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Using Deep Learning to Determine Time and Geographic Trends of Sentiments Towards Covid-19 Vaccine

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Abstract. Vaccine hesitancy is one of the challenges faced in the battle against the Covid-19 pandemic. Understanding the sentiments of the public regarding Covid-19 vaccine across various locations throughout the pandemic will allow policy makers to better craft vaccine rollout plans. This paper examines the use of deep learning models to analyze sentiments towards Covid-19 vaccine using Twitter data to analyze time and geographic trends. The LSTM model achieved 61% accuracy, the GRU model achieved 60% accuracy, and the simple RNN achieved 48% accuracy. The time graph showed that the sentiments varied in quantity but generally exhibited the same trend behavior. The geo map did not show any significant information, due to the lack of location data, for trend analysis to reliable conducted.

Keywords; Covid-19 vaccine; deep learning; geographic trend; sentiment analysis; time trend

1. Introduction

Covid-19 was most urgent public health issue in 2020 [1]. As vaccines were already available, the next challenge is to attain herd immunity by mass vaccination [2]. Understanding the sentiments of the public over time and location will allow governments to better understand the vaccine hesitancy situation and craft a more effective vaccine rollout plan [1]. Sentiment analysis on health-related issues is not new [3]. Machine learning approaches has been used for sentiment analysis [4]. Deep learning is a subset of Machine Learning narrowed towards artificial neural networks

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[5]. This paper aims to perform model development and model operationalization to analyze time trends and geographic trends towards Covid-19 vaccine.

2. Review of Related Literature

Sentiment Analysis (SA) is the field of study that analyzes feelings, sentiments, emotions, and other semantics towards various entities using textual data [3][6]. Sentiment analysis requires a huge amount of data. It is just recently with the booming of the Internet that volumes of opinionated data became available allowing for flourishing of research in sentiment analysis [6]. Sentiment analysis is often tackled using a lexicon-based approach, machine-learning (ML) based approach, or a combination of both [7]. Several studies have found that ML-based approaches performed better than lexicon-based approaches [7].

Deep Learning architecture is the application of machine learning algorithms that use neural network [9]. Deep learning models require more training data and computing power compared to traditional learning models [5]. Recurrent Neural Networks (RNNs) are neural networks that can model inputs as sequences adding a time dimension [9][5]. For this reason, RNNs are suitable for sequential data such as speech, videos, music, etc. [9].

Even before Covid-19, research on sentiments and outlook towards vaccines have already been conducted [4][10][11]. While sentiment analysis is a saturated field in a lot of topics, there has not been much work that tackles Covid-19 related sentiments in the Philippine context [12][13][14]. M. B. Garcia [13] analyzed the sentiment of Manila-based Twitter users toward Covid-19 using a lexicon-based approach [13]. Delizo et al.

[12] utilized a multinomial naive bayes classifier and conducted sentiment analysis to classify Covid-19 tweets from January 2020 to March 2020. Villavicencio et al. [14] conducted a sentiment analysis towards Covid-19 vaccines of Twitter users in the Philippines using tweets from March 1, 2021, to March 31, 2021 in the Philippines.

3. Methodology

The study was composed of seven (7) phases: Data Collection, Data Annotation, Exploratory Data Analysis, Data Preprocessing, Model Training and Development, Model Operationalization, and Trend Analysis.

Twitter tweets were used as the data of this study. Data was filtered from January 1, 2020, to December 31, 2022 for a total of 1,096 days. In collecting tweets, a loopscraping strategy was employed. Various hashtags such as #covidvaccineph, #WeHealAsOnePH, #CovidHoax, and others were used to search for relevant Covid-19 vaccination tweets. A random sample of 10,000 tweets was manually annotated for model development as positive, neutral, or negative, and the rest is left as operational data. Exploratory Data Analysis using graphs and word cloud was done to check for any potential problem in the data for model development.

Data preprocessing was composed of data cleaning and word embedding generation. Data Cleaning was done using Natural Language Toolkit (NLTK) Python library [16]. The embeddings were generated using the word2vec algorithm by Mikolov et al. [15].

The deep learning models used were Simple Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). The same architecture was utilized for all three models. Repeated architecture trial and testing was done to find the best architecture. Hyperparameters were tuned through repetitive testing. The performance metrices used were accuracy, precision, and recall.

After model development, the operational data was fed to the models. All three models were used in the operationalization and a voting method was used to determine the final sentiment classification. The voting power of the model was determined by their validation accuracy. After classification of operational data, these were subjected to trend analysis using a time graph and a geomap.

