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Modelling Individual Negative Emotion Spreading Process with Mobile Phones

Zhanwei Du,Yongjian Yang, Chuang Ma, Yuan Bai
Jilin University
Changchun, 130012 PRC
zwdu@acm.org, yyj@jlu.edu.cn,machuangstu@163.com, baiyuan722@163.com

Abstract

Individual mood is important for physical and emotional well-being, creativity and working memory. However, due to the lack of long-term real tracking daily data in individual level, most current works focus their efforts on population level and short-term small group. An ignored yet important task is to find the sentiment spreading mechanism in individual level from their daily behavior data. This paper studies this task by raising the following fundamental and summarization question, being not sufficiently answered by the literature so far:Given a social network, how the sentiment spread?

The current individual-level network spreading models always assume one can infect others only when he/she has been infected. Considering the negative emotion spreading characters in individual level, we loose this assumption, and give an individual negative emotion spreading model. In this paper, we propose a Graph-Coupled Hidden Markov Sentiment Model for modeling the propagation of infectious negative sentiment locally within a social network.

Taking the MIT Social Evolution dataset as an example, the experimental results verify the efficacy of our techniques on real-world data.

Introduction

Well-being is a important measure of people's quality of life. Increasing people and organizations place greater emphasis on exploring the secret of individual emotion shift. Emotional contagion in social network plays a significant role to understand people's emotional change. Sentiment, such as oppression and unhappiness, can contaminate others, just like the virus (Miller 2011). Emotional states can be transferred directly from one individual to another by emotional contagion, perhaps by the emotionally relevant bodily actions, particularly facial expressions, seen in others.

Many works do the emotional contagion research in computer-mediated communication systems (Hancock et al. 2008). 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. Besides, it is generally expensive and difficult for us to track many people's communication and mood everyday (Bolger, Davis, and Rafaeli 2003). 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. Specifically, we focus on the negative emotion spread process, due to its greater emotional contagion and independence of positive emotion(Golder and Macy 2011). Studying people's negative sentiment contamination is challenging: macroscopic laws may not apply to individual level. The social network may play a different role. So in individual level, how negative sentiment spread?

In this paper, we introduce a metric to measure people's frustrating energy, and give a general sentiment spread model to simulate and compute this metric, with considering the differences between sentiment contamination and traditional epidemic contamination.

Problem Definitions

Here, we introduce the following statistic metric Fru_i to assess people's negative emotion contamination ability (Du et al. 2014). This metric represents the probability a person's encounters feel negative.

Problem (The Emotion Spreading Problem) Given a dynamic social network, how the negative sentiment spread in the network between people featured by frustrating score Fru_i?

To solve the Emotion Spreading Problem, a general sentiment spread model is needed to simulate and compute this metric, with considering the differences between sentiment contamination and traditional epidemic contamination.

A General Emotion Spread Model

In this section, we will introduce a general emotion spread model to simulate the epidemic process and compute the Fru_i. Inspired by the epidemic model used in MIT Social Evolution Dataset (Dong, Pentland, and Heller 2012), the following model is proposed to model the spread of negative sentiments. A Gibbs sampling method is also given out to solve this model. Here, in keeping with the SIS model, we assume that there are certain transmission rates for the infection of one person by another, and likewise a recovery rate for an infected individual.

We can not just use this epidemic model directly. **There are several major differences between sentiment contamination and traditional epidemic contamination**: The first is the understanding of the encountered people. Some sharp-tongued people, even with good mood, can also make others frustrate to a large extent. Here, people, without 'virus', can also infect others with negative sentiment. But in the epidemic research, only when the encountered people are infected, it is considered as an effective encounter. Thus, in our general emotion spread model, each undirected edge (u,v)$\in G_t$ is constructed when u and v encountered, no matter whether one of them is infected and the other is suspend. Second, we still consider the dynamic infectious probability for each person, which means the i-th person has the different infectious power for the j-th person in different days. Third, when individuals feel negative, it is not always because of the encountered people. He/she may fall ill at that moment. So, we de-noise these noise data in the experiment.

Based on the above analysis and the generative epidemic model, the main formulas of our proposed Graph-Coupled Hidden Markov Sentiment Model (GCHMSM) is described as the following equations:

$$P(X_{n,t+1} = 0 | X_{n,t} = 1) = \gamma_i \quad (1)$$

$$P(X_{n_i,t+1} = 1 | X_{n_i,t} = 0, X_{n_j,t}, \{n_i, n_j\} \in G_{t+1}) = \beta_{i,j} \quad (2)$$

$$P(X_{n,t+1} = 1 | X_{n,t} = 0, X_{e:\{n,\cdot\} \in G_t}) \approx \alpha_i + \sum_{j}^{|X_e:\{i,\cdot\} \in G_t|} \beta_{i,j} \quad (3)$$

Here $\{n_i, n_j\} \in G_{t+1}$ represents interactions between agents n_i and n_j at time t+1. γ_i is the probability that i-th previously-sad individual recovers and so again becomes susceptible $P(X_{n,t+1} = 0 | X_{n,t} = 1)$. α_i represents the probability that the i-th sad person from outside infects a previously-susceptible person within the network. $\beta_{i,j}$ represents the probability that the j-th infectious person infects the i-th previously-susceptible person when they encounter. $X_{n,t} \in \{0, 1\}$, where 0 represents the susceptible state and 1 the infectious state of agent n at time t.

As for this model's inference algorithm, we use the Gibbs Sampling method, inspired by (Dong, Pentland, and Heller 2012), where more details can be found.

Evaluation

GCHMSM is tested on the MIT Social Evolution Dataset (Madan et al. 2012). We choose the period between Jan 09, 2009 and Apr 24 due to the coexist of the call log and proximity. We can get each people's inference frustrating value shown in Figure 1, as the averaging $\beta_{i,j}$ in this period, comparing with Fru_i. X-axis is indexed by subjects, Y-axis represents the frustrating score value. We can see that the average $\beta_{i,j}$ is in agreement with Fru_i. And the 27-th person is the peak in both of the two curves, and is considered as

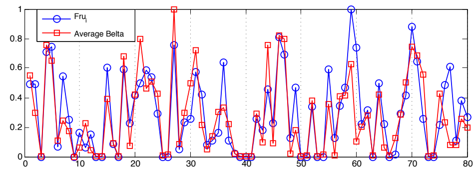

Figure 1: Comparison of GCHMSM' normalized average $\beta_{i,j}$ with Fru_i.

the most frustrating person people in this monitoring group. If we divide people into 3 groups by their Fru_i or average $\beta_{i,j}$, 83.75 % nodes are in agreement according to the two metrics.

Conclusion

We give a Graph-Coupled Hidden Markov Sentiment Model for modeling the propagation of infectious negative sentiment locally within a social network. Evaluations on real-world data show the effectiveness and efficiency of the proposed methods. However, we just derive a virtual social network of students in small students populations. Although some behavior differences are extracted, more evidences should be given with trying many more other datasets. Besides, the outside world may also cause people feel bad.

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