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Short Paper

Analyzing Public Concern Responses for Formulating Ordinances and Laws using Sentiment Analysis through VADER Application

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Abstract

Purpose – This paper aimed to develop a system that applies VADER Sentiment Analysis to tweets collected using a developed twitter scraper tool to identify the insights of public responses based on their tweets on certain government services rendered to them thus providing legislators of the province of Laguna an additional tool in writing future legislations.

Method – This study may serve as an additional tool to the Sangguniang Panlalawigan of Laguna in identifying sentiments of the public in terms of government services that are rendered and lack thereof based on the collected tweets written in Tagalog, English or Taglish (Tagalog and English). Data collected through the Twitter scraper tool are preprocessed taking into consideration the special characters that also have impact on scoring sentiments, emojis, and emoticons. The compound score is computed by normalizing the sum of the polarity scores for each tweet.

Results – Aside from a tabular visualization of VADER's results, the system also provides graphical representation of the evaluation result with the percentage of positive neutral and negative tweets. Based on the result of the testing and evaluation, the VADER model is 80.71% accurate and had an F-score of 84.33%.

Conclusion – The reports generated from the system be utilized to serve as potentially additional basis for legislators of the province of Laguna in writing legislations such as resolutions and ordinances based on the sentiment or voice of the community.

Recommendations – It is recommended to collaborate with linguists to develop a native language of VADER's lexicon to improve the accuracy of the sentiment scores.

Keywords – Public Concerns, Sentiment Analysis, VADER, Laguna, Ordinances, Laws

INTRODUCTION

Governments across the world are facing unique challenges today than ever before. It is a growing trend that governments are trying to move closer to the citizen centric model, where the priorities and services would be driven according to citizen needs rather than Government capability (Arunachalam & Sarkar, 2013). Such trends are forcing the Governments in innovating and applying emerging technologies on how to communicate and collect public responses. Several technologies particularly social media sites are opening new opportunities to the Governments to enable innovations in such interactions. Governments are fast realizing that it can be a great vehicle to get closer to the citizens. It can provide deep insight in what citizens want (Tran & Bar-Tur, 2020). Thus, in the current gloomy climate of world economy today, governments can reorganize and reprioritize the allocation limited funds, thereby creating maximum impact on citizens' life.

In accordance with the Philippine Republic Act No. 7160 more commonly known as the "Local Government Code of 1991", The Sangguniang Panlalawigan of Laguna exercises the local legislative power of the province of Laguna. The legislative body is generally in charge of enacting ordinances, approving resolutions, and appropriate funds for the general welfare of the province and its inhabitants keeping in mind the proper exercise of the corporate powers of the province. It is important to the local legislators of the Sangguniang Panlalawigan of Laguna to consider their citizen's insights on government services rendered (or lack thereof) to them. Governments aim to deliver quality government services that are efficient, cost-effective, and socially just while keeping the needs of the public at the center of the provided services (Alqaryouti, Siyam, Monem & Shaalan, 2020).

Twitter, with over 319 million monthly active users, has now become a goldmine for organizations and individuals who have a strong political, social and economic interest in maintaining and enhancing their clout and reputation (Jianqiang, Xiaolin & Xuejun, 2018). With the advances in machine learning and natural language processing techniques it is now possible to analyse the obtained data to measure citizen's satisfaction with the services provided. Sentiment analysis provides these organizations with the ability to surveying various social media sites in real time. Moreover, it is also useful in determining viewers/users in YouTube their interest to learn through application of lexicon-based sentiments analysis which confirms that video are valuable resources in learning discipline (Miranda and Martin, 2020). Sentiment analysis in this research is carried out to find out public sentiments and opinions towards government services particularly to tweets posted by the citizens of the province of Laguna, whether positive or negative dominant. Sentiment Analysis builds systems that try to identify and extract opinions within text (Shelar & Huang, 2018).

For Filipinos, the use of social media in the context of democratic consolidation is exceptionally remarkable because for the past four years the Philippines have topped social media users worldwide. They rank first globally in internet usage with an average daily screen time of 10 hours. And almost half of the adult population uses the internet (Yusingco, 2020; Pablo, 2018). Additionally, in a country such as the Philippines, it is an important principle of a governmental system that public policies are decided upon by the people. Constitutional and legal reforms have led to a national 'citizen charter' which has enabled citizens and citizen groups to complain to officials whenever the delivery of public services is inadequate (Porio, 2017). Citizen participation represents a key component, as it is the way to adapt government decisions to the real expectations of citizens (Buccafurri, Fotia & Lax, 2015). This further supports that the citizens are the source of power and that their opinions should at least be considered in molding the actions of the government. The Sangguniang Panlalawigan of Laguna also faces these kinds of problems.

