2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining

Automatic Construction of an Emoji Sentiment Lexicon

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***Abstract*—Emojis have been frequently used to express users' sentiments, emotions, and feelings in text-based communication. To facilitate sentiment analysis of users' posts, an emoji sentiment lexicon with positive, neutral, and negative scores has been recently constructed using manually labeled tweets. However, the number of emojis listed in the lexicon is smaller than that of currently existing emojis, and expanding the lexicon manually requires time and effort to reconstruct the labeled dataset. This paper presents a simple and efficient method for automatically constructing an emoji sentiment lexicon with arbitrary sentiment categories. The proposed method extracts sentiment words from WordNet-Affect and calculates the co-occurrence frequency between the sentiment words and each emoji. Based on the ratio of the number of occurrences of each emoji among the sentiment categories, each emoji is assigned a multidimensional vector whose elements indicate the strength of the corresponding sentiment. In experiments conducted on a collection of tweets, we show a high correlation between the conventional lexicon and our lexicon for three sentiment categories. We also show the results for a new lexicon constructed with additional sentiment categories.**

I. Introduction

In recent digital communication via emails and social media, emojis play an important role because of their usefulness for expressing sentiments, emotions, and feelings. Emojis are used all over the world: For example, it is known that more than half of the posts on Instagram[1] contain emojis [1], and Twitter[2] found 6.6 billion emojis were used in tweets during 2015 [2]. Analyzing user sentiment from such big social media data is valuable for several applications, including marketing, event detection, and health care, and thus, various approaches for analyzing the sentiment of short texts have been proposed [3]. However, although emojis can be valuable features in sentiment analysis, little attention has been given to providing resources that associate emojis with sentiment. As a pioneering work, Novak et al. [4] recently constructed an emoji sentiment lexicon named Emoji Sentiment Ranking (ESR), in which each emoji is assigned a positive, negative, or neutral score. Specifically, the authors in [4] asked 83 annotators to label 1.6 million tweets in 13 European languages with any of the three sentiments and then calculated the ratio of the number of occurrences of the emoji in each sentiment category. This work relied on the manually labeled dataset, and consequently, expanding the lexicon with new emojis or new categories requires time and effort to reconstruct the labeled dataset.

To solve this problem, this paper presents a simple and efficient method for automatically constructing an emoji sentiment lexicon with arbitrary sentiment categories. The proposed method leverages the existing English dictionary WordNet-Affect [5] as a sentiment information source. Specifically, we calculate the co-occurrence frequency between sentiment words obtained from WordNet-Affect and each emoji in a collection of tweets. Based on the ratio of the number of occurrences of each emoji among all sentiment categories, we calculate a sentiment score for each sentiment for the emoji. Finally, each emoji is represented by a multidimensional vector whose elements are the sentiment scores. To verify the effectiveness of this method, we conduct two experiments using our tweet dataset. First, we compare our lexicon constructed for positive, negative, and neutral sentiment with the conventional ESR. The experimental result shows a high rank correlation of 0.896 between them, which indicates the reliability of our automatic construction approach. Second, we show the results of applying our method to five additional sentiment categories.

[1]https://www.instagram.com
[2]https://twitter.com/

ASONAM '17, July 31 - August 03, 2017, Sydney, Australia

ACM ISBN 978-1-4503-4993-2/17/07/ $15.00
http://dx.doi.org/10.1145/3110025.3110139

II. Related work

To analyze sentiment in short informal texts on social media, some methods focus on the use of emojis in the texts [6], [7]. For example, Hussien et al. [6] manually classified commonly used emojis into four sentiment categories (i.e., *joy*, *sadness*, *anger*, and *disgust*) and used them to directly label a given tweet with the corresponding emoji sentiment. Zhao et al. [7] also manually labeled 95 emojis with any of the four sentiment categories and trained a Naïve Bayes classifier using tweets containing emojis and their sentiment labels. However, this approach encounters the following problems: (i) The labeled

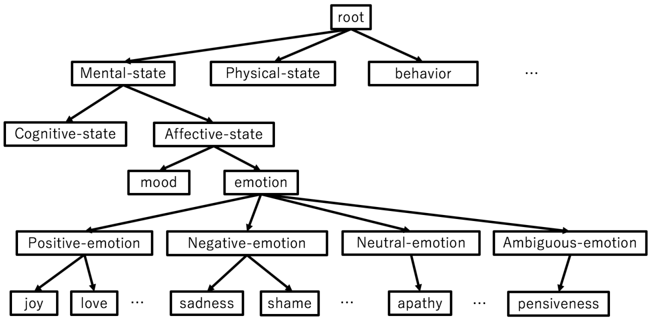

Fig. 1. The hierarchical structure of affective labels in WordNet-Affect.

