Classifications of Emotion Expressed by Filipinos through Tweets

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Abstract—**This study attempted to classify the emotions of Filipinos expressed through their tweets. Based on these classifications, a personalized recommendation was generated to counter negative emotions. The seven basic affect states studied were happiness, sadness, anger, fright, surprised, disgust, and neutral. Majority of the tweets gathered were neutral (f = 236,834; 79%), and happy (f = 53,829; 18%). Using Naïve Bayes Algorithm, it was revealed that the developed software had 70% accuracy on classifying the tweets. Thus, the emotions of Filipinos based on their tweets were classified effectively. Nonetheless, it was recommended that other Filipino dialects be incorporated to increase the effectiveness of the classifier. It was also suggested that the training data be enriched to capture more words describing emotions.**

Index Terms—**classification of emotion, emotion, Filipino, Naive Bayes' Classifier**

I. Introduction

The Philippines is considered the social media capital of the world. According to Stockdale and McIntyre [1], 93.9% and 16.1% of the Philippine population have Facebook and Twitter accounts, respectively. The authors further commented that Filipinos are very active in social networking to get the latest news and trends in the society. It is not surprising that the Philippines ranked first as heavy users of social networking sites [1].

Twitter is a site for people who like to post anything and to check the trending topics in the world. This makes twitter a big source of data because there is an average of 500 million tweets per day [2]. Using data mining techniques, these tweets can be studied and analyzed. One field of study is to analyze the emotions expressed through words. Currently, Twitter has the capability classifying tweets (i.e., expressed emotions through messages) as positive, negative or neutral. This classification is very limited. Also, only English tweets can be classified.

According to Montecillo [3], there are about 9.5 million Filipino Twitter users. This means that at least 9.5 million tweets per day are submitted by Filipinos. These vast amounts of tweets produce a rich area of research which may have academic, scientific, business or even political value. Considering this vast amount of data, it is relatively untapped since very few studies have so far been conducted to analyze the tweets of Filipinos in terms of emotions expressed through tweets. Thus, the reason this study was conceptualized. Specifically, it aims to 1) classify the emotions of Filipinos expressed through tweets according to their states (i.e., happiness, sadness, anger, fright, surprised, disgust, and neutral) using the Naive Bayes algorithm; 2) determine the effectiveness of the software; and 3) develop an automated recommender system that would generate suggestions to counter negative emotions.

Manuscript received December 2014; revised January 2015. This work was supported by the University of the East.

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II. Literature Review

A. The Filipino Language

Filipino is the official language in the Philippines. According to the Article XIV Section 6 of the 1987 Philippine Constitution [4], "the National language of the Philippines is Filipino. As it evolves, it shall be further developed and enriched on the basis of existing Philippine and other languages." Filipino is mainly based on the Tagalog dialect. The constitution also provides provision for the use of English as provided by law. The provision to use English was traced from the influence of American occupation of the Philippines. The adoption of Filipino and English resulted to bilingualism of the Filipinos. Since the Filipino language had other traces of language influences of Chinese, Sanskrit, Arabs, and Mexicans, the inclusion of English added complexity to the Filipino language [5].

However, at the end of Marcos regime, a new "language" was evolved from English and Tagalog [6]. The English language and the Tagalog dialect were mixed to form semantically-acceptable sentences. This was the birth of Taglish (TAGalog + EngLISH). "*Magpe-present ako ng paper sa conference.*" is an example of Taglish sentence which could be translated in English as "*I will present a paper in a conference*." The convenience of mixing Tagalog and English in the Philippines is very prominent. It has been observed by linguists that "today, written Taglish is commonly encountered in tabloids, comics, and the Internet" [5, p.3].

B. Twitter and Classifications of Emotion

Twitter has a built-in function, called Twitter Streaming API (application programming interface) [7] that can analyze stream of tweets in real time. This API can provide users insights about the public opinions on a wide range of topics [8]. It can analyze whether the tweets are subjective or objective and whether opinions expressed are positive or negative [9, 10]. This analysis is often called sentiment analysis or opinion mining [8]. However, it can only analyze tweets posted in English.

