Emoticon Recommendation in Microblog using Affective Trajectory Model

Wei-Bin Liang, Hsien-Chang Wang*, Yi-An Chu and Chung-Hsien Wu
Department of Computer Science and Information Engineering, National Cheng Kung University, Tainan, Taiwan
E-mail: chunghsienwu@gmail.com
*Department of Information Management, Chang Jung Christian University, Tainan, Taiwan
E-mail: wangbb@mail.cjcu.edu.tw

Abstract—An emoticon is a metacommunicative pictorial representation which is widely used in text-based online communication such as Plurk and Facebook to convey the user’s emotions. However, these social networks still lack a mechanism to provide appropriate emotion recommendation according to the input posts. Therefore, this paper develops an approach to emoticon recommendation in microblog. Generally, a blog post is composed of at least one emotional topic. Therefore, topic tracking is the key information for emoticon recommendation. In this paper, a fixed-size window is first employed to segment a post into a number of segments. Then, these segments are projected to emoticon profiles in the emoticon space through latent Dirichlet allocation (LDA). An affective trajectory model characterizing the emoticon profiles of the segment sequence is proposed to construct a recommendation model based on k-medoids algorithm. Finally, emoticon recommendation can be realized by similarity measure based on Hausdorff distance. To evaluate the performance of our proposed approach, the experimental data were crawled from Plurk for training and evaluation. The results show the effectiveness of the proposed approach.

Index Terms: emotion recognition, emoticon recommendation, microblog, trajectory

I. INTRODUCTION

One of the primary functions of the internet is to connect people online. Recently, hundreds of millions of people around the world actively used social media such as Plurk and Facebook for communication or information sharing. Therefore, there is great interest in affective computing [1] of the social media across a variety of domains, for example, health monitoring [2][3] and product recommendation [4][5]. Emotions play an important role to realize the application of these domains because emotion affects human intelligence, rational decision making, social interaction, perception and more. Although emotion recognition can be achieved from speech, facial expression, physiological signal and text, text-based emotional analysis does not lose its popularity. Previous research for emotion recognition from texts considered a variety of textual contents, for example, microblogs, stories [6][7], news [8], and spoken dialogs [9].

An emoticon is a metacommunicative pictorial representation composed of strings of symbols and has been widely used in text-based online communication to convey emotions. The use of emoticons contributes to facilitation of the social interactions, especially in microblogs. Figure 1 demonstrates the example posts with emoticons. Compared to conventional text-based communication, the bottom example has ambiguity of emotion because the words Haha and good are often used to indicate the happiness but the word not presents opposite meaning.

Two main and mostly used approaches for emotional modeling are categorical and dimensional [10] representations. The categorical approaches is based on classification of emotions as basic emotions such as happiness, sadness and boredom that are hard-wired in human brain and recognized universally. Social networks nowadays has already provided various emoticons more than Ekman’s six basic emotions [11]. On the other hand, within the dimensional approach, researchers argue that emotional states are not independent from one another but related in a systematic manner. To determine the emotional dimensions is a challenging issue; however, the two dimensions, arousal and valence, has shown to cover the majority of affect variability and been widely used [12][13]. One of the famous work is affective norms for English words (ANEW) [14] that comprises a set of normative emotional ratings for English words; however, how to rate and assess emotions is still questionable. Emotion classification approaches can be broadly classified into lexicon-based approach and learning-based approach. An emotional lexicon comprises a set of affective terms for each emotion, for example, ANEW, LIWC and WordNet-Affect [15]. The lexicon-based approach is a straightforward solution; however, ambiguity of word sense and the lack of linguistic information result in implicit expression of emotions. Another way of emotion classification is to train a model to classify input observations into different emotions. Machine learning approaches such as Naïve Bayes, support vector machine [16], vector space models e.g., LSA, pLSA [17], and latent Dirichlet allocation (LDA) [8].

Current mechanism of social network is that users manually pick a proper emoticon from the supplied emoticon pool.
Sometimes, it is hard to select and there are a lot of mental burden for users. Therefore, the goal of this paper is to develop a text-based automatic emoticon recommendation system. First, we will perform emoticon analysis through affective text-mining for input posts. Then, a recommendation model considering the advantage of either categorical emotions or dimensional emotions will be trained.

