda is a super typhoon that hit the Philippines in 2013. Yolanda is the subject of the 2018 study that investigates Filipino twitter sentiments before, during, and after the natural disaster [26]. The study showed twitter data collection using hashtags and using Neural Network to perform sentiment analysis. Improvements on TF-IDF is a focal point of a 2020 study [27] that also classifies disaster-related tweets. The study, as mentioned above, shows the importance of enhancing the TF-IDF that leads towards classification effectiveness.

Collectively these related studies provide essential insights on approaches toward sentiment analysis in the Philippines where Tagalog and English are both spoken. In particular, the use of MNB as a classifier together with TF-IDF on collected Twitter data.

3. FRAMEWORK AND METHODOLOGY

This study follows the methodological approach, as shown in Figure 1.

3.1. Data Collection

Covid19 related tweets from January 1 until March 31, 2020, are downloaded using #coronaph and #covid19ph hashtags as filters. Retweets are also filtered out. A total of 29,514 tweets are stored during the download.

Special characters, hyperlinks, hashtags, and mentions are removed from the tweets. Whole posts are removed from the batch during the cleaning process if it contains less than three characters in length and less than two words. A total of 27,839 lines remained at the end of the process.

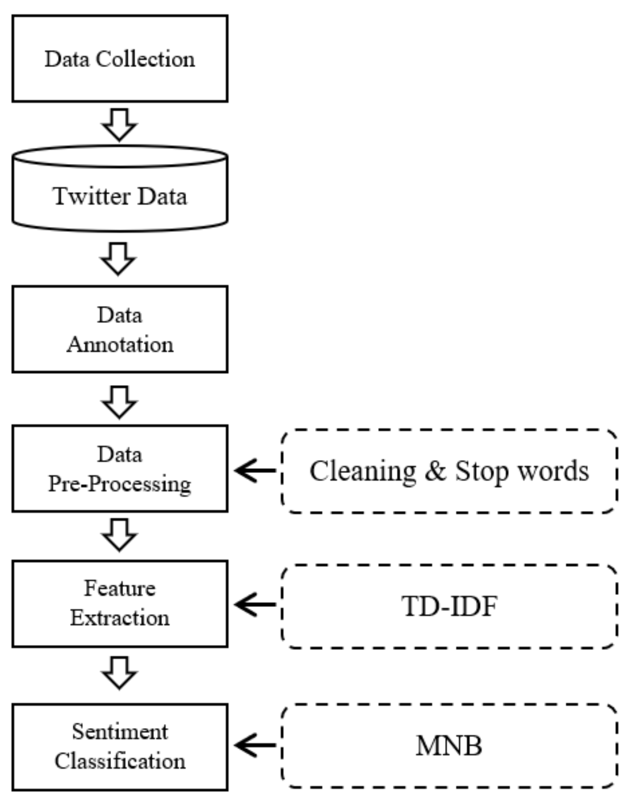

Figure 1: Methodology

3.2. Data Annotation

10% of the cleaned tweets are sampled randomly for manual labeling. The 2784 tweets are categorized by hand to be either positive or negative.

3.3. Data Pre-Processing

The annotated tweets went through a different cycle of cleaning, which removes stopwords—a well-known technique to reduce the noise of textual data as described by Saif H., et al. [28]. This study used both English and Tagalog sets of stopwords. The cleaning cycle also went through the changing of words to its lowercase equivalent. Posts with less than three characters and less than two words are removed from the annotated dataset by the cleaning cycle.

Pre-processing includes dividing the data into two datasets. 70% is allocated as a training set, whereas the remaining 30% for testing. Pre-processing split is done randomly

3.4. Feature Extraction

For this study, the TfidfVectorizer from the scikit-learn library [29] performed the feature extraction from the training set. TfidfVectorizer implements tokenization, occurrence counting, and then transformation into a normalized TF or TF-IDF representation

3.5. Sentiment Classification

The Multinomial Naïve Bayes classifier is the implementation of the Naïve Bayes algorithm in the scikit-learn library [29]. The study used the MultinomialNB model provided by the library using its default parameters

4. RESULTS AND EVALUATION

The initial objective of the study was to perform a sentiment analysis on Tagalog and English tweets during the Covid-19 pandemic. As mentioned in the literature review, several studies suggest the use of Multinomial Naïve Bayes as a classifier together with TF-IDF.

4.1. Training and Testing Dataset

The categorization of the 2,784 annotated tweets shows that 47% is negatively classified, and 53% are positive. The annotated tweets served as the classifiers' training and testing data.

4.2. Multinomial Naïve-Bayes Classifier

K-fold Cross-Validation is used to evaluate the chosen classifier of this study. Scikit-learn [29] provided a cross-validation library that offers an evaluation of the estimator performance. The MNB classifier used in the study was cross-validated in 5 consecutive times. The output showed a 72% accuracy.

Moreover, to show for the precision and accuracy of the MNB classifier, a confusion matrix was utilized [30]. The classifier accuracy is derived at 72.17%, while precision is at 75.31%. Figure 2 shows the confusion matrix results.