Different studies extended the capabilities of the API and made subsequent analyses from the tweets gathered. Chuang and Wu [11] identified the emotions from speech signals and textual content. They utilized the Support Vector Machines (SVM) sentiment classification to recognize the emotional states. Emotional keywords on seven emotional states (happiness, sadness, anger, disgust, surprise, fear, and neutral) and emotion modification words were defined manually. This method achieved an average accuracy of 65.5%. On the other hand, when combined with acoustic features in the speech data, the accuracy of the classification was improved to 81.5%.

The study of Seol et al. [12] utilized a hybrid system that identified the emotions in an English text. The hybrid system utilized the traditional keyword-based approach and the knowledge-based artificial neural network (KBANN) emotion classifier. In the keyword-based approach, emotions were directly detected and classified using the keyword in a text. The keyword is then matched in emotional keyword directory. However, in the absence of a keyword, emotion cannot be classified. This shortcoming is augmented by KBANN. The KBANN alone had an accuracy ranging from 45% to 65% in classifying eight emotions (i.e., anger, fear, hope, sadness, happiness, love, thank, and neutral). On the other hand, when both methods were combined, the accuracy rate ranges from 50% to 80%.

Balabantaray et al. [13] collected tweets from 1,000 randomly selected Twitter users. Foreign language tweets were removed from the dataset and only tweets in English were retained. The resulting dataset had 8,150 tweets. Emotions were classified based on Ekman [14] six basic emotions – happiness, sadness, anger, disgust, surprise, and fear with an additional neutral state of emotion. Thus, there were seven states of emotions analyzed. Using the Support Vector Machines (SVM) sentiment classification, they achieved 73.24% accuracy on classifying emotions. They also reported that this approach were significantly higher than the previous approaches of Seol et al. [12] and Chuang and Wu [11].

Emotion identification can also be detected using emotional labels. Mohammad [15] said that using emotional labels (i.e., hashtags) in a tweet can reflect the emotions of a person. The author further commented that a message like "my sister took my book", may look like a neutral state but if a hashtag followed it like "my sister took my book #mad", it may mean that the person who tweeted is angry. This approach may capture the expressed emotion of a twitter user.

C. Naïve Bayes Classifier Algorithm

Naïve Bayes classifier algorithm is based on applying Bayes' theorem [16, 17]. Text classification and document analysis are some of the applications of this algorithm. The equation for Bayes' theorem and its algorithm is given on Formula 1 and Figure 1, respectively.

$$\text{posterior probability} = \frac{\text{class prior probability} \times \text{likelihood}}{\text{predictor prior probability}} \quad (1)$$

```
Start
  For
    Each word in a tweet
    Find word in the word bank
    Classify word
  End For

  Count number of words with the same classification
  Use Naive Bayes Formula
  Classify tweet
End Start
```

Fig 1. Naive Bayes' Algorithm

The algorithm shown in Figure 1 will first classify all the words in the tweet according to the different affect states. This will be done using the word bank. When the classification is done, the algorithm will use the formula to classify the tweet. The formula will multiply the number of times the classification occurred in the tweet (class prior probability) and the probability of observing the classification in the tweet (likelihood). This will then be divided to predictor prior probability.

III. METHODOLOGY

A. Data Gathering Procedure and Word Bank

The software developed and utilized in the study is called the phTweet. It is an emotion classifier software with a recommender system. As depicted in Figure 2, a script was deployed on a server that gathered tweets from the Twitter API. The tweets were then stored in a database. Filipino words were scanned and matched in the word bank. The word bank consisted of Filipino words and emoticons. A sample word bank is given in Table 1.