4. Results and Discussion

The findings of this study are primarily divided into three (3) sections: (A) Data Collection, Processing, and Analysis, (B) Model Development, and (C) Operationalization of Model and Trend Analysis.

A. Data Collection, Processing, and Analysis

After duplicate removal, language filtering, and location validation, a total of 12,794 tweets has been collected for model data development and model operationalization. A random sample of 10,000 tweets was selected from the 12,794 for manual annotation. From the sample, 1,597 tweets were given negative labels, 2,814 negative labels, and 5,589 were given positive labels. To address this data imbalance, oversampling using the SMOTE was done [17].

Fig. 1 shows the word cloud for negative, neutral, and positive sentiments. Generally, Covid-related terminologies such as “covid19”, “vaccine” and others were common across sentiment classes. It, however, was difficult to look for prominent terms that semantically differentiate the sentiment class (e.g. keywords present in positive classes that were not in negative classes). The differentiating terms were less prominent as seen in the word clouds. This characteristic of the dataset may have also made it difficult for the model to learn differentiating features.

(a)Negative (b) Neutral (c) Positive

Figure 1. Work Cloud of Sentiments

In the word cloud for negative sentiments (Fig. 1a), the terms that marked the sentiment as negative included the terms “side effect”, “vaccine hesitancy”, and “halt covid”, which were not prominent in the word cloud. The neutral sentiment word cloud (Fig. 1b) contained prominent terms such as “region”, “recovery”, and “case active”. Skimming through the neutral sentiments would show that these are often informational tweets such as recovery rate for that date, the number of active Covid cases in the region, and other news tweets. The word cloud for positive sentiments (Fig. 1c) showed pro-vaccine terms such as “bidabakunation”, “resbakuna”, and “bidasoluyon”.

B. *Model Development*

The manually annotated data composed of 10,000 tweets were preprocessed in preparation for use in model development. Word embeddings were generated from the entire corpus of tokens using the word2vec algorithm with an embedding dimension of 150. The max number of tokens found in the longest sequence was 52 tokens. An epoch size of 30 with a batch size of 128 garnered the most optimal results. The *adam* optimizer was used. The categorical cross entropy function was used for the loss function.

In terms of accuracy, the LSTM (accuracy =0.61) scored the highest followed closely by the GRU (accuracy=0.60). The Simple RNN (accuracy=0.48) scored lowest. In terms of precision, the LSTM (precision=0.67) and GRU (precision=0.67) generally started high and achieved the same power. Although the Simple RNN (precision=0.78) achieved the highest precision, it was fluctuating throughout the training. The trend that LSTM and GRUs performed better than simple RNN was consistent with literature [19]. The models performed subpar in comparison to other deep learning models in the literature [8] and other machine learning models [7].

Overall, the models did not perform well enough for practical applications. This could be attributed to poor data quality. As already observed in 4.A, distinguishing terms were not prominent across the sentiments. This made it difficult for models to learn patterns that could be generalized for classification purposes. The abundance of Filipino stopwords was also a potential cause of this. While model architecture plays a significant role in a model's prediction power, the model architecture used in this study was fairly deep with three (3) hidden layers, and even other studies with shallower networks but had quality data had produced more powerful models[18].

C. Operationalization of Model and Trend Analysis

After model development, the models were operationalized to classify the sentiments of the data that was not manually annotated for training. The 2,794 model-annotated data was then used for the generation of the time graph and geo map. The positive class had the highest count of 1,685 (60.31%). The negative class had a count of 847 (30.31%). The neutral class had a count of 262 (9.38%).

Fig. 2 shows the time graph generated from the model-annotated data. The time graph had a count peaking at around 37 and a date range from January 1, 2021 until August 2022. The peak count of 37 tweets for a particular day was relatively small considering the popularity of Twitter and how hot the Covid-19 vaccine topic was. This could be easily explained by the small size of the operationalized data. Hence, it was expected that if the training data was plotted as well, a higher frequency count may be observed across all dates. Additionally, it was possible that some tweets during the later part of the dataset's entire date range (e.g. tweets on December 2022) were included in the training data and not in the operationalized data, which was why there were no data points for this date range in the time graph. This possibility helped explain why the generated time graph only visualized data points until September of 2022.

