Identification and Analysis of COVID-19-related Misinformation Tweets via Kullback-Leibler Divergence for Informativeness and Phraseness and Biterm Topic Modeling

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***Abstract*—The interaction of Filipinos transitioned to a virtual setting making social media, like Twitter, their source of information since the pandemic started. The infodemic it caused has opened up avenues to understand the characteristics of misinformation tweets regarding COVID-19. In this paper, we present the classification and analysis of misinformation tweets related to COVID-19 towards identifying themes. We used pointwise KL divergence in scoring "informativeness" and "phraseness" to extract misinformation tweets and BTM for topic modeling. With a testbed of 7,711 tweets, the classifier model identified 3,533 misinformation tweets with an accuracy of 74.25%. The results of the topic modeling were analyzed and clustered to expose possible narratives in the data set. The three narratives showed that most Filipinos use Twitter to share jokes, spread information and awareness about the virus, express opinions about the government's response, and share tips to prevent the disease. A wider date coverage could be included in future works.**

***Index Terms*—COVID-19, misinformation, tweets, KLIP, BTM**

I. Introduction

The COVID-19 pandemic started after the first casualty outside China, in the Philippines, and inflicted a lasting impact on the lives of many people. COVID-19 or Coronavirus disease is caused by the newfound coronavirus, SARS-CoV-2 virus, that is transmissible through saliva droplets or nose discharge. With the pandemic, an "infodemic" or information outbreak has started and it contains both true and false information [1].

To lower the risk of acquiring the disease, people used social media to stay connected with the world. Social media, like Twitter, gives people access to news and information about the disease. It is also through it that people spread their knowledge, views, and opinion about the situation.

Twitter has become widely used by the public and organizations for gathering and spreading information during emergency situations. Its design and features particularly the short burst style of posting, publicly available posts, attaching hyperlinks, easy way of re-posting or sharing, and multimedia capacities make Twitter an accommodating platform for people in sharing their personal experiences, express opinions and concerns, ask questions, and seek and share information. During emergencies and crisis situations, the platform acts as a broadcasting medium and a venue for sourcing news because of its capability for rapid information dissemination that reaches a vast audience; and also a place for people who seek help and who wants to give help during the disaster. Communicating through the platform is driven by the need to contribute to the situation and to connect with others and work together in helping the victims of the disaster [2].

In the Philippines, the presence of false information is not new. Disinformation campaigns are very common in the Philippine politics, and are systematic and strategic [3]. The presence of misinformation on social media platforms such as Twitter may have an impact on the spread of COVID-19. Understanding and detecting misinformation is important to prevent them from further spreading and creating more damage.

Extracting the common themes or topics can show the characteristics of a data and make sense out of it. An investigation on selected Telegram and WhatsApp groups in Iran were investigated to find the themes of misinformation related to COVID-19 [4]. Topic modeling on Twitter data during calamities, disasters, and other events can show how people behave and how they use social media during these times [5][6].

What are the themes of COVID-19-related misinformation? This is the main question that this study needs to address. But before determining the common topics of misinformation tweets about COVID-19, we first need to identify them. Misinformation tweets from the data set were identified using the key terms or distinctive terms that were discovered using pointwise Kullback-Leibler divergence. Themes were extracted from COVID-19-related misinformation tweets using topic modeling and manual qualitative analysis.

II. Related Work

A. *Misinformation*

Misinformation has been claimed to have a contribution to the spread of COVID-19. As misinformation regarding COVID-19 spreads rapidly on social media, several studies have been conducted to investigate its magnitude on Twitter. Understanding and detecting misinformation is important to prevent them from further spreading and creating more damage.

Basic characteristics of texts of fake and real news articles can be compared against each other. Kapusta et al. [7] did this in their study to show if there are statistically significant difference between the two and can be vital in choosing the suitable characteristics to use for the later classifier models of fake news. Their study showed that articles containing fake information have a more negative sentiment. The results also show that fake news articles tend to be more complicated and more descriptive than the real ones to mislead the reader and convince them that what they are reading is accurate [7].

