Emotion-Weather Maps: Representation of Spatial Distributions of Mass and Complex Emotions

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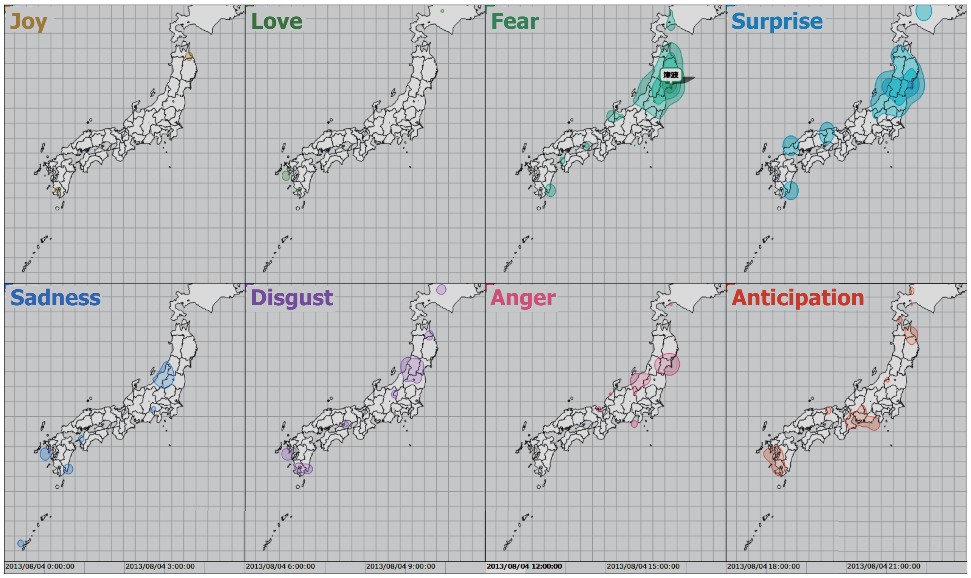

Figure 1: Emotion-weather maps from 12:00 to 13:00 on August 4th, 2013: On that day, Japan had an earthquake off the Pacific coast of Miyagi Prefecture. There were many emotions of fear and surprise in the Tohoku region (northeast region in Japan).

Abstract

Emotion-weather maps are some kinds of thematic maps to represent emotions. The maps represent spatial distributions of complex emotions of masses. Data of emotions have been extracted from social media. The data have some biases in some aspect of time, space, and categories of emotions. The biases obstructs observation of relatively few emotions. To address such problem, collected data are normalized. As a use case a sets of maps is presented. These maps represent distributions of emotions of an actual day. An earthquake on that day caused fear and surprise in a region in Japan.

1 Introduction

Purpose of our research is to help grasping spatio-temporal distributions of emotions of a large number of people. There are three issues to be addressed for the purpose.

1. How do we collect emotions of large number of people?
2. How do we process data expressing emotions?
3. How do we represent emotions expressed as data?

We focus on 2 and 3. For 1, there have been various research activities to collect emotions [3, 4]. We believe that we can use results of such activities in near future. On the other hand, we need more effort to make computers interpret the spatio-temporal distributions of emotions and interactions among emotions. So, we try to visualize the collected emotions to utilize capabilities of visual perception of human.

We have considered a way to represent the spatio-temporal distributions of emotions as a thematic map. A thematic map is a map to show a theme related to a geographic area. For example, thematic maps are used to represent the population of each area, traffic volume of each road, and so on. Although some researchers have drawn thematic maps representing emotions, most of them treat the emotion as one-dimensional value like unpleasant/pleasant, joy/sadness, and so on. However, our natural emotions are much more complex and diverse. We have developed a thematic map called "emotion-weather maps," which represents multidimensional emotions.

2 Related Work

There are many researches on visualizing themes on maps (e.g., [8, 1]). Hao et al. have challenged to make a thematic map for visual sentiment analysis[2]. They classified the opinions into positive, neutral, and negative, and then assign them green, gray, and red. Shook et al. extracted emotions with geotags from Wikipedia, and then represented them on a map[7]. They assigned blue to joy and red to sadness, and used the gradation from blue to red via white to express emotional degrees. Schwartz et al. drew a thematic map representing satisfaction of life in USA[6]. They estimate satisfaction of life from tweets with geotags. They used gradation from green to red via greenish-yellow. Plutchik presented three-dimensional circumplex model describes the relations among

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emotion concepts[5]. The model is similar to a color wheel and includes eight primary emotions.

