Analyzing Emotions in Twitter During a Crisis: A Case Study of the 2015 Middle East Respiratory Syndrome Outbreak in Korea

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***Abstract*—Social media has emerged as an effective source to investigate people's opinions in the context of a variety of topics and situations. In particular, many recent studies try to investigate social media during the crisis situations that range from natural disasters to man-made conflicts. In this paper, we investigate people's emotional responses expressed on Twitter during the 2015 Middle East Respiratory Syndrome (MERS) outbreak in South Korea. Specifically, we first present an emotion analysis method to classify fine-grained emotions in Korean Twitter posts. Then, we conduct a case study of how Korean Twitter users responded to MERS outbreak using our emotion analysis method. Experimental results on Korean benchmark dataset demonstrate the superior performance of the proposed emotion analysis approach on real-world dataset. Moreover, our analysis results on tweets related to MERS outbreak help to understand the behaviors of humans and the characteristics of sociocultural system. Further, our method can be harnessed by the media to automatically investigate public opinions as well as the authorities to gain insights for quickly deciding the assistance policies.**

I. Introduction

In recent years, people have begun to exchange useful information and express their opinions using social media. Microblogs such as Twitter stand out among many social media that allows people to connect with others, discuss a variety of topics, get up-to-date news, and share useful information. Naturally, microblogs have been actively mined in the field of computer science to investigate public opinion, get real-time information, and even forecast future events. Especially, many researchers are showing interests in the analysis of Twitter, the most widely used microblogging platform, during a crisis situation, which range from natural disasters [1]–[3] such as earthquakes or floods to man-made conflicts [4], [5] such as wars. Immediate Twitter updates during a crisis situation can be harnessed by the media to investigate real-time public opinions or information about the crisis. The authorities can utilize the tweets for quickly deciding the assistance policies. Further, analyzing the tweets may provide insights to researchers into human behaviors in a crisis situation and the characteristic of sociocultural systems.

In this paper, we conduct a case study to investigate how people responded to the 2015 Middle East Respiratory Syndrome (MERS) outbreak in South Korea. In particular, we exploit emotions expressed in twitter messages to analyze public opinions about MERS. First, we introduce an emotion analysis method that classifies real-world Korean Twitter messages into fine-grained emotions. Our emotion analysis approach performs machine-learning classification using emotion lexicons as well as fine-grained and language-specific features. Our method classifies neutral tweets as well as fine-grained emotional tweets and can be directly applied to real-world data. Experimental results proved that our approach performs better in real-world dataset, which includes neutral tweets and ambiguous emotion labels, compared to the state-of-the-art method. Next, we analyze the Korean Twitter posts related to the MERS outbreak. Using the proposed emotion analysis, we are able to gain insight into the emotion dynamics during the crisis situation, including trend of the emotional intensities and responses to different topics.

The rest of this paper is organized as follows. Section II overviews related work and Section III introduces our dataset. In Section IV, we explain our emotion analysis method with experimental results. We describe how we analyze tweets about the MERS outbreak in Section V, followed by conclusion in Section VI.

II. Related Work

In this work, we analyze fine-grained emotions in Korean Twitter messages for the purpose of a case study. Very few attempts have been made to analyze fine-grained emotions particularly attuned to Korean Twitter text. Lee, *et al.* [6] classifies Korean tweets into seven emotions and achieves 52% accuracy when using the multinomial naïve Bayes algorithm. Do and Choi [7] classifies Korean tweets into six emotions using emotion lexicons and a variety of language-specific and fine-grained features. Our work differs from the aforementioned Korean studies because we discern neutral cases as well as the fine-grained emotional tweets. Our method is directly applicable to real-world tweets, which includes messages without emotions (neutral).