Analysing the differences and similarities between misinformation regarding COVID-19 and general COVID-19 content can be crucial in understanding what kind of misinformation spreads on social media. In a study by Ranera et al. [8], they used Doc2Vec to retrieve judicial decisions of Philippine Supreme Court cases semantically similar. They used cosine similarity to quantify the similarity between two document vectors. The results prove that finding similar case decisions can be possible through Doc2Vec [8].

What are the key ideas in COVID-19-related misinformation tweets that are not in the general or not misinformation COVID-19-related tweets? This is one of the questions in the exploratory study of Shahi et al. [9] that they answered. Using pointwise Kullback-Leibler divergence for scoring both informativeness and phraseness (KLIP), which is combined into a single score to rank the phrases, they investigated the distinctive terms in their misinformation data [9].

In the approach presented by Tomokiyo and Hurst [10] in extracting distinctive terms or keyphrases, KL divergence or relative entropy was used to measure the difference between two language models. A *keyphrase* has two features namely *informativeness* and *phraseness*. Phraseness is a concept in which it determines how a cohesion of consecutive words be called a phrase. They defined informativeness as the ability of a phrase to represent the key ideas in the data, and the "new information" that we can get from a specific set of documents with respect to a background or general data set. They created language models for a *foreground corpus*, which is the target document from which phrases are to be extracted, and for a *background corpus*, to which the target document is compared. The unigram model for the foreground corpus was denoted as LM^1_{fg} and higher order or N-gram model, where *N* is greater than 1, as LM^N_{fg}. The unigram model for the background corpus was denoted as LM^1_{bg} and N-gram model as LM^N_{bg} [10].

The amount of loss between LM^1_{fg} and LM^N_{fg} is related to phraseness and the amount of loss between LM^N_{fg} and LM^N_{bg} denotes informativeness. Fig. 1 illustrates this relationship.

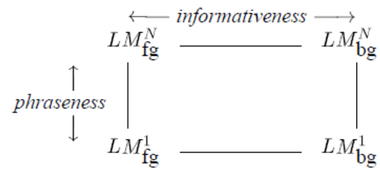

Fig. 1. Phraseness and informativeness as loss between language models

To compute the amount of loss between the language models, pointwise KL divergence $\delta_{\text{w}}(p\|q)$, where *w* denotes phrase, was used [10].

$$\delta_w(p||q) = p(w)log\frac{p(w)}{q(w)} \tag{1}$$

The phraseness of *w* is calculated by getting the amount of loss from assuming the independence of each word by comparing the N-gram from the unigram [10].

$$\delta_w(LM^N_{fg}||LM^1_{fg}) \tag{2}$$

The informativeness of *w* is calculated by getting the amount of loss from assuming that the phrase is extracted from the background instead of the foreground [10].

$$\delta_w(LM^N_{fg}||LM^N_{bg}) \tag{3}$$

B. *Topic modeling*

Themes show the characteristics of the data, and theme extraction is the way to make sense out of it. Using discourse analysis, themes like "disease statistics", "treatments", "vaccines and medicines", "prevention and protection methods", "dietary recommendations" and "disease transmission" were discovered from COVID-19-related data from specific Telegram and Whats App groups in Iran [4].

One of the common topic modeling techniques is the latent dirichlet allocation (LDA). It is very effective in capturing topics in a document-level, but may not be very effective with short texts like tweets [5]. To capture the topics from typhoon-related tweets, Ligutom et al. [5] used biterm topic modeling (BTM) and used open coding to assess the topic models to show how Filipino people act during typhoons. The results show that certain behaviors like determination, unity and resiliency, and antagonism can be noted from the topics. The results also show that Filipinos express their opinions about the typhoon. They also stated that some topic models can be misleading as some tweets containing "typhoon" or "bagyo" are not connected to typhoons but are included in the topic model [5].

Gorro et al. [11] used BTM and word2vec to answer the research question about the common topics on participants' suggestions on disaster risk reduction (DRR) in their locality. The study showed that BTM and Word2vec can be used for qualitative analysis of data, like DRR, aside from using traditional manual approaches [11].