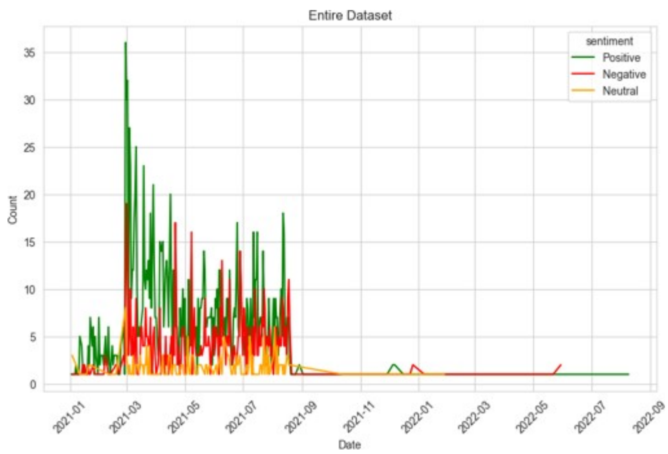

Figure 2. Sentiment-Time Graph of Entire Operational Data

It could be seen that the trend was generally similar between positive and negative sentiments. Although these two classes vary in intensity (i.e. frequency count), the sudden increase of one was almost immediately preceded or followed by the sudden increase in the other. The same trend was for decreases in intensity. The neutral sentiment, however, showed a more consistent and stable trend throughout. This was because these sentiments were from tweets that were often news updates (e.g. number of covid cases, recovery rate), which was why these were consistent relative to dates.

Although there were unusually high increases at times, this was attributed to events that resulted in more news articles (e.g. arrival of vaccines, approval of newly developed vaccines). The general trend across all the sentiments was generally invariant, which meant that the frequency may be correlated to external real-life events. This was supported by the observed trend of neutral sentiments, which was consistent with how news updates were posted.

Fig. 3 shows the geo map generated from the model-annotated data. The geo map shows a small amount of data points. This could be attributed to the lack of location information of some tweets. The clustering of data points in some areas only and severe lack of data points in others emphasized that sentiments in some areas were not represented, or just simply non-existent. There was a greater cluster of sentiments in the NCR area and much less in the Visayas and Mindanao areas. For sentiments across classes, the geographic trend was essentially non-existent. This was attributed to the small number of data points, which also restricted the level of trend analysis done.

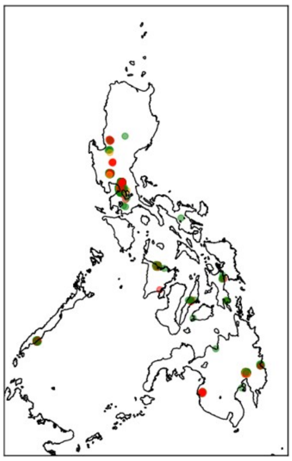

Figure 3. Sentiment-Geo Map of Operational Data

In terms of sentiments across classes, the geographic trend was essentially non-existent in the dataset. This was attributed to the small number of data points, which restricted the level of trend analysis that could be done. It, however, could already be observed that except for a few outliers, that in places where positive sentiments were plotted, there were also negative sentiments exactly or near these places. More data points were necessary to verify if this was really a trend or merely a fluke. A geo map across a certain time range to see both time and geographic trends at the same time may be explored in future works.

5. Conclusion and Future Works

The study was able to develop and operationalize regular RNN, LSTM, and GRU for Sentiment Analysis towards Covid-19 vaccine using Twitter data and analyze time and geographic trends. The performance of the model was generally poor. The poor performance of the models was attributed to the poor quality of data. The model-classified sentiments were used as data points for plotting a time graph and a geo map. The time graph showed that trends across classes were generally similar with the quantity varying relative to real life events. The geo map, however, did not exhibit any reliable trend due to the lack of data points but generally showed an imbalanced distribution of data points across Philippine geography.

Future works could address the same goals of analyzing time and geographic trends but utilize better quality data or pre-trained models. The result of this study reemphasizes the importance of quality data for deep learning tasks.

References

[1] J. Liu, S. Liu, H. Wei, and X. Yang, “Epidemiology, clinical characteristics of the first cases of COVID-19,” European Journal of Clinical Investigation, vol. 50, no. 10, p. 6, Jul. 2020.

[2] R. M. Anderson, C. Vegvari, J. Truscott, and B. S. Collyer, “Challenges in creating herd immunity to SARS-CoV-2 infection by mass vaccination,” The Lancet, vol. 396, no. 10263, pp. 1614–1616, Nov. 2020, doi: 10.1016/S0140-6736(20)32318-7.

[3] R. Singh and R. Singh, “Applications of sentiment analysis and machine learning techniques in disease outbreak prediction – A review,” Materials Today: Proceedings, p. S2214785321032764, May 2021, doi: 10.1016/j.matpr.2021.04.356.