Using the proposed emotion analysis method, we analyze real-world Twitter messages that were posted during

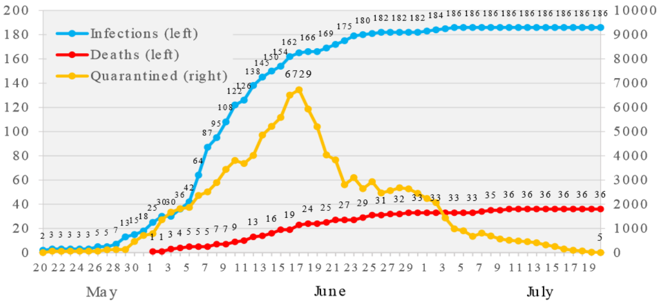

Fig. 1. 2015 MERS outbreak in South Korea

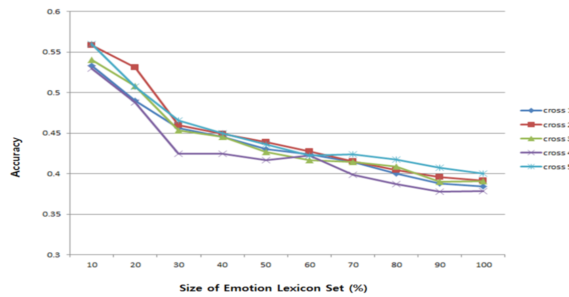

Fig. 2. Results of lexicon-based experiments for filtering noisy emotion lexicons.

the MERS outbreak. Similarly, there is a growing number of crisis information research that leverage microblogs as a lens to understand people in crisis contexts. Qu, *et al.* [8] conduct a case study to investigate how Chinese microblogging system was used after 2010 Yushu Earthquake, including analysis of contents, topics, and information spreading process. Kawamoto [9] investigates the pattern of activity usage after the earthquake. Starbird, *et al.* [2] investigate the generative, synthetic, derivative, and innovative properties of microblogged information during the flooding of the Red River Valley in 2009. Related to the research observing affective responses, De Choudhury, *et al.* [4] examine negative affect, activation, and dominance in Spanish Twitter postings in relation to the Mexican Drug War. Vo, *et al.* [3] perform emotion classification using machine-based algorithms to track responses during the 2011 Great East Japan earthquake. Muralidharan, *et al.* [1] examine Facebook and Twitter usage by nonprofit and media organizations including analysis of emotional angles. Similar to our research, Zarrad and Aljaloud [5] analyze Arabic Tweets related to the MERS infection in Saudi Arabia using lexicon-based sentiment analysis.

III. Background and Dataset

A. The Middle East Respiratory Syndrome Outbreak in Korea

The Middle East Respiratory Syndrome (MERS) outbreak occurred in South Korea from May to July, 2015. The initial MERS case in South Korea was reported on 20 May 2015, by a 68-year-old Korean man returning from the Middle East. He was diagnosed with MERS nine days after he first sought medical help, and during the nine days, he visited three hospitals where infections began. This deadly outbreak not only killed 36 people and infected 186 people but also triggered widespread panic and stymied economic growth. The outbreak is recorded as the biggest outbreak of the virus outside Saudi Arabia.

B. Data Description

The dataset includes Korean Twitter messages that took place over 25-day period, from 5th June to 30th June, when the virus was most active; the number of new MERS cases increased sharply in early June, peaked in mid-June, and declined in late June as shown in the Fig. 1[1]. We collect 6,454,530 Korean tweets by submitting a query “메르스” (MERS) in Twitter Search API. Interestingly, about 76.7% of tweets are RTs which infers active information sharing via Twitter about the crisis. We remove tweets with RT, URL links, and replies, and results in 145,098 unique tweets for our research.

[1]Ministry of Health and Welfare

IV. Our Emotion Analysis Method and Evaluation

In this paper, we investigate public responses about MERS outbreak by exploring emotions expressed in Twitter. To conduct the analysis, we develop an emotion classification scheme that is particularly attuned to Korean and Twitter domain. We classify Korean Twitter messages into seven categories that include neutral (no emotion) and Ekman’s six basic emotions: happiness, sadness, anger, disgust, fear, and surprise. The Ekman’s emotion types [10] are the most frequently used in the field of computer science for emotion mining [11]. We first explain our emotion classification method, followed by evaluation of our analysis method by conducting experiments using a benchmark dataset.