III. Methodology

A. Data Collection

A Python library in getting historical tweets called GetOldTweets3 was used to collect tweets from January 1, 2020 to March 22, 2020. The keywords "covid", "ncov", and "coronavirus" were used to filter out COVID-19-related tweets. A total of 12,631 publicly available Twitter data from Metro Manila and nearby areas were gathered. From the total data gathered, 4,695 tweets prepared by the domain experts will be used for training, 508 tweets were labeled as "misinformation" and 4,187 tweets were labeled as "not misinformation".

B. Data Preprocessing

Various preprocessing techniques are done in Natural language processing to prepare text data before proceeding to the actual experiment. An important step in the study is the cleaning of data wherein irrelevant and noisy data are removed to prevent misleading results. In this study, the following were performed:

1) Removal of URLs
2) Removal of words preceded by "#"
3) Removal of words preceded by "@"
4) Removal of punctuations
5) Tokenization
6) Lowercasing
7) Removal of English and Filipino stop words
8) Removal of words containing digits only
9) Removal of words with less than 2 characters
10) Removal of tweets with less than 2 words

A total of 4,634 tweets for the training data and 7,711 tweets for testing data were left after cleaning.

C. Analysis and Classification

1) KLIP: KL divergence or relative entropy is used to calculate the difference of two probability distributions. In extracting keyphrases, Tomokiyo and Hurst used pointwise KL divergence to score informativeness and phraseness. To do this, a foreground corpus and a background corpus is needed [10].

KLIP was used in this study to get the keyphrases from the data consisting of tweets tagged as misinformation and use these keyphrases to identify more tweets that contains misinformation. The tweets in the training data set was manually classified as "misinformation" or "not misinformation" by the domain experts. The tweets that are tagged as 'misinformation' with 506 tweets and as "not misinformation" with 4,128 tweets was set as the foreground corpus and the background corpus, respectively.

2) Biterm Topic Modeling: BTM is used to extract topics from short texts, like tweets, based on the collection of biterms from a whole corpus to address the problem with sparsity of data at document level [12]. This technique of topic modeling discovers the topic distribution over data set or corpus level instead of tweet or document level by using co-occurrence patterns in the whole corpus.

3) Open Coding: Open coding is a manual qualitative analysis used in labeling the various topic models generated by the BTM. Different topic models contain keywords which, as a whole, represents a topic. The tweets containing at least one of the keywords in a topic model are analyzed manually to formulate a label for that topic model.

IV. Experimental Results

To classify which among the tweets contain misinformation, we used the keyphrases obtained from using KLIP. A unigram and bigram model was created for the "misinformation" corpus, foreground, with 6,687 words; and a bigram model with Kneser-Ney smoothing to handle zero occurences for the "not misinformation" corpus, background, with 54,444 words. For each bigram (x,y) in the foreground corpus, we calculated the phraseness from $p(x, y)_{fg}$ and $p(x)_{fg}p(y)_{fg}$, and the informativeness from $p(x, y)_{fg}$ and $p(x, y)_{bg}$. Table I shows the top 15 keyphrases or informative terms in COVID-19-related misinformation tweets compared to the not misinformation tweets.

TABLE I
Top Keyphrases in COVID-19-related Misinformation tweets

Phrase	KLIP score
sec panelo	29.13652
winning labas	28.16712336
crowds never	28.16712336
large crowds	28.16712336
next election	28.02828692
becomes full	27.76165825
wisely next	27.76165825
checked regularly	27.47397618
chupa valentines	27.47397618
bio weapon	27.35619314

From the list of keyphrases, additional misinformation tweets were discovered by checking which of the tweets contains at least one of the keyphrases. From the 7,711 unlabeled data set, A total of 3,533 tweets were tagged as misinformation. A random sampling of two thousand tweets, one thousand each from the misinformation-tagged data and from the tweets not tagged as misinformation, was done to evaluate the model using confusion matrix, shown in Table II ("1" for "Misinformation" and "0" for "Not Misinformation"). Table III shows the metrics for every threshold for KLIP score.

