Emotion Evolution under Entrainment in Social Media

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Abstract. Emotion entrainment refers to the phenomenon that people gradually synchronize to other's emotion states through social interactions. Previous studies mainly focus on conducting laboratory experiments or small-scale offline surveys. Large-scale empirical studies on real-world emotion entrainment among individuals are still to be explored. Especially, determinants that influence this process are not clear. Also, how emotion evolves among people in a large scale population is still unknown. In this study, we attempt to conduct a large-scale empirical analysis on emotion entrainment based on online social media information. For this purpose, we develop a model-free framework to measure entrainment strength among people. Experimental results indicate that interaction partners with strong reciprocal entrainment tend to assume similar emotion states, and negative emotion is more empathetic in an intimate relationship. Especially, when the relationship is balanced, users are more emotionally similar to each other.

Keywords: Emotion Entrainment, Transfer Entropy, Social Media.

1 Introduction

The principle of emotion entrainment accounts for the convergence of people's rhythmic emotions through social interactions. For instance, when an individual feels unhappy, his friends may also feel unhappy, depending on the intimacy of their relationship. This principle is highly relevant to people’s daily life, since it provides the basic currency in social relationships, and it is essential to the quality and scale of people’s routine experience. Despite its importance, we have little understanding of the emotion dynamics in different kinds of relationships, as well as the determinants that steer the emotion trajectory during entrainment process. In addition, most previous investigation on entrainment only investigate through small scale or laboratory experiments, thus how emotion entrains over time in a large-scale, real-world setting remains a puzzle.

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In this paper, we attempt to explore the dynamics of emotion entrainment in a large scale setting. However, modeling emotion dynamics on a large scale at any detail is often challenging. Traditional bottom-up approaches are limited by their scalabilities due to high complexity in modeling, while more recent network based approaches are incapable to depict emotion dynamics accurately. As such, we propose to utilize a model-free approach, *transfer entropy*, to model emotion dynamics and derive a metric to quantify entrainment strength. Experiments on a dataset collected from Livejournal – a popular social media platform in the west – suggest that interaction partners with strong reciprocal entrainment tend to assume similar emotion states, and negative emotion is more empathetic in intimate relationship. When the relationship is balanced, the users are more emotionally similar to each other. Findings revealed in this paper may be useful for researchers and practitioners in understanding people's online relationships based on their emotion interactions, and informing whether their relationships are balanced or not.

The rest of the paper is structured as follows. Section 2 describes the dataset used and the metric for quantifying emotion entrainment. Section 3 reports the results of emotion evolution from three different perspectives. Section 4 concludes this paper with a summary and a discussion for future work.

2 Dataset and Metric

In this section, we first describe the dataset used, then proceed to present the technical details of modeling framework for emotion entrainment.

2.1 Dataset

Livejournal[1] is a blogging platform that allows its users to tag emotional labels when posting messages. Apart from system defined labels, Livejournal also allows users to define their own emotion labels. The dataset used in following studies (named as CHI06) is collected by Leshed and Kaye [1], and contains about 1.6 million bloggers who generate 18 million English blog posts. Besides, it provides a whole observation period from 1st May 2001 to 23rd Apr. 2005. This represents us with an entire emotion entrainment history.

Table 1. Categories of mood labels

Category	Examples of Mood Labels	Sample Number
Positive	great, elated, cheerful, ecstatic, jovial, fantastic, whee, triumphant, perky	285
Neutral	calm, so so, at peace, normal, ready for bed, working, thirsty, busy, blah, snuffly, warm	665
Negative	bored, sore, depressed, homicidal, crappy, yucky, remorseful, bitchy, befuddled, edgy	499
Total		1449

[1] `http://www.livejournal.com/`

For computation convenience, we select the most commonly used emotion labels (totally 1449) in the dataset, and group them into three categories: positive, neutral, and negative (Table 1). For the sake of mathematical manipulation, we assign labels in positive, neutral, and negative category with charges of [+1, 0, -1] respectively.

To facilitate analysis, in following studies, we randomly select 20,000 users who have posted more than 5 messages from the whole community.