A. Korean Twitter Emotion Classification

We construct classifiers based on machine learning algorithm to categorize Twitter messages represented by a feature vector. The features we use for classification are based on [7] as the following:

1) Emotion lexicons that are the 10% top-valued weighted tweet frequency (weighted TwF) lexicons [7].
2) Emotion lexicons constructed by thesaurus-based approach (finding synonyms of emotion words) and translation-based approach (translating existing English lexicons to Korean).
3) Punctuation
4) Emoticons and symbols
5) Korean emotion letters
6) Korean exclamations of surprise
7) Korean swear words

We filter noisy emotion lexicons that are produced by weighted TwF approach [7] by conducting lexicon-based experiments. Lexicon-based approach simply aggregates the Weighted TwF values of the words presented in tweets and predict the emotion by choosing the one with maximum

TABLE I
PERFORMANCE OF EMOTION CLASSIFCATION

Method	Accuracy (%)
Neutral/Emotional Classification	81.9
Ekman's Six Emotion Classification	54.6
Our Approach	**73.4**
SVM [7]	**61.4**

value. Erroneous emotion lexicons mostly have low weighted TwF values, thus we can filter out those noisy lexicons by adjusting the size of the lexicon sets. As shown in Fig. 2, the best accuracy is observed when only the 10% of the top-valued lexicons is left. After making feature vectors of tweets, we perform two-step classification; neutral/emotional classification and Ekman's six emotion classification. We first construct a classifier using Support Vector Machine (SVM) to discern neutral and emotional tweets. After classification, we construct another SVM classifier to classify Ekman's six emotions and apply to those tweets that are classified as emotional from the first classifier. Before constructing a machine learning classifier, we apply the synthetic minority oversampling technique (SMOTE) [12] to the training dataset, a well-known oversampling method, which is known to be more effective than the plain oversampling method with replication. As a result of two-step SVM classifiers, the tweets are classified into one of the seven emotion types.

B. Evaluation

1) Training Dataset: We use Korean Twitter Emotion Analysis (KTEA) dataset [7] to train classifiers before we test them on the MERS tweets. KTEA dataset contains 5,706 valid Korean tweets labeled by seven types of emotions, Ekman's six emotions and neutral. Each tweet was labeled by three annotators, producing three individual emotion labels per tweet. Additionally, three annotators discussed one final emotion label for each tweet, producing an additional emotion label named "discussion". In our work, we utilize the whole KTEA dataset to train our classifier using the discussion labels.

2) Performance Measure: We use accuracy to evaluate the classification performance for each emotion type. Accuracy is defined as the proportion of the total number of predictions that are correct. Although discussion labels in KTEA dataset are useful for training, the agreements between the three annotators were very low, meaning that the emotions are very subjective and it is difficult to argue conclusive emotion of each tweet. Also, it would not make much sense to let a machine classify things for which even humans do not agree so well. Thus, we propose a relaxed measure of accuracy that utilizes the three emotion labels produced by annotators individually, instead of using discussion labels. We assume that a prediction is correct if the emotion belongs to any of the emotions that annotators felt.

3) Experimental Results and Evaluation: We evaluate our emotion classification method by comparing against the state-of-the-art method [7]. Using the KTEA dataset with 5-cross validation, we measure the performance of our emotion classification method and the results are shown in Table I. Our approach consists of two classifiers for the purpose of neutral/emotional classification and fine-grained emotion classification. The performances of each individual classifier are 81.9% in neutral/emotional classification and 54.6% in fine-grained emotion classification. We propose a classification method that combines the two classifiers and we obtain 73.4% accuracy that is superior to the simple SVM classification method performed in [7]. Further, our method makes up for the weaknesses of the [7] that are summarized as follows:

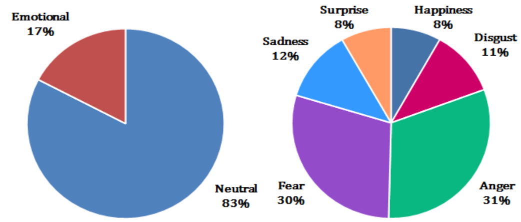

Fig. 3. Emotion distribution of Twitter messages

1) Our approach effectively classifies the neutral cases whereas [7] does not. Discerning neutral tweets in real-world applications is critical because the actual Twitter posts include a huge amount of neutral tweets.
2) We improve the performance of classification by filtering out erroneous emotion lexicons by conducting lexicon-based experiments.
3) We propose a relaxed measure of accuracy that considers multiple emotions in one tweet. This is a more reasonable measure for real-world tweets where agreements of emotions are low.
4) Our approach is applied to the whole KTEA dataset containing 5706 tweets, whereas [7] is only tested to a small portion of the dataset, which is 899 tweets. This means that our approach is directly applicable to the real-world dataset.