II. SYSTEM OVERVIEW

Figure 2 illustrates the framework of the proposed emoticon recommendation system in which the top panel is the training phase and the bottom panel is the test phase. For an input post from the collected microblog corpus, we assume that one post comprises the primary emoticon and the embedded emoticons because of emotional fluctuation. Moreover, blog posts often lack explicit punctuation marks so that the sentences even paragraphs are not easy to identify. To alleviate this problem, a blog post is regarded as a emotion trajectory. Therefore, the first step is to segment the input post into a number of segments using a fixed-size sliding window. In addition, ambiguity of word sense also confuses the perception of a blog post. So, each post segment is then projected to the emoticon profiles in the emoticon space. To project the post segments, the state-of-the-art of natural language processing - LDA is employed to obtain the emoticon profiles. Thus, the system can estimate the probability of each emoticon for an input post. The problem for the generated emoticon trajectory is that the sizes of trajectories are not equal for all trajectories. Moreover, for an unknown post, we do not know which segment can represent the primary emoticon. In other words, the posts of two emoticons may be projected to the same trajectory. In the proposed system, the k-medoids clustering with the Hausdorff distance metric is employed to cluster the trajectories in the next step. Hence, the centroids and the occurrence probability of the j-th trajectory $e_j$ conditioned on the i-th cluster $c_i$ is obtained. To measure the confidence to a trajectory cluster, the Gaussian density is employed to model a probability to each input post. In the affective trajectory modeling, both of the centroids of the clustered trajectories $E$ with the parameters of Gaussian density and the occurrence probabilities are included into the affective trajectory model. The last procedure of this system is to recommend the emoticon $e^*$ by concluding the information from occurrence probability of the j-th emoticon conditioned on the i-th cluster and the information from the likelihood of the j-th emoticon estimated by the Gaussian mixture model based on the Hausdorff distance.

III. AFFECTIVE EMOTICON RECOMMENDATION MODEL

Give an input post $W$, the goal of our system is to recommend the most likely emoticon $e^*$ by estimating probability of $Pr(e_j|W)$ for j-th emoticon $e_j$ over all emoticons $\Omega_E$. Moreover, due to ambiguity of word sense, all emoticons are further clustered. Therefore, $Pr(e_j|W)$ is

$$e^* = \arg \max_{e_j \in \Omega_E} \Pr(e_j | c_i, W)$$
$$= \arg \max_{e_j \in \Omega_E: c_i \in \Omega_C} \frac{\Pr(W|e_j) \Pr(e_j | c_i)}{\sum_{e_j} \Pr(W|e_j) \Pr(e_j | c_i)}$$

where $c_i$ is the i-th cluster in cluster space $\Omega_C$. In this paper, the evidence in Eq.(1) is assumed to be equal and ignored so that the formula is further written as

$$e^* = \arg \max_{e_j \in \Omega_E: c_i \in \Omega_C} \Pr(W|e_j) \Pr(e_j | c_i).$$

Eq.(2) presents the recommendation model which estimate the probability of emoticon $e_j$ and $e_j$ is occurred underlying the cluster $c_i$ for input post $W$. We will describe how to compute these two terms in detail in the following sections.

IV. FEATURE EXTRACTION

A. Post Segmentation

For text-based online communication, the post are often organized by emotion fluctuation. In other words, a post may comprise not only the primary emoticon but also the number of embedded emoticons. Moreover, the sentence of primary emoticon can be allocated at any position. Therefore, it is not easy to capture the real affective state of a post. Figure 3 demonstrates an example that a post was tagged one primary emoticon whereas more than one emoticon can be tagged at segments. In this paper, we assume that the context of a post is a trajectory of emoticon. However, blog posts often lack explicit punctuation marks so that sentences even paragraphs are not easy to identify. Herein, a fixed-size sliding window is employed to segment a post into $M$ segments, that is,

$$W \rightarrow \{t_1, t_2, \ldots, t_M\}$$

B. Affective Trajectory Mapping

After post segmentation, the m-th segment $t_m$ is mapped to an emoticon profile and defined as

$$s_m = \begin{bmatrix} Pr(t_m | e_1) \\ Pr(t_m | e_2) \\ \vdots \\ Pr(t_m | e_{|E|}) \end{bmatrix}$$

where $|E|$ denotes the number of emoticon.

To compute the j-th element $Pr(t_m | e_j)$ of emoticon profile $s_m$, we employ the LDA to obtain the word sense of
emoticons. Figure 4 illustrates the concept of the LDA-based emoticon profile generation. The latent variable $Z$ is employed to connect the relation between emoticons and all words. Hence, the term $\Pr(t_m|e_j)$ is further written as

$$\Pr(t_m|e_j) = \Pr(t_m|Z)\Pr(Z|e_j)$$ (5)

For simplicity, the affective trajectory of the input post $W$ will be denoted as $S$.