2.2 Entrainment Metric

To quantify entrainment efficiently, we try to design our modeling framework with the fewest assumptions about exact social interactions. Also, we should distinguish entrainment directions as revealed by Will and Berg [2]. Consequently, we choose transfer entropy [3-6] as the metric to measure entrainment strength between each user pair. Specifically, if we record the emotion states of two users x and user y as two Markov processes $X = x_t$ and $Y = y_t$, then the entrainment strength from x to y can be defined as the transfer entropy from y to x, as shown in:

$$Entrain\ (X \to Y) = TE(\mathrm{Y} \to \mathrm{X}) = H\left(x_{t+1} \middle| \mathbf{x}_t^m\right) - H\left(x_{t+1} \middle| \mathbf{x}_t^m, \mathbf{y}_t^n\right) \tag{1}$$

where, $\mathbf{x}_t^m = \left(x_t, \ldots, x_{t-m+1}\right)$, $\mathbf{y}_t^n = \left(y_t, \ldots, y_{t-n+1}\right)$, while m and n are the orders of each of the Markov processes[2]; $H(*)$ calculates the entropy of the probability distribution enclosed.

This metric captures complex nonlinear emotion dynamics without modeling exact social interactions. In addition, it differentiates entrainment directions between dyadic interactions, which are often ignored by previous research. For detailed calculation of (1), please refer to Vicente *et al.* [3].

3 Emotion Evolution under Entrainment

In this section, we primarily examine how emotion evolves driven by entrainment process. Then, we further our study by exploring how each type of emotion evolves through dyadic interactions. Finally, we explore how emotion entrains in different kinds of social relationship.

3.1 Emotion Evolution in General Case

Entrainment level reflects the social closeness among people [7], and specific kind of emotion are only shared between intimate relationships [8]. Thus, we hypothesize people bearing intimate relationship tend to be emotionally similar.

To test this hypothesis, we first define a variable to depict emotion disparity for a given user pair. For a user v, we represent his sequential emotion states at each time

[2] For simplicity, we hereafter take m=n=3.

stamp t within an observation period T as a vector $\mathbf{V} = \{e_1, \ldots, e_t, \ldots, e_T\}$. For user v_i and user v_j, their emotional difference is defined as the angle cosine of their emotion vector $\mathbf{V_i}$ and $\mathbf{V_j}$ respectively[3]:

$$\text{Emo\_Diff}\left(v_i, v_j\right) = \text{Ar}\cos(\mathbf{V}_i, \mathbf{V}_j) \tag{2}$$

where, Arcos() calculate the angle cosine between the two vectors enclosed. Emo_Diff spans with an interval of [0, 180], and higher value suggest larger emotion difference.

As both entrainment strength and emotion state are in constant flux, (2) provides a reliable measure for the disparity of emotion states for each user pair in a long enough observation period. The distribution of emotion difference over entrainment strength is shown in Fig. 1.

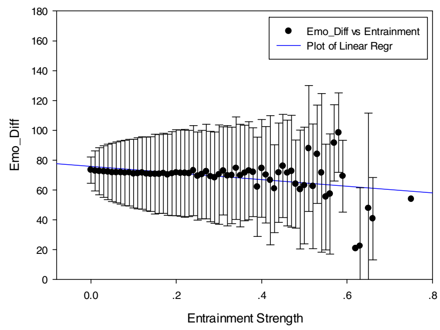

Fig. 1. Emotion difference over entrainment strength. Black node is the mean of Emo_Diff and error bars represent the standard deviation; blue line corresponds to the regression line ($y=b_0+b_1X$), where $b_1 = -22.197$.

Fig. 1 suggests that the Emo_Diff decreases as entrainment enhances (Pearson's correlation coefficient: -0.367, $p<0.05$). This implies that user peers tend to be emotionally similar under strong reciprocal entrainment, which, in turn, suggests that emotion empathy is more efficient between intimate relationships.

3.2 Emotion Evolution Based on Type

Types of emotion shared between people are usually relation dependent, i.e. bad moods are only shared between intimate relationships [8]. Thus, we further our study by examining whether each type of emotion evolves differently through dyadic interactions. As such, we divide the selected users into three groups according to their average emotion charge, as suggested by an indicator function C(v):

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[3] We take t as 1 day, and T as 7 days in this study.