We used the KLIP score threshold of exactly 20.2669 with a precision of 92.31% to get the misinformation tweets that can be combined with the training data containing misinformation. The combined data set of 671 tweets was prepared for topic

TABLE II
KLIP CLASSIFIER MODEL CONFUSION MATRIX

		Predicted 1	Predicted 0
Actual	1	593	108
	0	407	892

TABLE III
KLIP CLASSIFIER MODEL METRICS

Threshold	Accuracy	Precision	Recall	F-score
0	74.25%	59.30%	84.59%	70%
5	70.20%	67.80%	28.53%	40%
10	66.85%	61.31%	14.69%	24%
15	65.80%	61.64%	6.42%	12%
20	65.45%	85.71%	1.71%	3%
25	65.25%	87.50%	1.00%	2%

modeling. We removed the top 15 words from the data based from the data preprocessing methods of [5] before performing BTM. We extracted 10 topics from the data and used open coding to label each topic model as shown in Table IV with a corresponding tweet related to the topic.

After extracting and labeling the topic models, a thorough analysis of the themes to cluster them into narratives was conducted. It is a way of "building a story" and have a deeper understanding of the themes from the data set [13].

V. DISCUSSION

In Table I, it shows the top keyphrases in the misinformation data set compared to the background data set about COVID-19. The phrase "sec panelo" got the highest KLIP score which indicates that this is the most distinct or informative phrase in the misinformation training data set. Here is an example tweet from the misinformation training data that contains the phrase "sec panelo": "Para maiwasan ang NCoV, Palakasin ang immune system sabi nga ni Sec. Panelo 'no need to ban Chinese friends, you just need to boost your immune system', so tayo na po ang mag adjust. -Baka hindi pa nakainom ng gamot si Tatang. Paka obob. Before and After" [in order to avoid NCov, strengthen your immune system as what Sec. Panelo said 'no need to ban Chinese friends, you just need to boost your immune system', so let us adjust]. The tweet implies that the Chief Presidential Legal Counsel of the Philippines, Salvador Panelo, said that you only needed to strengthen your immune system to prevent yourself from contracting the COVID-19. Although it was the most informative phrase for our misinformation data, it did not appear in the unlabeled data set. The highest scoring phrase that appeared in the unlabled data set was "next election" which got a score of 28.028. A sample tweet is "May this covid-19 pandemic remind us to #VoteWisely next election," which implies that the COVID-19 pandemic reached the Philippines because of the government's mishandling of the situation and let it be a reminder to vote worthy leaders next time. The phrase "ncov virus" got the

TABLE IV
BTM RESULTS

Topic	Label	Topic models
Topic 1	Frustrations	kasi, bansa, baka, tapos, natin, ayan, tuloy, positive, sakit, kumain, pati, muna, safe, sitwasyon, please, like, hospital, mama, lockdown, buong
Topic 2	Government's pandemic response	confirmed, cases, hospital, government, case, pilipinas, malapit, lalo, sobrang, natin, naka, philippines, mamatay, kamay, kasi, nakakatakot, inyo, number, deadly, building
Topic 3	Social responsibilities	always, matataong, keep, ligtas, home, lumayo, time, masks, jakol, everyone, maligo, safe, makaiwas, inside, sanitize, vitamins, clean, hygiene, lugar, message
Topic 4	Remedies or cure	people, natural, infected, kasi, please, prevent, safe, masyadong, everyone, testing, vitamin, china, epidemic, global, buying, vaccine, case, boost, meron, prevention
Topic 5	Undermining the virus	happy, needs, health, gave, like, pilipinas, outbreak, sars, masks, philippines, infected, year, period, really, people, going, prevent, china, proper, possible
Topic 6	Local governments' pandemic responses	outbreak, niyo, city, officials, social, could, health, would, distancing, cases, spread, buti, sure, instead, know, like, corona, country, started, hirap
Topic 7	Boosting the immune system to fight COVID-19	help, washing, epidemic, satin, government, contact, vitamins, wash, experiencing, point, protect, wearing, proper, stupid, philippines, safety, natin, sakit
Topic 8	Precautionary measures	wash, precautions, need, sure, masks, distancing, quarantine, even, crowded, social, still, healthy, much, sanitizer, wear, vitamins, make, home
Topic 9	Fighting COVID-19	nasa, doctors, tapos, like, even, boost, araw, prevent, work, bwisit, symptoms, panlaban, advice, food, lysol, puro, vitamin, know
Topic 10	COVID-19 vs other illnesses	death, even, china, missing, first, without, public, year, something, must, outside, alerted, sars, competent, less, lethal, contagious, male, infectious, suddenly