To accomplish this, the researcher used the scraping tool developed to collect social media posts from Twitter. The scraping tool utilized the Twitter API to adhere to Twitters policies and regulations when collecting and extracting tweets. However, these initially collected tweets are considered as unstructured data and needs to be cleaned and preprocessed. Special functions were used to carefully clean the data particularly special characters such as emoji and emoticons. VADER (Valence Aware Dictionary and Sentiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media (Singh, 2020; Bose, Aithal & Roy, 2021). VADER was then used to identify the polarity and compound score of the collected data.

The training and testing process is carried out through the comparison of the VADER results to the human-rated result on the same data set.

The researchers aimed of developing a web-based system that enables users to collect public responses using the Twitter scraping tool developed and apply VADER Sentiment Analysis to identify the polarity of tweets whether they identify as positive, neutral and negative.

LITERATURE REVIEW

There have been previous studies relating to the application of sentiment analysis, some are used for product sentiments and there are also sentiments about the political situation of an area. Research on politics has been carried out by Meduru, Mahimkar, Subramanian, Padiya and Gunjgur (2020) about the people's opinion regarding various subjects with respect to the governmental issues and political reforms on social media platforms using tweets, status updates and blogs. Their research corpus data for testing were taken crawling from Twitter using the hashtag "Modi" which pertains to the Indian Prime Minister, Narendra Modi. It represents an integration of the masses' opinion from North, South, East and West of India along with the users who have disabled their location on Twitter. The results of their sentiment analysis showed the analysis of 1952 tweets based on regions such as North with 311 positive, 178 negative and 237 neutral sentiments. East with 35 positive, 29 negative and 26 neutral sentiments. South with 95 positive, 104 negative and 113 neutral and West with 112 positive, 70 negative and 95 neutral sentiments. Their research also considered Tweets that has disabled region which resulted in 238 positive, 140 negative and 169 neutral sentiments. Moreover, the study of Miranda and Bringula (2021) applied sentiments analysis to reveal the sentiments of Philippine Presidents' SONAs and to discover the topics emerged from their speeches and found out patterns of sentiments which incoming president had lower sentiments than that of the outgoing. Besides the political aspect, sentiment analysis can also be used in determining the government services. In the study of Umali, Miranda and Ferrer (2020) used sentiment analysis to determine the people comments/sentiments in social media like YouTube in different government offices in the Philippine. The study able to present the most frequent words using Word Cloud through lexicon-based approach which obtain the perception of the YouTube uses toward government organization with bilingual comments Tagalog and English words.

VADER Sentiment analysis has also been used to analyze native language tweets (Tymann, Lutz, Palsbröker & Gips, 2019). The researcher's approach was to translate VADER's lexicon to German which is the native language of their corpus. Their developed tool was called GerVADER. The system was then tested with parts of the SCARE dataset which contains around 800,000 app reviews app reviews for different app categories from the Google Play Store. The results show that GerVADER lacks some additional work to increase its classification accuracy, but it promises better results considering how well the original performed. Test results on some parts of the SCARE corpus particularly the sports news apps showed that GerVADER classified 70% correctly. Especially the F1 score for positive labels is very good with more than 85%.

In their work, Elbagir and Yang (2019) aimed to use the Valence Aware Dictionary for Sentiment Reasoner (VADER) to classify the sentiments expressed in Twitter data. In their research, they proposed three (3) phases: Their first phase was concerned the acquisition of Twitter data. The second phase focused on the initial preprocessing work carried out to clean and remove irrelevant information from the tweets. Phase three dealt with the use of the NLTK's VADER analyzer as well as the scoring method applied to the VADER results to assess its ability to classify tweets on a five-point scale. The researchers utilized the NLTK package in Python to perform sentiment analysis using VADER. Results of the performed sentiment analysis using NLTK package revealed the results of VADER when used in a dataset that contains 1,415 tweets which was consisted of political tweets pertaining to the U.S. presidential elections in 2016. Results of their research indicated that the VADER Sentiment Analyzer was an effective choice for sentiment analysis classification using Twitter data with the system having 29% of the tweets expressed positive opinions, 22.89% of the tweets expressed negative opinions and 46.7% of the tweets expressed neutral opinions. Their study showed that VADER easily and quickly classified huge amounts of data.