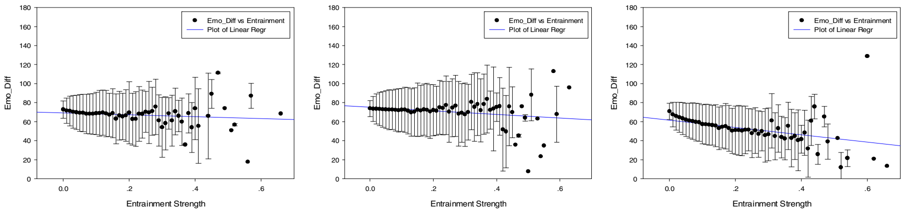

Fig. 2. Emotion evolution of each type. (a), (b), and (c) correspond to the evolution of positive, neutral, and negative emotion respectively; blue line corresponds the regression line ($y=b_0+b_1X$), where b_1 in (a),(b), and (c) are -10.329, -18.894 and -38.234.

$$\mathrm{C}(v)=\begin{cases}\text{POS}, & \mathit{if}\ 1/|\mathbf{M}|\sum_{m\in\mathbf{M}} Char(m)>\theta_{up},\\ \text{NEG}, & \mathit{if}\ 1/|\mathbf{M}|\sum_{m\in\mathbf{M}} Char(m)<\theta_{low},\\ \text{NEU}, & \mathit{otherwise.}\end{cases} \tag{3}$$

where, **M** is a set of |**M**| = N blog messages *m* written by user *v; Char(m)* represents the emotion charge of message *m*; θ_{up} and θ_{low} are respectively the upper and lower charge boundary separating each user group. By assigning θ_{up0}=0 and θ_{low}=-0.334[4], we obtain 4261, 10625 and 5114 users in POS, NEU and NEG group respectively.

In separating selected users, we assume that users in each group generally experience a certain kind of ‘emotion tone’. For instance, users in POS group overall experience positive moods in the whole observation period.

Under this grouping framework, we then examine how each type of emotion evolves within each user group, as shown in Fig. 2.

Fig. 2 indicates that for all the three types of emotion, their difference between user pairs decreases as entrainment strength enhances. This implies a noticeable correlation between emotion disparity and reciprocal entrainment strength. Pearson’s correlation coefficients in POS, NEU, and NEG group are -0.138, -0.211, and -0.384 respectively ($p<0.05$). This result reveals that negative emotion appears to be more empathetic in intimate relationships. Also, this finding may explain why negative emotion is more influential to people, and why it spreads faster than other types of emotion in social media [9].

3.3 Emotion Evolution Based on Network Structure

Synchronization delay or phase shift is a common phenomenon in entrainment process [10, 11]. For instance, at the initial stage of emotional interactions, people’s entrainment potential is high whereas their emotion states may be quite different. In such situations, the correlation between emotion difference and entrainment strength

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[4] This corresponds to two times of the average emotion charge for all selected users, i.e. -0.167.

can be weak. However, this correlation tends to be strong in more stable relationships. In this subsection, we explore whether distinct type of friendship influences emotion evolution.

Previous research argues that network structure of friendship also influences social interactions [12, 13]. Among these, social balance theory [14, 15] examines triads of individuals in social networks, and argues that people in an unbalanced relationship are incentive to adjust their social states toward more balanced formation [16, 17]. Thus, we wonder whether people's emotion entrains differently in balanced and unbalanced relationship.

To study this issue, we first redefine a pairwise binary relationship in a triad as:

$$\mathrm{E}\left(v_i, v_j\right) = \begin{cases} +, & \text{if } \min\left(Entrain\left(v_i \rightarrow v_j\right), Entrain\left(v_i \leftarrow v_j\right)\right) \geq \beta, \\ -, & \text{if } \max\left(Entrain\left(v_i \rightarrow v_j\right), Entrain\left(v_i \leftarrow v_j\right)\right) < \beta, \\ NULL, & otherwise. \end{cases} \tag{4}$$

where, $\mathrm{E}(v_i,v_j)$ denotes the polarity of the singed relationship (+ or -). min(), and max() calculate the minimum and maximum value of the two arguments enclosed. β is the threshold that distinguishes positive and negative relationships[5].

Given (4), the constructed triads in balanced and unbalanced formation are shown in Fig. 3. According to the social balance theory, a triad is said to be balanced if the algebraic multiplication of signs in the triad relation has a positive value, or unbalanced otherwise.