TABLE I
WORD BANK

Emotion	Sample Words and Emoticons	No. of Words in the Word Bank
Happy	joy, happy, *masaya*, *nakakatuwa*, *saya*, :), (:, :-), :D	62
Sad	*lungkot*,*malungkot*, lonely, pained, unhappy, :(, :-(	61
Disgust	ew, yuck, yucky, *nakakasuka*, xp	19
Fear	frightened, scared, terrified, fearful, *takot*, *nakakatakot*, 0_0	18
Anger	angry, furious, mad, *asar*, *bwisit*, *galit*, >:(, >:-(, x-(	35
Surprise	omygad, wow, superb, suprising, *nakakagulat*, :0, :-0, >:0	24
Neutral	*Words that are not classified from the six previous emotions.*	—

Afterwards, tweets were then subjected to classification using the Naive Bayes Algorithm. If a negative emotion was detected, the recommender system would suggest recommendations (i.e., online reading materials on how to counter negative emotions). Websites that offer life advice, such as lifehack.org or buzzfeed.com were utilized because the writers of these websites are life coaches. Their pieces of advice are generic and are applicable to everyone. They do not only give advice on coping with one's emotions; they also give advice on how to handle other events such as a sudden financial crisis.

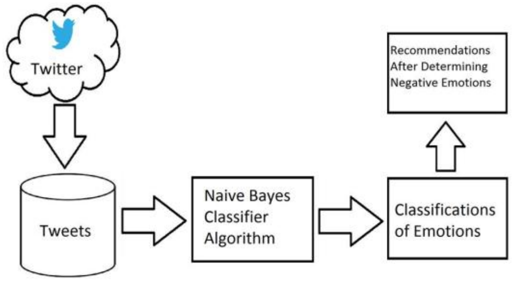

Fig. 2. Systems Architecture

Only tweets posted by Filipinos were gathered. Since Filipinos are bilingual, both English and Filipino tweets were considered. Ethical guidelines set by Twitter were followed in gathering the messages. Data gathering were conducted within a span of one week. There were 300,000 tweets gathered.

B. *Measures and Analysis*

The effectiveness of the software was measured in terms of accuracy and precision. Accuracy is the overall correctness of the classification (See Formula 2.). On the other hand, precision is the correctness of the classification on each class or category. This is depicted in Equation 3. Table 2 shows the confusion matrix for the derivation of accuracy and precision.

TABLE II
CONFUSION MATRIX

		Predicted	
		Negative	Positive
Actual	Negative	*a*	*b*
	Positive	*c*	*d*

$$\text{Accuracy} = \frac{a+d}{a+b+c+d} \qquad (2)$$

$$\text{Precision} = \frac{d}{b+d} \qquad (3)$$

where
a: the frequency of an incorrect emotion was classified incorrectly
b: the frequency of an incorrect emotion classified correctly
c: the frequency of a correct emotion classified incorrectly
d: the frequency of a correct emotion classified correctly

Using Sloven’s Formula (N = 300,000; e=0.10), a sample of 100 tweets were computed. This sample was used to test the effectiveness of the developed software. The 100 sample tweets were randomly generated in the software. The second measurement of precision and accuracy was done by allowing a psychologist identify the emotion in a tweet. This was also the reason why the study only had a small sample size. The scale in Table 3 was utilized to determine the verbal equivalent of the numerical findings.

TABLE III
EFFECTIVENESS SCALE

Percentage Range	Verbal Interpretation
0.81-1.00	Highly (Effective/Accurate/Precise)
0.61-0.80	Effective/Accurate/Precise
0.41-0.60	Moderately (Effective/Accurate/Precise)
0.21-0.40	Slightly (Effective/Accurate/Precise)
0.00-0.20	Not (Effective/Accurate/Precise)

IV. RESULTS AND DISCUSSIONS

Table 4 shows the collected tweets within the span of one month. As shown in Table 3, there were 300,000 tweets collected. Seventy-nine percent (79%) of these tweets exhibited neutral emotions. Happy emotions were the second most exhibited emotion. There were 53,829 tweets (18%) that exhibited happy emotions. It is interesting to note that Twitter has become a vehicle for Filipinos to express their jolly nature. Meanwhile, there was a relatively small number of tweets showing fear (f = 417, 0.14%), disgust (f = 475, 0.16%), anger (f = 652, 0.22%), and surprise (f = 1, 0.0003%).