Similarly, Shelar and Huang (2018) also utilized VADER on captured tweets using Tweepy which is a Python library used to download tweets via the Twitter API. The researchers aim was to o capture the polarity of collected tweets towards fundraising and donating concept. The study presented the number of records (tweets) with mentions of the keywords captured for the experiment. The keyword "charity" is the highly cited word with 154,010 mentions. Their researcher was also able to depict the polarity of sentiments showing the number of positive, negative and neutral scores for each category with charity gaining the highest percentage in total positive, negative and neutral score yielding 58.59%, 41.54% and 42.27% respectively. Furthermore, sentiment analysis can be applied in assessing opinion to emotion mining especially in disaster application in which community sentiments contribute big help to determine the impact of Typhoon (Vinluan et al., 2021).

METHODOLOGY

This paper focuses on the mining of public tweets from the social networking site Twitter, which permits users to post a maximum of 280-character long status update called "tweet". The developed system uses a sentiment analysis model called Valence Aware Dictionary for Sentiment Reasoning or VADER to categorize the polarity of collected tweets as positive, negative and neutral. It also determines the intensity of the sentiment based on the compound score generated by the VADER model.

A. Data Collection and Preprocessing

Figure 1 illustrates the data collection and preprocessing steps applied by the developed system.

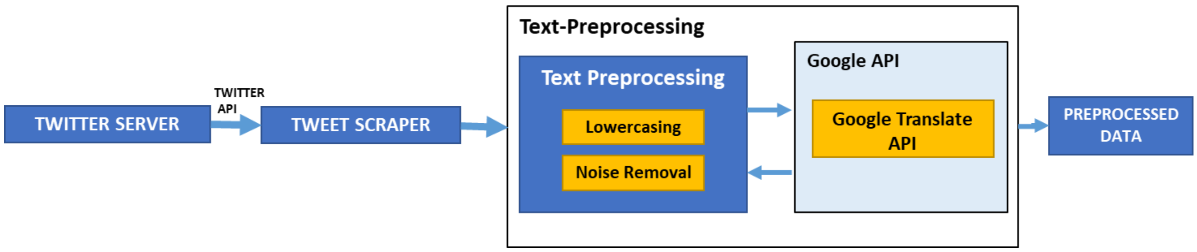

Figure 1. The Data Collection and Preprocessing stage.

1. *Data Collection*

Social media can be a gold mine of data in regards to consumer sentiment. Platforms such as Twitter lend themselves to holding useful information since users may post unfiltered opinions that can be retrieved with ease (Beck, 2020).

To collect the data to be used for analysis, the researchers used the Twitter scraping tool developed. This system module adhered to Twitter's search API using a Twitter developer account. Public tweets were returned starting from June 21, 2021 to June 26, 2021. The researchers used the search keywords "face shields", "vaccine" and "bakuna" to build the test data set since these keywords or topics are what most of the people in the Philippines talk about during the time of test data collection. To specifically identify that tweets were posted from the province of Laguna, the geocode of the Provincial Government of Laguna was also specified as a search parameter to identify the epicenter of the search with a 25mi search radius to also include municipalities and cities surrounding the specified geocode.

2. *Data Preprocessing*

2.1. *Lowercasing*. The developed system ran the strtolower() function to the data set to convert all contents to lowercase characters.

2.2. *Noise Removal*. The developed system also applied the Noise removal preprocessing technique since these social media posts are usually unstructured and contains unnecessary special characters for sentiment analysis. Since VADER's results are also affected by punctuation, special characters that are used to apply punctuation such as "!" are not removed if it is used as a punctuation for a sentence. Additionally, Emoticons and Emojis are not removed since they also hold value and affects the outcome of VADER.

2.3. *Google Translate API.* Tweets that contain Tagalog words and terms are converted to English in order for VADER to evaluate and rate such words. The developed system utilized the Google Translate API for such task. Aiken (2019) provided an updated evaluation of Google Translates accuracy. Results for the Filipino language translation showed an 18% increase in accuracy between the initial evaluation results in 2011 using BLEU (bilingual evaluation understudy) version 1 (52%) and version 3 (70%). Additionally, the system users are also provided with a module to manually provide the translation of the collected tweets in the case of an inaccurate translation via the Google Translate API.