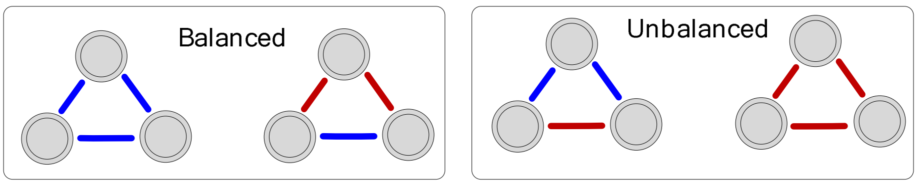

Fig. 3. Social Balance. Blue edge and red edge correspond to positive (+) and negative (-) relationship respectively. The two left triads are balanced, while the two right triads are unbalanced.

We then make a hypothesis that entrainment procedure enhances social ties. Under this assumption, social networks should become gradually balanced as entrainment process proceeds. To test this hypothesis, we introduce the global balance index [16] to measure social balance for a given social network, as defined below:

$$BI = \frac{\sum_{J \leq I} T_{balanced}}{\sum_{I} T_{total}} \tag{5}$$

[5] Without loss of generality, we set β as the average entrainment strength.

where, T_{balanced} denotes the number of balanced triads, T_{total} denotes the total number of triads in the whole networks, J and I represent the number of balanced and whole triads respectively.

We now investigate how the balance level changes along with proceeding of entrainment. To this end, for every seven days, we calculate the entrainment relationship for all selected users, as shown in Fig. 4.

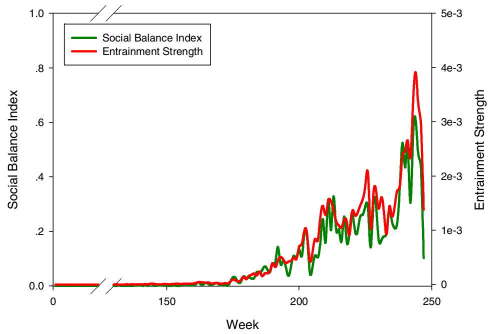

Fig. 4. Evolution of social balance. Green curve corresponds to the social balance index, and the red curve corresponds to the evolution of entrainment strength.

In Fig. 4, the balance level of the community on Livejournal increases as the entrainment strength develops. This finding verifies our previous hypothesis about entrainment and social balance. In addition, it is also consistent with Heider's conclusion that every social network tends to achieve higher balance level [14].

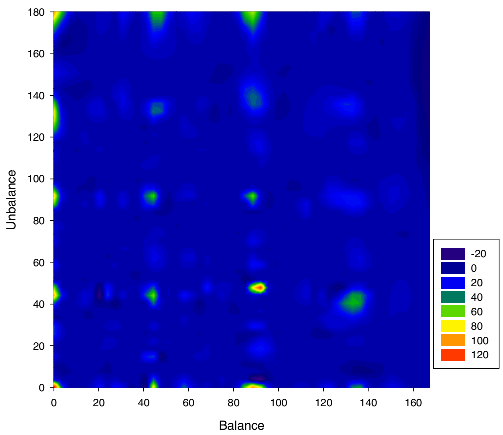

Fig. 5. Emotion difference in balanced and unbalanced friendship

Further, for each specific user pair, we explore how their emotion changes in balanced and unbalanced structure, and whether their emotions develop more similar to each other in balanced social relationship.

To clarify this issue, for each user pair, we plot the EMO_Diff in balanced relationships over that in unbalanced relationships (Fig. 5).

In Fig. 5, we notice the average Emo_Diff in a balanced relationship (average value: 60.065) is smaller than that in unbalanced one (average value:73.218). This difference is statistically significant with a p-value smaller than 0.001 according to a paired two-tailed t-test. This finding reveals that the emotion states are more similar within user pairs bearing balanced social relationships.

4 Conclusions and Future Work

In this paper, we explored emotion evolution under entrainment in a large-scale, real-world setting. We also tried to examine the determinants that may steer the emotion trajectory during entrainment procedure. To facilitate analytics, we proposed a model-free metric to quantify entrainment for a huge amount of user pairs. With this metric, we attempted to explore emotion evolution in general case and for each specific emotion type. Experimental results suggest that interaction partners with strong reciprocal entrainment tend to assume similar emotion states, and negative emotion is more empathetic in an intimate relationship. Besides, emotion evolution is also relation dependent, analysis based on social balance theory reveals that users are more emotionally similar to each other in balanced relationships.

In our future study, we hope to develop an interaction model to capture the emotion dynamics, and then try to give theoretical explanations for findings discovered in this paper.

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