[4] H. Piedrahita-Valdés et al., “Vaccine Hesitancy on Social Media: Sentiment Analysis from June 2011 to April 2019,” Vaccines, vol. 9, no. 1, p. 28, Jan. 2021, doi: 10.3390/vaccines9010028.

[5] J. Patterson and A. Gibson, Deep learning: a practitioner’s approach, First edition. Sebastopol, CA: O’Reilly, 2017.

[6] B. Liu, Sentiment Analysis and Opinion Mining. in Synthesis Lectures on Human Language Technologies. Cham: Springer International Publishing, 2012. doi: 10.1007/978-3-031-02145-9.

[7] E. Aydogan and M. A. Akcayol, “A comprehensive survey for sentiment analysis tasks using machine learning techniques,” in 2016 International Symposium on INnovations in

Intelligent SysTems and Applications (INISTA), Sinaia, Romania: IEEE, Aug. 2016, pp. 1–7. doi: 10.1109/INISTA.2016.7571856.

[8] J. Joseph, S. Vineetha, and N. V. Sobhana, "A survey on deep learning based sentiment analysis," Materials Today: Proceedings, vol. 58, pp. 456–460, 2022, doi: 10.1016/j.matpr.2022.02.483.

[9] A. P. López-Monroy and J. S. García-Salinas, "Neural networks and deep learning," in Biosignal Processing and Classification Using Computational Learning and Intelligence, Elsevier, 2022, pp. 177–196. doi: 10.1016/B978-0-12-820125-1.00021-X.

[10] X. Luo, G. Zimet, and S. Shah, "A natural language processing framework to analyse the opinions on HPV vaccination reflected in twitter over 10 years (2008 - 2017)," Human Vaccines & Immunotherapeutics, vol. 15, no. 7–8, pp. 1496–1504, Aug. 2019, doi: 10.1080/21645515.2019.1627821.

[11] R. Mahajan, W. Romine, M. Miller, and T. Banerjee, "Analyzing Public Outlook towards Vaccination using Twitter," in 2019 IEEE International Conference on Big Data (Big Data), Los Angeles, CA, USA: IEEE, Dec. 2019, pp. 2763–2772. doi: 10.1109/BigData47090.2019.9006136.

[12] J. P. Delizo, M. Abisado, and Ma. I. De Los Trinos, "Philippine Twitter Sentiments during Covid-19 Pandemic using Multinomial Naïve-Bayes," IJATCSE, vol. 9, no. 1.3, pp. 408–412, Jun. 2020, doi: 10.30534/ijatcse/2020/6491.32020.

[13] M. B. Garcia, "Sentiment Analysis of Tweets on Coronavirus Disease 2019 (COVID-19) Pandemic from Metro Manila, Philippines," Cybernetics and Information Technologies, vol. 20, no. 4, pp. 141–155, Nov. 2020, doi: 10.2478/cait-2020-0052.

[14] C. Villavicencio, J. J. Macrohon, X. A. Inbaraj, J.-H. Jeng, and J.-G. Hsieh, "Twitter Sentiment Analysis towards COVID-19 Vaccines in the Philippines Using Naïve Bayes," Information, vol. 12, no. 5, p. 204, May 2021, doi: 10.3390/info12050204.

[15] M. Abadi et al., "TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems." arXiv, Mar. 16, 2016. Accessed: Jun. 29, 2023. [Online]. Available: http://arxiv.org/abs/1603.04467

[16] E. Loper and S. Bird, "NLTK: The Natural Language Toolkit." arXiv, 2002. doi: 10.48550/ARXIV.CS/0205028.

[17] M. Alghamdi, M. Al-Mallah, S. Keteyian, C. Brawner, J. Ehrman, and S. Sakr, "Predicting diabetes mellitus using SMOTE and ensemble machine learning approach: The Henry Ford ExercIse Testing (FIT) project," PLoS ONE, vol. 12, no. 7, p. e0179805, Jul. 2017, doi: 10.1371/journal.pone.0179805.

[18] K. Baktha and B. K. Tripathy, "Investigation of recurrent neural networks in the field of sentiment analysis," in 2017 International Conference on Communication and Signal Processing (ICCSP), Chennai: IEEE, Apr. 2017, pp. 2047–2050. doi: 10.1109/ICCSP.2017.8286763.

[19] W. Aljedaani et al., "Sentiment analysis on Twitter data integrating TextBlob and deep learning models: The case of US airline industry," Knowledge-Based Systems, vol. 255, p. 109780, Nov. 2022, doi: 10.1016/j.knosys.2022.109780.