B. Sentiment Analysis Approach

Sentiment analysis is a text analysis method that detects polarity (e.g. a positive or negative opinion) within the text, whether a whole document, paragraph, sentence, or clause. Sentiment analysis aims to measure the attitude, sentiments, evaluations, attitudes, and emotions of a speaker/writer based on the computational treatment of subjectivity in a text (Beri, 2020).

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a pre-trained model that uses rule-based values tuned to sentiments from social media. It evaluates the text of a message and gives an assessment of not just positive and negative, but the intensity of that emotion as well (Hutto & Gilbert, 2014). It uses a dictionary of terms that it can evaluate which includes examples like:

- Negations - a modifier that reverses the meaning of a phrase ("not great").
- Contractions - negations, but more complex ("wasn't great").
- Punctuation - increased intensity ("It's great!!!").
- Slang - variations of slang words such as "kinda", "sux", or "hella".

VADER sentiment analysis relies on a dictionary that maps lexical features to emotion intensities known as sentiment scores. The sentiment score of a text can be obtained by summing up the intensity of each word in the text which is also called the compound score/polarity.

The compound polarity score is computed by summing the valence scores of each word in the lexicon, adjusted according to the rules, and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive). This is the most useful metric if you want a single unidimensional measure of sentiment for a given sentence. Calling it a 'normalized, weighted composite score' is accurate.

It is also useful for researchers who would like to set standardized thresholds for classifying sentences as either positive, neutral, or negative. Typical threshold based from the research of Hutto and Gilbert (2014) are:

- positive sentiment: compound score >= 0.05
- neutral sentiment: (compound score > -0.05) and (compound score < 0.05)
- negative sentiment: compound score <= -0.05

Since the compound score also tells the intensity of the sentiment based on the compound score, the researchers adjusted the threshold to further classify sentiments from the content. The adjusted thresholds are:

- highly positive sentiment: (compound score >= 0.05) and (compound score > 0.50)
- moderately positive sentiment: (compound score >= 0.05) and (compound score <= 0.50)
- neutral sentiment: (compound score > -0.05) and (compound score < 0.05)
- moderately negative sentiment: (compound score <= -0.05) and (compound score <= -0.50)
- highly negative sentiment: (compound score <= -0.05) and (compound score > -0.50)

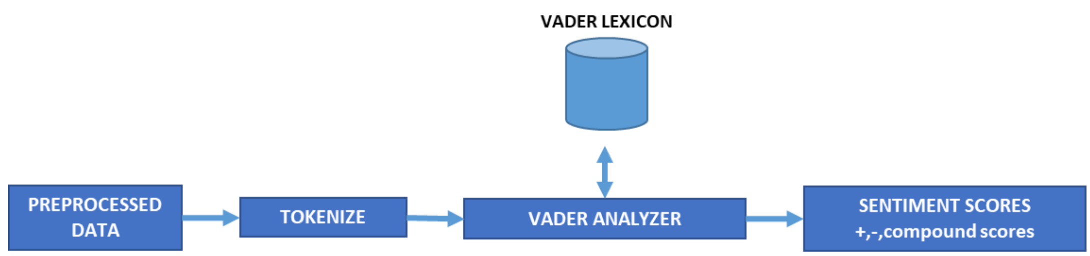

Figure 2. VADER Sentiment Analysis model.

Figure 2 illustrates the VADER Sentiment Analysis model used by the developed system to classify a collected dataset based on their sentiment scores. The processes of the figure are explained further below:

1. *Tokenize.* Tokenization process starts by breaking down contents into individual words. Emojis, on the other hand, are detected first, and then appended with whitespaces for VADER to separate and read each emoji. Each tokenized word and special characters were then assigned to separate indices and were then processed by the VADER Analyzer module.

   Additionally, since VADER uses a dictionary/lexicon to determine the sentiment scores of tokenized words from sentences, Stemming was not implemented. Figure 3 illustrates the tokenization process implemented by the developed system.

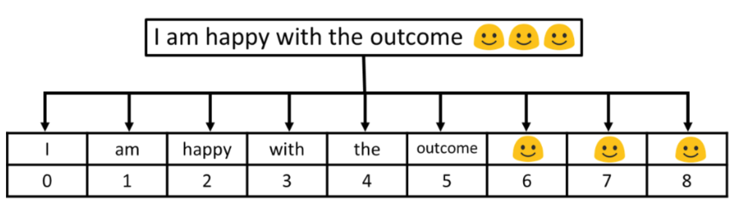

Figure 3. Tokenization process for contents/tweets with emoji.