lowest score with 0.009 which implies that it can not represent the key idea of the misinformation training data set.

A total of 3,533 tweets were tagged as misinformation with 74% accuracy, 59% precision, and 85% recall, as shown in Table III. The results show that almost all the tweets from the 4,178 testing data are correctly tagged by the model as "not misinformation". With a precision of 92.31%, we used the 20.2669 KLIP score threshold to filter the misinformation tweets that can be combined with the training misinformation data for topic modeling.

After addressing the identification of misinformation tweets, topic modeling is performed to understand COVID-19 misinformation in Twitter. We extracted 10 themes from the misinformation data set as shown in Table IV. From conducting a final stage of manual analysis, we propose three narratives, among other possible narratives, clustered from the ten themes. The first narrative is about the tweets that contain humor and underestimating the COVID-19. The second narrative is grouped from the tweets expressing frustrations during the start of COVID-19 outbreak in the Philippines. The third narrative is about the true nature of the virus according to the authors of the tweets.

A. *"It is just COVID"*

The first narrative emerges from the tweets that implies the inferiority of the COVID-19 among other illnesses. These tweets usually contain the words "less" and "more". The tweet "I just don't understand why people are more afraid of the nCOV than measles which has a higher mortality rate" is one of the tweets that can be interpreted that we should not be afraid of the new strain of coronavirus since it is less dangerous. Similar tweets compare COVID-19 and other specific viral infections like HIV and common flu.

Using the term "lang" [just/simply/only] is also common in tweets included in this narrative. The term is usually found in phrases like "ncov ka lang" [you are just nCoV] or "covid lang yan" [it is just COVID]. People tend to justify a future plan or an action done amidst the pandemic ("HAHAHHA ARAT COVID LANG YAN GALA TAYO" [it is just COVID let us hang out]).

Tweets with satirical content are also prevalent with 76 occurrences in the data set. Satirical tweets can be hard to detect without knowing their context. Tweets like "mas marami pa ang infected ng tiktok virus kesa covid jusko mama" [more are infected by the tiktok virus than COVID oh my God mama] could be interpreted in different ways such as: it could imply that the new strain of coronavirus should not be a concern since there are more people using the TikTok app and "infected" by it than the number of people in the Philippines infected by COVID-19, or it could suggest that a new virus named "Tiktok" does exist. Some tweets may suggest, as a joke, a cure for COVID-19; like "Puno na nang alcohol katawan ko malamang neto covid free nako" [my body is full of alcohol I'm probably COVID free]. There are also tweets that contain puns and word plays. One example is a portmanteau of Kobe Bryant and COVID-19, COVID Bryant. Other tweets show a different meaning to the terms "nCoV" and "COVID". For instance, "NCoV- NEED CASH ON VALENTINES".

The tweets covering this narrative show that Filipinos find hope in a disaster by making big problems seem small. Downplaying the COVID-19 by comparing it against other fatal virus may be from the fact that COVID-19 was new in the country at the time of posting such tweets that is why people had the impression on COVID-19 being a weaker virus. Adding humor to tweets about COVID-19 is another way of downplaying the virus and its effects that may demonstrate a less cautious way to live through the pandemic.