V. ANALYSIS RESULT

Using our emotion analysis method, we classify tweets during the MERS outbreak into six emotion categories and neutral. As illustrated in Fig. 3, we observe that over 80% of the tweets is neutral that means the classification between neutral/emotional tweets is very important. We found that fear and anger dominates in emotional tweets that talk about MERS. This is because many people are afraid of the MERS infections (fear) and criticize the government officials for sluggish and inadequate reaction (anger).

We investigate trends of emotions over time and the result is demonstrated in Fig. 4. We show the linear regression results as well as the emotion intensities per each day during the outbreak. The number of anger responses increase over time that reflects the increasing anger of the public about the crisis situation, mostly blaming the Korean government. On the other hand, the number of fear and sadness responses decrease. This observation is understandable as the government was taking

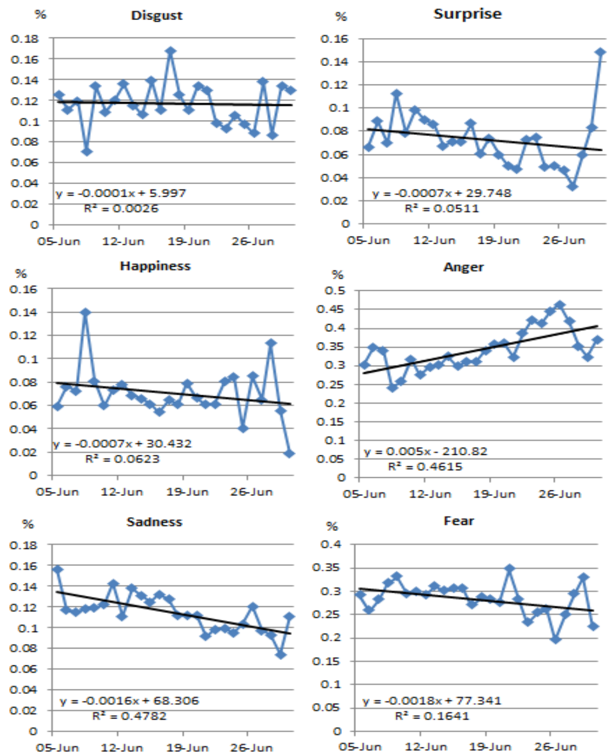

Fig. 4. Trend of emotions expressed over time

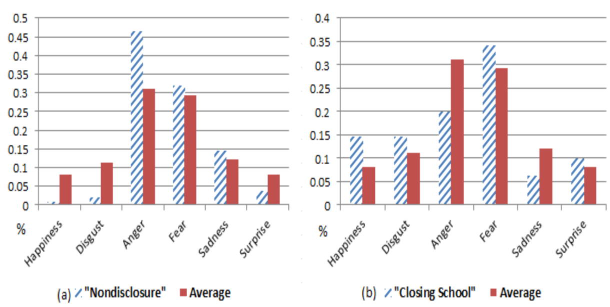

Fig. 5. Emotional responses of specific topics

more and more actions to prevent the infection and the number of new MERS cases decreased as time goes. Happiness, disgust, and surprise responses are relatively constant over time. The government can utilize this observation to gauge the changes of public opinions.

Case Study 1. Nondisclosure of the names of hospitals The government has drawn criticism as they hesitated to announce the names of all the affected hospitals where MERS victims had visited. We search for the tweets containing the word "비공개" (nondisclosure) and analyze the emotions. Compared to the average responses, relatively greater anger is observed about this issue as shown in Fig. 5(a). Authorities would have made quick decision, if they had known about the responses about the disclosure issue.

Case Study 2. School closing Nearly 2,704 schools across the country were closed to prevent the spread of MERS. We observe the emotional responses about the closing and the result is shown in Fig. 5(b). Interestingly, happiness tweets is observed more than the average. This is because there were many youngsters who were happy about the school closing as they wanted extra vacation. This observation may give insight to the behavior of Korean students and reflects the culture.

VI. Conclusion

In this paper, we analyze emotions of Twitter during the 2015 MERS outbreak in South Korea. For the analysis, we present an effective emotion analysis method particularly attuned to Korean Twitter messages. Interesting observations are made using our emotion analysis method in tweets talking about MERS outbreak and related topics. We believe this work not only opens a new window to investigate socio-cultural systems but also can be harnessed to effectively gauge public opinions.

Acknowledgment

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