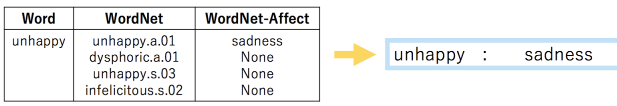

Fig. 2. Determination of the sentiment label of a word using WordNet-Affect.

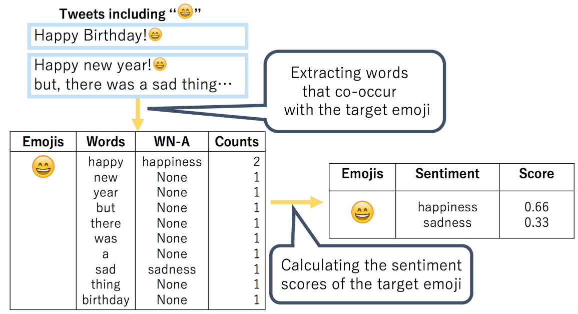

Fig. 3. A schematic illustration of calculating emoji sentiment scores.

emojis in these works have not been published on the Web, (ii) the labels heavily rely on the authors' subjectivity, and (iii) the number of emojis used in the methods is low compared with the actual number of emojis used on social media. Our method can construct an emoji sentiment lexicon that avoids these problems in a simple and efficient way.

The sentiment of emoticons such as **:-)** and **:'-(** has also been evaluated in several works. In [8], 60 annotators provided 59 emoticons with scores for 10 sentiment categories. In [9], 10 annotators evaluated the sentiment of each of 100 emoticons on 10 sentiment axes. In [10], a 14-dimensional sentiment vector of an emoticon was calculated using the co-occurrence frequency between predefined 288 emotional words and the emoticon, which is the work most related to our study. The contribution of our work compared with these conventional works is to validate the effectiveness of the word co-occurrence approach for constructing an emoji sentiment lexicon by showing a high correlation with the existing ESR that was constructed using a manually labeled dataset.

III. Proposed Method

This section presents a method for constructing an emoji sentiment lexicon with arbitrary sentiment categories. Our method requires a dataset of tweets and a list of sentiment words. First, we extract sentiment words from WordNet-Affect (see Section III-A). Then, we calculate an emoji sentiment score vector based on the co-occurrences between the emoji and sentiment words (see Section III-B).

A. Extracting sentiment words from WordNet-Affect

In this subsection, we describe how to extract sentiment words from WordNet-Affect. WordNet-Affect is an English dictionary that assigns sentiment labels to synsets defined in WordNet [11]. Figure 1 shows the hierarchical structure of the affective categories in WordNet-Affect. A set of sentiment categories used in the proposed method is denoted by S (e.g., S = {*joy*, *love*, *sadness*}). For each word w in a target dataset, we first extract from WordNet a set of synsets to which w belongs. Then, we retrieve their affective labels from WordNet-Affect. Figure 2 shows an example of determining the sentiment label of word w = "unhappy" from S. In this example, w is associated with the following four synsets in WordNet: "unhappy.a.01", "dysphoric.a.01", "unhappy.s.03", and "intelicitous.a.02". Among these synsets, only "unhappy.a.01" exists in WordNet-Affect, and it is labeled with *sadness*. In this case, the sentiment label s of w (= "unhappy") is determined to be *sadness*; this information is then added to the list of sentiment words. For word w that belongs to multiple synsets with different affective labels, the word is labeled with the sentiment that occurs the most frequently in the affective labels. Note that if the top two affective labels occur equally in the synsets, the word is discarded from the list of sentiment words to avoid ambiguity. Finally, the sentiment labels of words are represented by an indicator function $a(w, s)$ that outputs 1 if the sentiment word w is labeled with sentiment s and 0 otherwise.

B. Calculating emoji sentiment score vectors

In this subsection, we describe how to calculate the sentiment scores of a target emoji. Figure 3 shows the schematic illustration of the proposed method. As shown, using the co-occurrence frequency of each emoji and sentiment words, we calculate the ratio of the appearance of emojis for each sentiment. Specifically, for each emoji e_i (i = 1, 2, $\cdots$, E; E is the total number of emojis) and a sentiment word w_j (j = $1, 2, \cdots, W$; W is the total number of sentiment words), let n_{ij} be the number of their co-occurrence frequency in the dataset. We calculate the sentiment score $ES(e_i, s)$ of emoji e_i for sentiment s using the following equation:

$$ES(e_i, s) = \frac{\sum_{j=0}^{W} a(w_j, s) n_{ij}}{\sum_{j=0}^{W} n_{ij}}. \quad (1)$$

A larger value of $ES(e_i, s)$ indicates a closer relationship between the emoji e_i and the sentiment s. Finally, each emoji is represented by a $|S|$-dimensional vector whose elements are $\{ES(e_i, s)\}_{s \in S}$.

