Negative Energy Detector using Cellphone Bluetooth and Contact list

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Abstract

Individual mood is important for physical and emotional well-being. Despite the physiological reasons, emotional contagion between peoples is also pivotal to understand and further predict people's emotional change. However, an ignored yet important task is to find the behavior differences between easygoing and sharp-tongued persons in daily life.

We present a novel metric to measure people's capacity to make their encounters negative. Then Latent Dirichlet Allocation topic model and multimodal exposure features(MME) are used to study the behavior differences, extracting the probable contact patterns of different kinds of people and how they contact with each other. Finally, to make practical, a MME Feed-forward Neural Network is given out to judge people's role in emotion contamination, with using people's own mobile-phones contact list. Taking the MIT Social Evolution dataset as an example, the experimental results verify the efficacy of our techniques on real-world data.

Author Keywords

Sentiment Contamination; Latent Dirichlet Allocation; Feed-forward Neural Network

ACM Classification Keywords

H.2.8 [Database Applications]: Data mining

General Terms

Algorithms; Performance; Design

Introduction

Individual emotion, as an important factor for physical and emotional well-being, is pivotal to improve people's life quality. Sentiment, such as oppression and unhappiness, can contaminate others, just like the virus [7].

Many works do the emotional contagion research in computer-mediated communication systems [4] and so on. Unfortunately, identifying how contagion begin and develop in these environments is difficult because estimation is confounded by the incomplete monitor of people's daily life. Thus most current works focus their efforts on population level and short-term small group.

Here we focus on the long-term daily data in individual level, to explore the negative sentiment spreading mechanism. In our life, there are sharp-tongued people, who have the magic to infect others with their mood, especially the negative sentiment. They can give others with much pressure and make their encounters feel negative with high probability. Talking to such people is harmful to our mental and physical health, especially for some weak people. It is valuable in human resource management to keep the team with passion and happiness, reducing the number of sharp-tongued people and increasing easygoing members [1].

Studying people's negative sentiment contamination can be used into the universities, especially for the professors and their PhDs. A motivated PhD should not receive too much or non negative pressure from their professors. So how to measure the negative pressure from their professors is the start point, and then we can study how many is proper in the future.

There are some challenges: macroscopic laws may not apply to individual level. The social network may play a different role. So in individual level, what is the difference of easygoing and sharp-tongued person's behaviors in day life, comparing with others? The easygoing person may exist different behavior patterns, comparing with sharp-tongued people. Once we find this pattern difference, a classification model can be used to identify them in daily life.

In this poster, we first formulate the frustrating metric as the negative emotional energy [1] and introduce a improved LDA topic model into the analysis of the behavior patterns. Then MIT Social Evolution dataset is used as a case study to find different people's behavior patterns and use a classification algorithm to identify people's role .

Problem Definitions

We assume that the higher probability a person's encounters feel sad, the greater his frustrating power is. Thus, we propose the following statistic metric to assess people's negative emotion contamination ability, shown in Equation 1 and 2. Ns_i^t is the number of the negative person group countered by the i-th node in the t-th day. N_i^t is the total number of the people encountered by the i-th node in the t-th day. Fru_i^t is the statistic Frustrating value of the i-th node in the t-th day, with its average Fru_i. This metric represents the probability a person's encounters feel negative.

$$Fru_i^t = \frac{Ns_i^t}{N_i^t} \qquad (1)$$

$$Fru_i = mean(Fru_i^t) \qquad (2)$$

To the end, one fundamental problem(Members Patterns Problem) is proposed here: What is the behavior difference between different class members with the help of mobile phone? To address the members patterns problem, a patterns detection model is used to explore the behavior difference.

Modeling Emotion Change with Topic Models

We divide people into three classes(devil, normal or sheep) according their Fru_i and study their behavior difference. Specifically, Devil, as the sharp-tongued people, is the top third people ranked by Fru_i in the monitoring group. Sheep, as the easygoing people, represents the bottom third. And Normal means the middle third. With the help of mobile phone, we can formulate multimodal vectors of exposure features (MME). With LDA topic model, we could get the unique patterns for people.