V. AFFECTIVE TRAJECTORY MODELING

A. Trajectory Clustering

Even the post is projected to emoticon profile, the effect for emoticons having similar trajectories is inevitable. To alleviate this problem, $k$-medoids clustering scheme with a distance matrix [18] is employed to group the trajectories in to $I$ clusters. In contrast to the $k$-means algorithm, $k$-medoids chooses datapoints as medoids (or center) and work with arbitrary matrix of distance between datapoints instead of $L_2$-norm. In common with most other similarity measure such as $L_2$-norm and cosine measure, the recommendation system adopts the Hausdorff distance (HD) for similarity estimation. Figure 5 illustrate an example why $L_2$-norm cannot be employed directly for our task in which the major problem is the different lengths of two emoticon trajectories.

B. Distance measure

The Hausdorff distance (HD) is a metric between two sets of points extracted from the object model and the test data. The classical HD measure [19] between two trajectories $S_k$ and $S_l$ is defined as

$$H(S_k, S_l) = \max(h(S_k, S_l), h(S_l, S_k))$$ (6)

where

$$h(S_k, S_l) = \max_{a \in S_k} \min_{b \in S_l} \|a - b\|$$ (7)

Hereby $h(S_k, S_l)$ is called the directed Hausdorff distance from set $S_k$ to set $S_l$ with some underlying $L_2$-norm $\|\cdot\|$ on the points of $S_i$ and $S_j$.

To compute the term $Pr(W|e_j)$ in Eq.(2) underlying cluster $C_j$, Gaussian density is utilized to quantize the HD-based similarity measure to confidence measure. Hence,

$$Pr(W|e_j) = Pr(S|e_j) = N(H(S, S_{ij})|\Lambda_{ij} = \{\mu_{ij}, \sigma_{ij}\})$$ (8)

where $N(s_m|\Lambda_{ij})$ is the Gaussian density with mean vector $\mu_{ij}$ and standard deviation $\sigma_{ij}$.

C. Trajectory Distribution

The last step of the recommendation model is to represent trajectory distributions by a large sparse matrix. In this paper, this matrix can be simply constructed after trajectory clustering. Therefore, the probability of the $j$-th trajectory...
conditioned on $i$-th cluster $Pr(e_j|c_i)$ can be computed by

$$Pr(e_j|c_i) = \frac{n_{ij}}{\sum_i n_{ij}}$$

where $n_{ij}$ is the number of trajectories of the $j$-th emoticon in the $i$-th cluster.

VI. EVALUATION

A. Data Collection

To evaluate the proposed method of the proposed emoticon recommendation system, we collected over 5,000 blog posts from the social network, Plurk (http://www.plurk.com/top/), which is one of most popular microblogging service in Taiwan. Plurk supports the search function, so we can collected the posts containing one emoticon only. Figure 6 demonstrates the post collection containing one emoticon by the query sentence with string "(hungry)". Then, a crawler was implemented to download and parse the query results. Finally, twenty-one most frequent emoticons as shown in Figure 7 were selected to for evaluation.

For the affective trajectory mapping, LDA was implemented by R package, topicmodels, and trained on the collected data and the number of topics was set to ten heuristically.

B. Results

Because of emotional fluctuation, top-k most likely emoticons will be recommended according to the input post in our proposed system. The first experiment was to evaluate the effect of the window size for post segmentation. Figure 8 shows the recommendation accuracy with different window sizes. The results reveal that the best recommendation performance of the proposed system achieved 76.05% accuracy where the window size was thirty for top-5 recommendation. It is reasonable that a Chinese post consists of about thirty words.

Based on the window size of 30 words, figure 9 shows the comparison between our proposed approach and the LDA-based baseline. This experiment was designed to evaluate the performance of affective trajectory. Because we cannot guarantee that the blog posts are always organized without emotional fluctuations, the LDA-based baseline is confused by the ambiguity of word sense.

VII. CONCLUSIONS

An emoticon recommendation system based on affective trajectory is proposed, implemented and evaluated. The main idea is that the blog posts are segmented into a sequence of segments using a sliding window, mapped to an affective trajectory by LDA-based method and the $k$-medoids clustering algorithm. Moreover, a sophisticated similarity measure of trajectory based on the Hausdorff distance is used to estimate the distance between two trajectories. Evaluation results show that the proposed approach using affective trajectory outperformed the systems based on LDA-based method.
REFERENCES