TABLE I
EXAMPLES OF THE SENTIMENT WORDS EXTRACTED FOR EACH CATEGORY IN S_2.

anger	sadness	fear	disgust	happiness
displease	tearful	shy	vile	happiness
umbrage	unhappy	fear	disgust	euphoric
pique	regrets	horror	sick	happily
aggravate	worse	shadow	distasteful	happy

TABLE II
TOP 10 EMOJIS WITH THE HIGHEST SENTIMENT SCORES.

Rank	Emoji	Score
1	🆓	1.00
2	🎂	0.95
3	🎈	0.95
4	🎊	0.95
5	🎇	0.95
6	🎆	0.95
7	🎉	0.94
8	🎁	0.93
9	💝	0.90
10	🍒	0.88

TABLE III
TOP 10 EMOJIS WITH THE LOWEST SENTIMENT SCORES.

Rank	Emoji	Score
1	🚨	-0.21
2	😠	-0.20
3	😷	-0.19
4	😡	-0.14
5	😖	-0.07
6	😞	-0.07
7	👎	-0.05
8	👿	-0.05
9	😣	-0.00
10	😓	0.00

IV. EXPERIMENT

In this section, we present experimental results to verify the effectiveness of the proposed method. In Section IV-A, we describe the details of the dataset used in the experiments. In Section IV-B, we measure the correlation between the conventional ESR and our lexicon with three sentiment categories (denoted as S_1 = {*positive*, *neutral*, *negative*}). In Section IV-C, we show the results for a new lexicon constructed with five sentiment categories (denoted as S_2={*happiness*, *disgust*, *sadness*, *anger*, *fear*}).

A. Dataset

Using Twitter API[3], we first collected a set of tweets that contain at least one of the sentiment words. Then, the number of tweets posted by the same user was limited to 30, and tweets posted within one day by the same user and retweets were removed. The final number of tweets in the dataset was 414,977. From each tweet, we removed hash tags, user IDs, URLs, and unnecessary symbols (e.g., @, ", and !). In the experiments, we focused on emojis that correspond to Unicode 6.0 emojis and that occurred in more than 150 tweets in the dataset. The number of resulting emojis was 236. Note that the following four emojis do not exist in ESR:"™", "‼", "🔑", and "🎯". The number of sentiment words extracted in Section III-A was 753 and 268 for S_1 and S_2, respectively. Some examples of the sentiment words for S_2 are shown in Table I.

B. Correlation with the ESR

We first constructed an emoji sentiment lexicon with S_1 to quantitatively evaluate the performance of our method. In this experiment, we calculated the sentiment score of an emoji in the same way as the ESR: That is, we subtracted the negative score from the positive score for each emoji as follows:

$$Score(e_i) = ES(e_i, positive) - ES(e_i, negative). \quad (2)$$

Table II shows the top 10 emojis that have the highest sentiment scores, while Table III shows the top 10 emojis that have the lowest sentiment scores. If a score is higher than zero, it means that the emoji represents a positive sentiment. However, if a score is lower than zero, it means that the emoji represents a negative sentiment. In the results, 227 emojis correspond to positive sentiments, while only nine emojis correspond to negative sentiments. This is the same tendency as observed in [4]. We consider from this result that most of the emojis are usually used in positive content.

Next, we investigated the correlation between the conventional ESR and our emoji sentiment lexicon for S_1. In the ESR, some emojis were evaluated using a very small number of tweets. To improve the reliability, we used only the top 100 emojis in terms of occurrence in the ESR dataset to measure the correlation. Figure 4 shows a scatter plot of the emoji sentiment scores in our lexicon and those in the ESR. We observed that these two lexicons have a high correlation.

We also measured the Spearman's rank correlation between our lexicon and the ESR. Specifically, the emoji sentiment scores from the two lexicons were sorted in descending order separately, and the following correlation was calculated:

$$r_{xy} = \frac{\sum_{i=0}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=0}^{n}(x_i - x)^2 \sum_{i=0}^{n}(y_i - y)^2}}. \quad (3)$$

where x_i and y_i are the rank variables of the lexicon and the ESR, respectively; and $\overline{x}$ and $\overline{y}$ are their averages. The closer the value r_{xy} approaches one, the more highly correlated the target two score sets. We obtained a correlation of 0.896, which demonstrates that our method can automatically generate an emoji sentiment lexicon whose quality is close to that of a lexicon constructed using a manually labeled dataset.