Multimodal Exposure Features and Topics
We formulate a multimodal vector of exposure features. A MME feature has the following structure (t,p_o,b,c,f,s,pd).

- Component (1) is the time where t $\in$ {10 pm-2 am, 2 - 8 am, 8 am-5 pm, 5 - 10 pm }.
- Component (2) is the people's sentiment frustrating class $p_o \in$ o and o is the set of frustrating classes.
- Component (3) is the type and amount of interaction where b is a measure of the cumulative exposure from bluetooth proximity to p_o and c is the cumulative exposure from the mobile-phones logs to p_o.
- Finally, the relationship metric is defined by f$\in$[friend, not friend], s$\in$[socialize, not socialize], and pd$\in$[political, not political].

Latent Dirichlet Allocation
LDA can be used to discover a set of latent topics from which a corpus of M documents d is composed via unsupervised learning. Topics are essentially clusters of dominating opinion exposures present over all individuals and days in the real-life data collection, described in terms of MME features [6].

Identifying people's role with Feed-forward Neural Network

We use the Feed-forward Neural Network, to explore the relationship between MME and the type of people. It is a method that can be used to classify subjects based on values of a set of predictor variables [3]. The inputs are the 8 members in MME, and the targets are the people's class. And classification results based on these 8 members are shown in the experiment part.

Evaluation

Our proposed models are tested on the MIT Social Evolution Dataset[5]. Data collection includes proximity, location, call log, daily physical and mental symptoms. Here, we choose the period between Jan 09, 2009 and Apr 24 due to the coexist of the call log and proximity.

Mining Interaction Patterns
In this part, we try to extract the interaction patterns between different people, using the MME-based LDA topic model. Here, we consider four documents, devil, sheep, devil-sheep and sheep-devil. Devil is the MME set for those Devil, sheep is for Sheep, devil-sheep is for the communication from Devil to Sheep and sheep-devil is for the communication from Sheep to Devil.

First, we check the communication patterns of devil, sheep without considering p_o. There patterns may help us

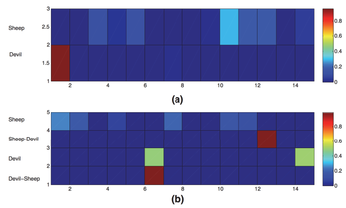

Figure 1: (Better viewed in color) (a) Mean topic distribution of sheep, devil. (b) Mean topic distribution of sheep, sheep-devil, devil and devil-sheep. Columns in this heat map are indexed by topics. Rows in this heat map are indexed by the type of people.

Table 1: Classification results

Class	Precision	Recall	F1-measure
sheep	1.00	0.80	0.89
normal	0.50	1.00	0.67
devil	1.00	0.67	0.80

to identify whether a user is a sharp-tongued people. We summary the results in Figure 1(a). The most probable topics for devil was topic 1, while for sheep is 10,11,12 and 5, which means devils predominantly contact strangers with few face to face, and no Calls or SMS in morning. As for sheep, they are like the devils, but in daytime.

Second, we check the contact patterns with considering p_o. The results is summaried in Figure 1 (b). The devils and sheep both like to contact normal and sheep strangers with few face to face at daytime. This difference may help devils find their victims in their cellphones' contact list.

With the above analysis, we could judge whether a user is a devil or sheep with the probable topics without p_o. We can also judge who is your sheep with the probable topics of devil-sheep with considering p_o.

Identifying People's Role

The prediction method is our Feed-forward Neural Network with 8 features. We get the statistic report, shown in Table 1. The sheep's indicators are the best, followed by devil and normal. People can use this mobile application to compute their own role in the social network. We can also identify who are the devils in sheep's contact list in the future work.

Conclusion

In this poster, we introduced a metric to compute people's negative emotion energy, proposed the members patterns problem, and studied the LDA model to solve this problem. Finally, we gave a prediction model to help users identify their role in sentiment spread, with the help of mobile phone. Evaluations on real-world data show the effectiveness and efficiency of the proposed methods. However, it is not easy to exclude the influence of homophily in the experiment. In our future work, we will conduct user studies with our designed wearable equipment[2] to collect more suitalbe data for this research.

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