2. *VADER Analyzer.* The module that checks polarity scores of tokenized words from the lexicon. VADER also takes into consideration word order and degree modifiers. The VADER Sentiment Analyzer was used to classify the preprocessed contents as positive, negative, neutral. It is also used to determine the compound value which is is a useful metric for measuring the sentiment in a given content.

3. *Sentiment Scores*. To calculate the sentimental score of the entire text, VADER scanned the text for known sentimental features, modified the intensity and polarity according to the rules, summed up the scores of features found within the text, and normalized the final score to (-1, 1) using the following illustrated function:

$$\frac{x}{\sqrt{x^2 + \alpha}} \qquad \textit{Equation 1}$$

In VADER, alpha is set to be 15 which approximate the maximum expected value of x. In addition to the compound score of the sentence, Vader also returns the percentage of positive, negative, and neutral sentiment features (Ying, 2020).

To further enhance the visualization of the sentiments identified by the system, summary of the sentiment scores are visualized using a pie chart and bar graph

C. Measures and Analysis

To determine the performance of the developed system it was evaluated based on accuracy, precision, recall and F-score. Accuracy is the total correctness of the classification (See Equation 2). An accuracy of one-hundred percent (100%) means that the predicted instances are precisely the same as the actual instances. On the other hand, precision is the accuracy of the classification on each class or category (Bilog, 2020). This is described in Equation 3. Table 1 shows the confusion matrix for the derivation of accuracy and precision.

Table 1. Confusion Matrix for the Evaluation of VADER

	Predicted Positive	**Predicted Negative**
Actual Positive Instance	Count of True Positive instances (TP)	Count of False Negative instances (FN)
Actual Negative Instance	Count of False Positive instances (FP)	Count of True Negative instances (TN)

$$\text{Accuracy} = \frac{\text{True Positive (TP)} + \text{True Negative(TN)}}{\text{Total Number of Observations}}. \qquad \textit{Equation 2}$$

$$\text{Precision} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Positive(FP)}}. \qquad \textit{Equation 3}$$

$$\text{Recall} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative(FN)}}. \qquad \textit{Equation 4}$$

$$\text{F1 Score} = \frac{2 * \text{True Positive}}{2 * \text{True Positive} + \text{False Positive} + \text{False Negative}}. \qquad \textit{Equation 5}$$

The portion of true positive instances that were predicted over the positive actual instances is called recall while the average of precision and recall is known as F-score. Table 2 shows the effectiveness rating scale to verbally determine the numerical findings of the result per metric.

Table 2. Effectiveness rating scale for the valuation of VADER

Percent Range	**Verbal Interpretation**
81.00%-100.00%	Highly Effective/ Highly Accurate/ Highly Precise
61.00%-80.00%	Effective/ Accurate/ Precise
41.00%-60.00%	Moderately Effective/ Moderately Accurate/ Moderately Precise
21.00%-40.00%	Slightly Effective/ Slightly Accurate/ Slightly Precise
00.00%-20.00%	Not Effective/ Not Accurate/ Not Precise

To verbally determine the numerical findings of the result per metric, this research adopted the effectiveness rating scale used by Bilog (2020) in their research Application of Naïve Bayes Algorithm in Sentiment Analysis of Filipino, English and Taglish Facebook Comments.

RESULTS AND DISCUSSIONS

In the figure 4 shows a snippet of the results from the Twitter scraper tool. The page contains the username, the unprocessed version of the tweet, the translated and the cleaned/preprocessed version of the tweet's translation. The translation of the content can either be automated through Google's Translate API or manually encoded if ever Google's translation for a certain tweet is not accurate.

Once the data set has been reviewed and finalized by the user, the system applies VADER Sentiment Analysis on the data set. Results are displayed on a web page where users can view the polarity scores specifically the negative, positive and the neutral score for each tweet. The system also shows the compound score which is the normalized summation of the polarity scores. An emoticon was then displayed beside the compound score to help the user easily identify the polarity of the tweet. Figure 5 illustrates the VADER result page.