C. Emoji sentiment lexicon with five sentiment categories

Finally, we calculated a five-dimensional sentiment score vector for each of the 236 emojis using the proposed method with the S_2 sentiment categories. To show the distribution of the resulting sentiment vectors, we applied principal component analysis to the vectors. Figure 5 shows the result of mapping the emojis into a two-dimensional space. We observed that emojis that have a similar sentiment were mapped close to each other: For example, emojis related to heart symbols exist on the right side of the map, while emojis representing sad faces or symbols are closely distributed on the left side.

Figure 6 shows the top five emojis with the highest scores for each sentiment in S_2. As shown, our method yielded rea-

[3]https://dev.twitter.com/overview/api

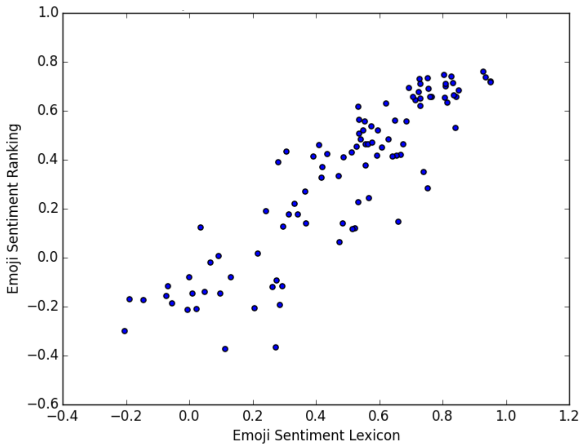

Fig. 4. A scatter plot of emoji sentiment scores in our lexicon and the ESR.

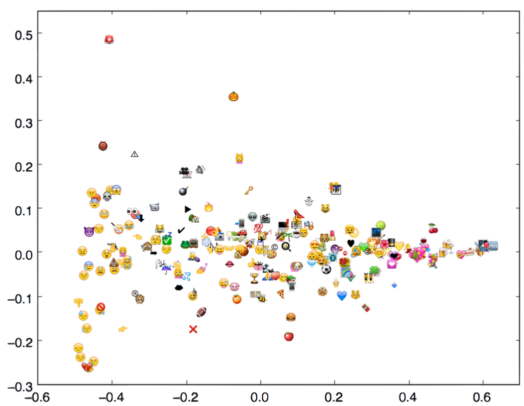

Fig. 5. Visualization of five-dimensional emoji sentiment vectors in a two-dimensional space.

sonable results for each sentiment. However, there is overlap among the top emojis in *anger*, *fear*, and *disgust*, from which it seems difficult to distinguish these sentiments using emojis. In future work, we will investigate effective categories for emoji-based sentiment analysis of social media posts.

V. Conclusion

This paper presented a method for automatically constructing an emoji sentiment lexicon based on the co-occurrence relationships between sentiment words and emojis. When the proposed method is applied in the case of three sentiment categories (i.e., *positive*, *negative*, and *neutral*), we obtained a high rank correlation with the conventional ESR. Our method does not require the cost of manually labeling tweets with sentiments, and thus, the lexicon can be updated efficiently with new emojis or new sentiment categories. We also constructed a new lexicon with five sentiment categories, and emojis that have similar sentiments were effectively distributed on a two-dimensional map. Our future work includes an application of the lexicon constructed using our method to sentiment

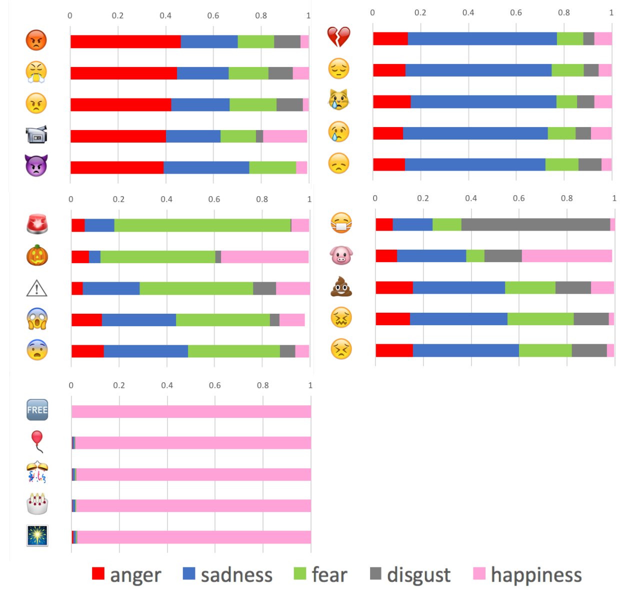

Fig. 6. Top five emojis for each sentiment.

analysis, as well as an investigation of effective sentiment categories that should be assigned to emojis.

Acknowledgment

This work was supported in part by Grant-in-Aid for Young Scientists (B) 17K12794.

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