TABLE IV
TWEETED EMOTIONS

Emotion	frequency	percentage
Happy	53,829	18
Sad	7,792	3
Disgust	1	0.0003
Fear	417	0.14
Surprise	475	0.16
Anger	652	0.22
Neutral	236,8	79
TOTAL	**300,000**	**100**

Figure 3 shows a sample emotion classification and recommendation based on the classification of phTweet. The tweets of the selected user were classified by a script according to its affect state. The recommender system analyzed the frequency of emotions exhibited through tweets of the person during that day and for the past week. It gave a recommendation based on the findings. On this page (shown in Figure 3), the administrator can send tweets to help the Twitter user to cope with negative emotions. The administrator may opt to add a personal message.

A sample tweet with its corresponding classification is shown in Table 4. As shown in Table 5, tweets are expressed in English, in Filipino, or both. A neutral emotion (“*I love MATH... MATHtulog!*”) is a juxtaposition of an English word (i.e., MATH) and of a Filipino word (i.e., “*tulog*” which means sleep) – a Taglish. Clearly, it is an example of a mixture of foreign languages to combine a new meaning. Meanwhile, a tweet “*Ayoko ng mag pe kaka@z@r kasi, umaga uniform hapon pe. Kapagod magbitbit no :(*” was classified sad since it involved the emoticon :(. Futher, a surprise tweet was classified accordingly because of the word “Wow”. This word is mainly used for interjection by most Filipinos. Lastly, the table also shows that the tweet “*ang hirap po maging maganda... HAHA CHAROT*” was classified as happy. This was an appropriate classification since the presence of “HAHA” in the tweet signifies a happy emotion.

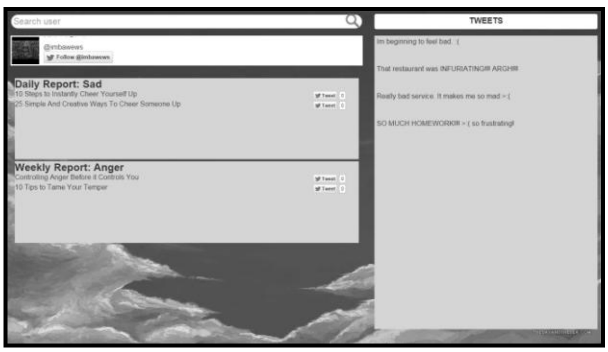

Fig. 3. Tweet Classification and Recommender System

Table V
Sample Tweets that Exhibit Emotion

Sample Tweets	**Classification by the Software**
I love MATH.... *MATHtulog*!	Neutral
Ayoko ng mag pe kaka@az@r kasi, umaga uniform hapon pe. Kapagod magbitbit no :(	Sad
@EllatheWanda Wow naman! Hahaa	Surprise
ang hirap po maging maganda... HAHA CHAROT	Happy

To compute for the precision and accuracy of the classification of phTweet, a confusion matrix was utilized. As shown in Table 6, neutral (f = 70) emotions were the most detected emotion followed by happy tweets (f = 24). There were small traces of sad (f = 4), fear (f = 1), and surprise (f = 1) tweets. However, there were no angry or disgust tweets. phTweet was able to detect correctly 15 happy tweets from the 24 tweets. Nine of the happy tweets should have been assigned to other emotions. In terms of sad tweets, 3 over 4 tweets were classified correctly. One surprise tweet was classified appropriately. Meanwhile, out of the 70 neutral tweets, only 51 were assigned correctly. Nineteen tweets should have been assigned to happy (f = 15), sad (f = 1), fear (f = 2), and anger (f = 1) emotions.