B. *"What now?"*

A second narrative emerges from tweets that express negative sentiments towards the situation. The tweets' subjects in this cluster of themes revolve around government's response (and lack of response). The phrase "vote wisely", with 9 occurrences, can also be seen in the tweets, sometimes paired with "next election", as a reminder for the people. There are tweets that express disappointment towards the mentioned name of official, either from a local or a national government post. A total of 9 tweets were seen mentioning 'Mayor Joy', mayor of Quezon City, Philippines. The phrase was seen together with words "anuna" or "ano na" [what now]. People also express their disappointment by not voting for the politician next election.

There are also tweets, a total of 32, that mention the name and nickname of President Rodrigo "Digong" Duterte. Some tweets contain a mockery of his own words, way of speaking, and strange solutions; for example, "Akala ko iihian na naman niya eh" [i thought he will pee on it again] wherein a solution Pres. Duterte proposed, last 13$^{\text{th}}$ of January 2020, to pee on the Taal volcano to stop the eruption was also suggested by a Twitter user to kill the coronavirus; and the term "veerus" which how he pronounced the word "virus" in his press conference last 3$^{\text{rd}}$ of February 2020. The tweet "State of calamity ba dahil ba sa coronavirus o sa Duterte Veerus!?! I really wanna know..." [state of calamity because of the coronavirus or the Duterte Veerus!?! I really wanna know...] implies that there is a possibility that Duterte was the one causing the big problem of the country. Some people are expressing their disapproval of not imposing a travel ban immediately – "4th is the very best, if this digong ordered at once the blocking of all chinese nationals from entering our ports and airports, there is no way for ncov to enter our country."

In the data set, it is common to see tweets that contain government's official announcements, protocols, and guidelines that comes with personal comments and opinions. Data shows that people are blaming the government for the COVID-19 outbreak in the Philippines.

C. *The virus*

The third narrative is clustered from tweets that tell stories or share knowledge about the COVID-19. In 7 tweets, it is implied that the COVID-19 was created as a "biochemical weapon". For example, "Lemme make my own assumptions regarding CoVId reaching S.Korea. Not sure if everyone knows that this started as a Biochemical Weapon being made by the Chinese people & was spread for reasons we are not sure how. Also its meant to be used to attack somewhere.. And how this spread."

There are also tweets that explains the weaknesses of the virus and how we can avoid contracting it. Some would say that heat can kill the virus ("Good amount of people wearing masks in Manila. Don't they know heat kills coronavirus?). Drinking liquor, according to them, could kill the virus ("uminom ka lang..mabisang panlaban yan sa covid" [just drink..effective against COVID]). Since rubbing alcohol is effective in surface sanitation and killing the virus, we could also drink it ("Tara inom ng alcohol iwas sa covid haha" [let us drink alcohol to avoid COVID haha]).

In addition to drinking liquor or rubbing alcohol, tweets about boosting and strengthening the immune system is recurring 33 times. It is said that adequate sleep, healthy diet, proper hygiene, and drinking vitamins are enough to survive from the virus or even prevent yourself from acquiring it ("I was told a ketogenic diet improves the immune system, thus a good incentive in fighting ncoV."). And people who have weaker immune system is more vulnerable to the disease ("Yari ako Kay CoVid-19 .., Mahina Immune system ko Hays" [i am doomed because of COVID-19.., my immune system is weak"]).

In the data pool, conspiracy theories are common. False knowledge about the nature of the virus could have an effect on how people will approach the situation. Some tweets covered by this narrative can also be taken as a joke especially the ones about drinking rubbing alcohol to kill the virus inside our body. It could also be observed that people share tips and reminders in fighting COVID-19 out of concern for others.

VI. Conclusion

The study aims to have a deep understanding of the misinformation about COVID-19 in the Philippines through the analysis of Twitter data. This analysis can be done after finding the misinformation tweets, and that is also addressed in this study.

One limitation of this study is the date coverage and the small data size for misinformation training data. Future work could use a wider date coverage to achieve bigger data size which could give us more misinformation data for training that could yield better results for automated classification of tweets. In conclusion, key phrases extracted from the misinformation training data set using KLIP can be used to identify additional misinformation tweets.