Username	Content	Translated	Cleaned	Data Source
Antifornicator	Other countries (like Malaysia) gave vaccination leaves for workers not only so they could get vaccinated, but also to rest if they get strong side effects. Hindi talaga makatao ang gobyerno natin. https://t.co/HFBDghiweR	Other countries (like Malaysia) gave vaccination leaves for workers not only so they could get vaccinated, but also to rest if they get strong side effects. Our government is not really humane. https://t.co/HFBDghiweR UPDATE MANUALLY	other countries like malaysia gave vaccination leaves for workers not only so they could get vaccinated but also to rest if they get strong side effects our government is not really humane	Collected User Data (Soc. Media/Forum)
paanipedro	RT: Other countries (like Malaysia) gave vaccination leaves for workers not only so they could get vaccinated, but also to rest if they get strong side effects. Hindi talaga makatao ang gobyerno natin. https://t.co/HFBDghiweR	RT: Other countries (like Malaysia) gave vaccination leaves for workers not only so they could get vaccinated, but also to rest if they get strong side effects. Our government is not really humane. https://t.co/HFBDghiweR UPDATE MANUALLY	other countries like malaysia gave vaccination leaves for workers not only so they could get vaccinated but also to rest if they get strong side effects our government is not really humane	Collected User Data (Soc. Media/Forum)

Figure 4. snippet of the Data set review page based on the collected tweets using the developed Twitter scraper module.

SENTIMENT ANALYSIS - TRANSACTION CODE: LMRPGIDL

Sentiment Analysis Based on the following criterion:

Search Term: JustDoIt | Country: Philippines | Data Source: Twitter

Sentiment Analysis performed based on **VADER (Valence Aware Dictionary and sEntiment Reasoner)**

Highliy Negative · Moderately Negative · Neutral · Moderately Positive · Highly Positive

Show 10 entries **Search:**

TWEET	NEGATIVE	NEUTRAL	POSITIVE	COMPOUND	COMPOUND
📍Los Baños City Unforgettable memories were created and one of the places that will remain in my heart and soul for a lifetime. 💜😭 #MayNamimissNaNaman @ Los Baños, Laguna, Philippines https://t.co/8ITtITzUx6	0.073	0.682	0.245	0.8074	Highly Positive
📍 Laguna State Polytechnic University	0	1	0	0	Neutral
💪Your maderpacker (and maderpacker friend) got the first dose of vaccine today! We'll just book a pick-up for tomorrow for all packed orders then will rest for the rest of the night! Packing will resume tomorrow evening! Thank you so much!!	0	0.921	0.079	0.5673	Highly Positive
💙 @ San Pedro, Laguna https://t.co/0pcyzjol4x	0	0.488	0.512	0.6369	Highly Positive
us is back to holding concerts and movie premieres tas tayo usaping face shield pa din nu? □ Anyway, stream #StandByYou #MileyPride Ang sayaaaa 🏳️‍🌈 It's almost end of June, Happy Pride my LBTQIA+ friends and fam 🌈	0	0.776	0.224	0.8852	Highly Positive
✅ Bharat Biotech's Covaxin ✅ Moderna Ligtas ang mga bakuna kontra COVID-19! Sama sama tayo sa BIDA BakuNation! #RESBAKUNA #BIDASolusyon Plus sa COVID-19 #ExplainExplainExplain #BIDAangMayDisiplina	0	0.824	0.176	0.717	Highly Positive
• Senate President Vicente Sotto III questions health department's basis for mandating use of face shields, hours after reading the agency's summary report on the matter https://t.co/g9cvbRxt9Q	0.053	0.906	0.042	-0.0772	Moderately Negative
• Senate President Vicente Sotto III on Wednesday questioned the health department's basis for mandating the use of face shields, hours after reading the agency's summary report on the matter. https://t.co/9eP1f8MDsX	0.046	0.918	0.036	-0.0772	Moderately Negative
• Palace says nothing wrong with gov't flip-flopping on #COVID19 rules https://t.co/mIOxoL5US3 • 'Practice what we preach': Binay blasts officials defying face shield rules https://t.co/wiW0vlZlF7	0	0.934	0.066	0.1569	Moderately Positive
"Wala pong mali mag-flip-flop kung mayroon kasing mga supervening events. Kaya nga po tayo nag-"flip-flop," kasi mayroon namang Delta variant," Palace spokesman Harry Roque said in a media briefing. #PressOnePH Story here: https://t.co/GyFhyAA1Yp	0	0.952	0.048	0.1569	Moderately Positive
TWEET	NEGATIVE	NEUTRAL	POSITIVE	COMPOUND	COMPOUND

Figure 5. Results of VADER Sentiment Analysis based on the test data set

Figure 6 show the summary graph based on the results of VADER using the test data set collected using the Twitter scraper tool.