The precision of classifying happy emotions was 0.48 ($Precision_{happy}$ = 0.48, moderately precise). This is verbally interpreted as moderately precise classification. The same classification was also achieved for sad tweets ($Precision_{sad}$ = 0.60, moderately precise). In terms of a surprise tweet, there was one surprise tweet that was detected correctly. Hence, a 100% precision was achieved. Nonetheless, it cannot not be concluded that the software can detect surprise emotion correctly due to the small representation of surprise tweets. More test data on surprise emotion is needed to arrive at a safer finding. Meanwhile, classification on neutral emotions got the highest precision of 0.86 ($Precision_{neutral}$ = 0.86, highly precise). Furthermore, precision of classification on fear, anger, and disgust could not be established because there were no data on these emotions on the sample.

The classification of emotions on happy and sad tweets revealed that the phTweet was only able to detect correctly the emotions expressed by Filipino users in a moderate extent. This could be attributed partly to the scanning analysis of the program. Example, a "haha" tweet that signifies happiness cannot be detected as the same as with "HAHA". In other words, phTweet is case sensitive. Second, there is a limit in the word bank used in the study. Chat terms like "lol" (laughing out loud) and "lolz" (laughing out loud many times) are not included in the word bank. Lastly, the third reason may also be attributed to the creativity of users in using different emoticons. Emoticons like ^_^, ^_~, and :">, which can be symbols of happy emotion, are not included in the word bank.

Table VI
Confusion Matrix of Classified Emotions by phTweet

Classes	HAP	SAD	FEA	SUR	ANG	DIS	NUE	Total
HAP	**15**	1	1	0	0	0	7	**24**
SAD	0	**3**	0	0	0	0	1	**4**
FEA	1	0	**0**	0	0	0	0	**1**
SUR	0	0	0	**1**	0	0	0	**1**
ANG	0	0	0	0	**0**	0	0	**0**
DIS	0	0	0	0	0	**0**	0	**0**
NEU	15	1	2	0	1	0	**51**	**70**
Total	**31**	**5**	**3**	**1**	**1**	**0**	**59**	**100**
Precision	**0.48**	**0.60**	**No Data**	**1**	**No Data**	**No Data**	**0.86**	

Accuracy = 0.70
HAP = Happy
SAD = Sad
FEA = Fear
SUR = Surprise
ANG = Anger
DIS = Disgust
NEU = Neutral

The overall accuracy of the classification was 0.70 (*Accuracy* = 0.70) which has a verbal interpretation of "Accurate". This finding indicates that the software could correctly classify emotions more than 50% of the time. Hence, the software is relatively effective in detecting emotions in Filipino tweets. This is the first attempt that such classification is done using Filipino tweets. Nonetheless, there are still about 30% of the tweets that could not be classified correctly by the existing program. As mentioned above, there were different reasons that may be used to explain this gap.

Though the results of the study did not exceed the accuracy of classifications reported in the literature section, it shows promising results. The accuracy of the classification in this study was at par from the studies presented earlier. This means that the Naive Bayes algorithm is an effective classification algorithm for Filipino tweets. Nevertheless, the study can still be improved using the same algorithm.

V. Conclusions and Future Works

This study attempted to classify emotions expressed by Filipinos in Twitter and made recommendations based on these classifications. A software called phTweet was utilized to achieve this goal. It was revealed that the software was effective in detecting neutral emotion but was only effective in moderate extent in detecting happy and sad emotions. Nonetheless, the overall accuracy of classification of the software was found effective.

The software has limitations and it can still be improved to increase its precision and accuracy. It is recommended that the scanning analysis of the program be improved. Case sensitivity could be avoided when detecting words. It is also suggested that an exhaustive collection of emoticons and chat terms be included in the word bank. Jejemon words (e.g., huehue, phuahaha) can also be included in the word bank. Lastly, it is suggested that the sample size in the analysis of tweets be increased. This would increase the chances that all emotions be represented in the sample.

Acknowledgment

The authors are greatly indebted to Dr. Ester A. Garcia, Dr. Linda P. Santiago, Dr. Olivia C. Caoili, Dean Rodany A. Merida, and Dr. Mark Fabella. This paper is funded by the University of the East.

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