After identifying which among the data gathered are misinformation, we used the best precision to filter the misinformation tweets before performing topic modeling and final stage of analysis. Results show different opinions, experiences, thoughts, and knowledge shared online. Ten topics were extracted, then clustered into three narratives. The suggested narratives showed that the shared misinformation on Twitter in the Philippines are from Filipinos who used Twitter during the start of the COVID-19 pandemic to share jokes, express frustrations, spread information and awareness, and share tips against the virus out of concern for others. Future work could also attach a demographic data like age, income, education, and career profession which could add insights on the misinformation data and how they spread, and deeper understanding on the authors or sharers of misinformation.

References

[1] W. H. Organization, "Novel coronavirus (2019-ncov): Situation report, 13," Technical documents, 2020, 7 p.

[2] C. C. David, J. C. Ong, and E. F. T. Legara, "Tweeting supertyphoon haiyan: Evolving functions of twitter during and after a disaster event," *PloS one*, vol. 11, no. 3, e0150190, 2016.

[3] J. C. Ong and J. V. A. Cabañes, "Architects of networked disinformation: Behind the scenes of troll accounts and fake news production in the philippines," *Architects of networked disinformation: Behind the scenes of troll accounts and fake news production in the Philippines*, 2018.

[4] P. Bastani and M. A. Bahrami, "Covid-19 related misinformation on social media: A qualitative study from iran.," *Journal of medical Internet research*, 2020.

[5] C. Ligutom, J. V. Orio, D. A. M. Ramacho, C. Montenegro, R. E. Roxas, and N. Oco, "Using topic modelling to make sense of typhoon-related tweets," in *2016 International Conference on Asian Language Processing (IALP)*, IEEE, 2016, pp. 362–365.

[6] C. R. Soriano, M. D. G. Roldan, C. Cheng, and N. Oco, "Social media and civic engagement during calamities: The case of twitter use during typhoon yolanda," *Philippine Political Science Journal*, vol. 37, no. 1, pp. 6–25, 2016.

[7] J. Kapusta, L. Benko, and M. Munk, "Fake news identification based on sentiment and frequency analysis," in *International Conference Europe Middle East & North Africa Information Systems and Technologies to Support Learning*, Springer, 2019, pp. 400–409.

[8] L. T. B. Ranera, G. A. Solano, and N. Oco, "Retrieval of semantically similar philippine supreme court case decisions using doc2vec," in *2019 International Symposium on Multimedia and Communication Technology (ISMAC)*, IEEE, 2019, pp. 1–6.

[9] G. K. Shahi, A. Dirkson, and T. A. Majchrzak, "An exploratory study of covid-19 misinformation on twitter," *Online social networks and media*, vol. 22, p. 100 104, 2021.

[10] T. Tomokiyo and M. Hurst, "A language model approach to keyphrase extraction," in *Proceedings of the ACL 2003 workshop on Multiword expressions: analysis, acquisition and treatment*, 2003, pp. 33–40.

[11] K. Gorro, J. R. Ancheta, K. Capao, N. Oco, R. E. Roxas, M. J. Sabellano, B. Nonnecke, S. Mohanty, C. Crittenden, and K. Goldberg, "Qualitative data analysis of disaster risk reduction suggestions assisted by topic modeling and word2vec," in *2017 International Conference on Asian Language Processing (IALP)*, IEEE, 2017, pp. 293–297.

[12] X. Yan, J. Guo, Y. Lan, and X. Cheng, "A biterm topic model for short texts," in *Proceedings of the 22nd international conference on World Wide Web*, 2013, pp. 1445–1456.

[13] Z. C. Pablo, N. Oco, M. D. G. Roldan, C. Cheng, and R. E. Roxas, "Toward an enriched understanding of factors influencing filipino behavior during elections through the analysis of twitter data," *Philippine Political Science Journal*, vol. 35, no. 2, pp. 203–224, 2014.