Figure 6. Visualization of the Summary of the VADER sentiment analysis model based on the test data set collected using the developed Twitter scraper tool

To test the overall accuracy of the VADER sentiment analysis model, the researchers created a confusion matrix. The researchers asked other people to rate the data set collected through the scraping module based on the content's sentiment without subjectivity. Results from the human-generated rating were then compared to the VADER Sentiment Analysis results to derive the confusion matrix.

Table 3. Confusion Matrix Data Result Based on the Test Data Set

	Predicted Positive	**Predicted Negative**
Actual Positive Instance	627	139
Actual Negative Instance	94	348

The sentiment analysis module classified the 348 negative tweets correctly over the 442 instances of negative tweets, and out of 766 total positive and neutral tweets, 627 tweets were correctly classified as shown in Table 3 Confusion Matrix Data Result Based on the Test Data Set. The confusion matrix was created by comparing the results of VADER Sentiment Analysis Module with an Actual human rater. To simplify the matrix, positive and neutral classifications are labelled as 1 and negative classifications are labelled by 2. A sentiment is predicted and actual positive if both VADER and the human rater labeled them as 1. A sentiment is predicted and actual negative if both VADER and the human rater labeled them as 2.

Table 4. Results per metric for VADER test

	Accuracy	**Precision**	**Recall**	**F-score**
Value	0.807119	0.869625	0.818539	0.843308
Percentage	80.71%	86.96%	81.85%	84.33%

Table 4 shows that the sentiment analysis module has 80.71% accuracy with the verbal interpretation of "accurate". The table also shows that the sentiment analysis modules had an 86.96% with the verbal interpretation of "precise" while the recall percentage returned a value of 81.85%. F-score returned a percentage of 84.33% which can be interpreted as "effective". Out of 1208 test data, there are cases of 975 in total that is classified accurately.

Based on the observation of the data set, the number of retweets greatly impact the values needed for the computation of the confusion matrix. The greater the number of retweeted tweets misclassified, the lower the accuracy value becomes. Also, it is found out that emojis that are not used properly also impact the compound score of content.

Social media platforms can be an effective tool for exercising freedom of expression, which is fundamental for citizens to participate more actively in public management and to pressure and direct government decisions. In relation to this, The Sangguniang Panlalawigan legislators could utilize the developed system to use the citizen's social media posts to base the drafting of their legislative documents.

CONCLUSIONS AND RECOMMENDATIONS

This study attempted to categorize tweets collected using the Twitter scraping tool whether it is positive, neutral or negative. A VADER sentiment analysis system module was used to attain this goal. It was exposed that the VADER sentiment analysis module was effective in distinguishing positive, neutral and negative tweets. Results of the VADER Sentiment Analysis module were then evaluated using the test data set collected using the Twitter Scraper tool through a confusion matrix and resulted in 80.71% Accuracy and 84.33% F-Score. It was observed based on the result of the confusion matrix that tweets with misspelled contents and was retweeted numerously affected the accuracy of the system.

To improve the accuracy and precision of the developed system, it is recommended in the future to collaborate with linguists to develop and test a native language (Tagalog) version of VADER's lexicon which can be used simultaneously with VADER's original lexicon. A much larger data set could also be developed through additional social media sources such as Facebook. It is also recommended that terminologies used by millennials and gen x like "so lit", "Lodi" and "Petmalu" be included in the lexicon database to further improve the accuracy of VADER's sentiment analysis capability.

IMPLICATIONS

With the emergence of the Internet and the growing maturity of more recent technologies a new potential emerged for supporting participation in the legislation process. Citizens sometimes has a need for their voices to be heard by legislators and Legislators also sometimes needs a way to collect identify whether the citizens approve of the services provided to them by the government. The development of a system with Twitter Scraper tool and Sentiment Analysis could potentially be an additional answer to this problem. Thus, improving the possibility of writing a more effective and useful legislation.

The application of Google Translate to tweets containing Tagalog words could help the users expand the scope of data collection thus also improving the data set where VADER will have applied. However, not all Tagalog sentences are accurately due to the fact that some Tagalog words have no English translation especially the millennial words.

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