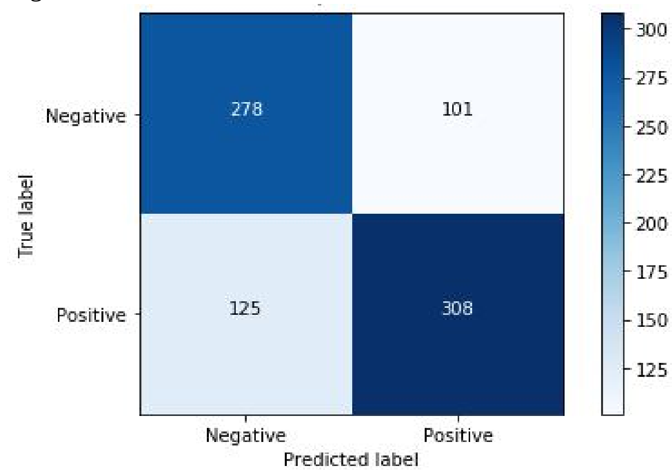

Figure 2: Confusion Matrix

4.3. Classification Results

The MNB classifier completed labeling the remaining 24,273 tweets. 12,613 or 52% of the tweets are classified as Positive, whereas 11,660 or 48% are negative. Figure 3 summarizes this report.

Figure 3 shows the trend of positive and negative tweets over time. The graph further shows that there has been a gradual increase in the number of tweets until March 22. A possible explanation for this might be that several notable events are happening in the Philippines. One of which is Proclamation No. 922, declaring a state of public health emergency throughout the Philippines. While another is the passing and signing of Republic Act No. 11469, granting special powers to the President. Table 1 shows several examples of commonly used words classified as positive or negative.

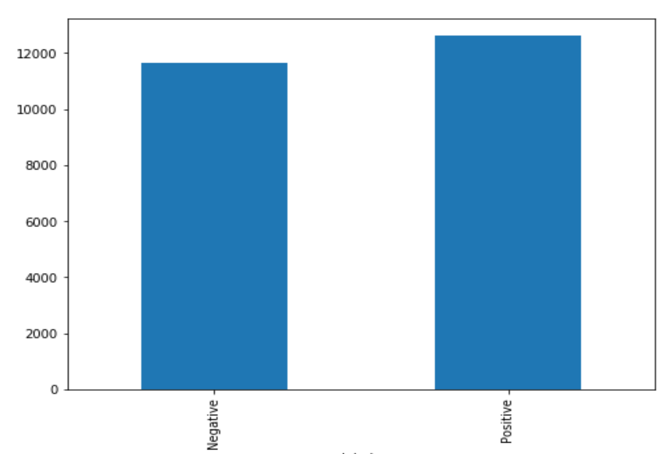

Figure 3: Processed Dataset

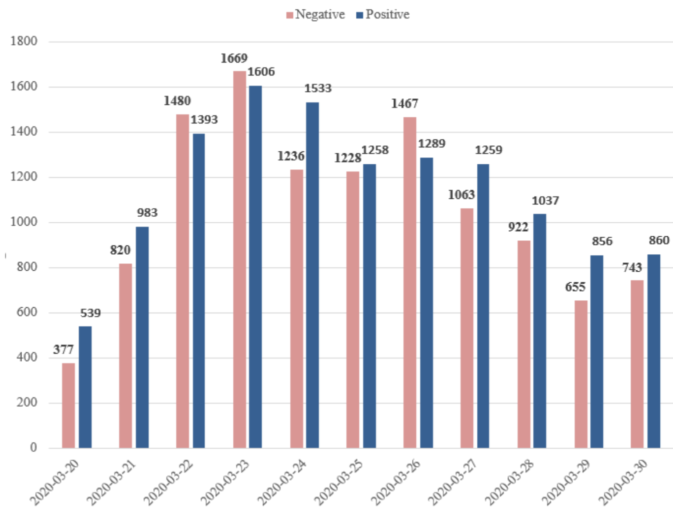

Figure 4: Processed dataset through time

Table 1: Word count per Classification

Positive	*Count*	*Negative*	*Count*
covid	1634	covid	1773
help	1123	cases	1385
frontliners	1013	naman	924
quarantine	921	testing	813
please	898	kayo	782
home	851	test	736
stay	833	health	720
health	733	people	679
people	732	total	662
thank	656	quarantine	646
government	571	positive	642
community	555	confirmed	561

5. CONCLUSION

This study was able to produce an MNB based classifier that uses TF-IDF. Once trained with the 2,784 annotated tweets, K-Fold cross-validation showed that the classifier has an accuracy of 72%. The classifier was then able to predict the polarity of the 24,273 tweets. Prediction results report that 52% of the tweets are positive, and 48% are negative, which expresses the overall sentiment of the Covid-19 related tweets from January to March 2020. The results of the word count per classification further support the concept of domain topic considerations when applied to text classification. For instance, the classifier labeled the word 'positive' as a negative label. After conducting a careful review, the results of the study can be, therefore, conclude that the produced classifier can effectively perform sentiment analysis on English and Tagalog tweets.

Future research could utilize the Kappa inter-annotator agreement during data annotations. The result of this study suggests that further improvements should include adding more data to increase the accuracy and precision of the MNB classifier and to use multi-class classifications

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