3 Emotion-Weather Maps

We have designed and developed emotion-weather maps, a kind of thematic map representing emotions.

3.1 Data Collection

We used Twitter as our target media. We collected tweets written in Japanese with geotags in Japan by using Streaming API of Twitter. Collected data include tweet sentences, timestamp, and latitude and longitude. As categories of emotions, we adopted eight primary emotions: joy, love, fear, surprise, sadness, disgust, anger, and anticipation. We compiled a simple dictionary[1] of emotional words classified into eight primary emotions. We converted every collected tweet into a 4-tuple (timestamp, user ID, category of emotion, latitude and longitude).

3.2 Normalization of Data

We found three kinds of biases in the collected data: the temporal biases, the spatial biases, and the emotional biases. Many tweets are tweeted at night, while less are tweeted in the morning. Enormous number of tweets are concentrated in metropolitan areas. Tweets including joy and love are obviously more than the others. To correct these biases, we normalized values in the data. For example, we corrected the temporal biases as follows. Let the ratio of the number of tweets to the maximum number of tweets in any unit times to be a correction value. We obtain normalized values by multiplying the correction values to the number of tweets. Normalization may cause some risks, which emphasize very few tweets too much. However, we expected that we can observe distributions of small emotions by the normalization. Hereafter, we call the normalized numbers of emotions emotional scores.

3.3 Drawing of Emotion-Weather Maps

We draw a map for each category of emotions. Categories of emotions are expressed by color and position of the map. We chosen each color from hues in the L*a*b* color space (see Figure 2). The reason why we have adopted the L*a*b* color space is to express relations between emotions adequately and to make selected colors uniform in their brightness.

We have used the colors expressed by the following equations:

$$L^* = 74 \tag{1}$$

$$a^* = 40 \cdot \sin\left(\frac{-2\pi i}{8}\right) \tag{2}$$

$$b^* = 40 \cdot \cos\left(\frac{2\pi i}{8}\right) \tag{3}$$

Where, i $(i = 0, 1, \ldots, 7)$ expresses a category of emotions: joy, love,…, and anticipation. The L*a*b* color space includes colors which ordinal displays cannot reproduce exactly. Avoiding such the colors, we chosen adequate colors with the same brightness and distant from each other.

We have used the two-dimensional metaballs to represent emotional scores. By drawing the influence of metaballs in stages, the emotional scores are represented gradually (see Figure 3). We have aimed to be able to grasp roughly spatial distributions of emotions.

4 Examples

We have drawn emotion-weather maps to confirm effectiveness of our method. We have chosen data of a day when many emotions tended to be induced. We collected data in 24 hours from 0:00 on

[1] All collected words are Japanese. So, nuances of words might be different from the original words.

Figure 2: Coloration in the maps

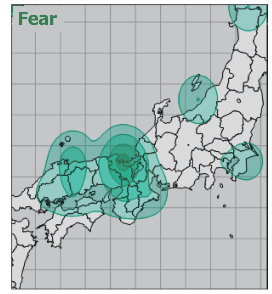

Figure 3: Representation of emotional scores

August 4th, 2013. On that day, we had an earthquake off the Pacific coast of Miyagi Prefecture in Japan.

We have collected 217,661 tweets. Collected data have been segmented to 1-hour units from 0:00, and to 1-degree squares. We hoped to see change of amount of emotions for each category of emotions. So, we drew maps with data normalized in viewpoints of space, time and categories of emotions.

Figure 1 shows a set of emotion-weather maps of that day. From the maps, we see there were many emotions of fear and surprise in the Tohoku region (northeast region in Japan), especially in Miyagi Prefecture in an hour from 12:00. A topic word "tsunami" was added at the center area of fear. We can guess that tsunami caused by the earthquake induced fear. From succeeding maps, we also see that while fear continued during two hours, surprise disappeared only in one hour.

5 Conclusion

We have designed emotion-weather maps and developed a system to draw the maps. The maps help to grasp distributions of complex emotions of masses. Development of the prototype made us aware of existing of biases in the data related emotions. We normalized data to avoid such biases and expose relatively few emotions. We also showed emotion-weather maps on an actual day and the maps described emotions related to an earthquake.

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