Modeling Online Collective Emotions Through Knowledge Transfer

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***Abstract*—Online emotion diffusion is a compound process that involves interactions with multiple modalities. For instance, different behaviors influence the velocity and scale of emotion diffusion in online communities. Depicting and predicting massive online emotions helps to guide the trend of emotion evolution, thus avoiding unprecedented damages in crises. However, most existing work tries to depict and predict online emotions based on models not considering related modalities. There still lacks an efficient modeling framework that promotes performance by leveraging multi-modality knowledge, and quantifies the interactions among different modalities. In this paper, we elaborate a computational model to jointly depict online emotions and behaviors. By introducing a common structure, we can quantify how user emotions interact with the corresponding behaviors. To scale up to large dataset, we propose a hierarchical optimization algorithm to accelerate the convergence of the model. Evaluation on Sina Weibo dataset suggests that prediction error rate is lowered by 69 percent with the proposed model. In addition, the proposed model helps to explain how user emotions influence consequent behaviors in extreme situations.**

Keywords—online emotions; knowledge transfer; social crises

I. Introduction

Along with the evolution and diffusion process, human emotions interact with multiple modalities. For instance, in sports events, fans' emotions gradually ignite as the match heating up. In extreme situations, fanatic emotions may cause series violent incidents. During social crises, online users may shape the public opinion by spreading certain emotions, opinions and topics [1]. In economics, Toyota launched several large-scale recall of vehicles, which incurred public concerns about Toyota's safety checks and quality controls. Without appropriate prediction and guidance, negative emotions in these crises may accumulate and eventually port hazards to individual or collective interests.

However, most existing studies investigate human emotions without considering related modalities (e.g., behaviors, social networks, and topics) [2]. These approaches thus are incapable to depict emotion dynamics with high accuracy, and also fails to reveal how emotions are influenced by endogenous and exogenous factors. There still calls for an efficient modeling framework to promote performance by leveraging multi-modality knowledge, and to quantify the interactions among different modalities.

As human emotions and behaviors are interwound in social activities, we here propose a unified model that accommodates emotion and behavior dynamics at the same time. In the proposed model, a common structure is utilized to encode knowledge transfer between human emotions and behaviors. The captured knowledge is assumed to benefit emotion description and prediction. To scale up to large dataset, we propose a hierarchical optimization algorithm to accelerate the convergence of the model. In empirical study, we analyze Sina Weibo data of the 2014 FIFA World Cup Brazil. Evaluation result suggests that the proposed model lowers prediction error rate by 69 percent. In addition, the model reveals that fans' emotions and behaviors are tightly correlated during the World Cup, yet behaviors are more influenced by emotions. This implication suggests that fan's emotions determine consequent behaviors, and supervise and guide online emotions may help to reduce potential violent behaviors.

II. Model

In this section, we present our proposed model, namely, EBI (Emotion & Behavior Interaction). Suppose we have two collection of time series:

- $X=\{x_1,x_i,\ldots,x_d\}$: emotion series of d groups with duration n, where x_i is a sequence of group i, (i.e., $x_i=\{x_i^t\}_{t=1}^{n}$).
- $Y=\{y_1,y_i,\ldots,y_d\}$: behavior series of d groups with duration n, where y_i is a sequence of group i, (i.e., $y_i=\{y_i^t\}_{t=1}^{n}$).

Given these two sets of co-evolving time series X and Y, our goal is to (a) capture the evolutions of X, (b) find the hidden relationship between each sequence, and (c) predict future dynamics of X.

Considering the characteristics of human emotions and their interactions with behaviors, we intend to describe the following three properties:

- **(P1)**: Non-linear evolution of emotions/behaviors.
- **(P2)**: Interaction coefficients within emotion/behavior groups.
- **(P3)**: Knowledge transfer between emotion groups and behavior groups.

Consequently, the co-evolving of human emotions and behaviors is described by the following difference equations:

$$x_i^{t+1} = u_i\left[x_i^t + \sum_{j=1}^{d} a_{ij} \cdot x_j^t\right] + (1-u_i)\sum_{j=1}^{d} \Theta_j \cdot x_j^t \tag{1}$$

$$y_i^{t+1} = v_i\left[y_i^t + \sum_{j=1}^{d} b_{ij} \cdot y_j^t\right] + (1-v_i)\sum_{j=1}^{d} \Theta_j \cdot y_j^t \tag{2}$$

where,

x_i^t : the size of emotion group *i* at time tick *t*.

y_i : the size of behavior group *i* at time tick *t*.

$a_{ij}^t \in \mathbf{A}$: emotional interaction strength pointing from group *j* to *i* at time tick *t*.

$b_{ij}^t \in \mathbf{B}$: behavioral interaction strength pointing from group *j* to *i* at time tick *t*.

In this model, elements in interaction Matrix **A** and **B** take real values. When two groups compete with each other, then $a_{ij}^t > 0(i \neq j)$, $b_{ij}^t > 0(i \neq j)$ (i.e., repulsive effect); when two user groups entrain each other, then $a_{ij}^t < 0(i \neq j)$, $b_{ij}^t < 0(i \neq j)$) (i.e., attractive effect). If there is no inter-group interaction (i.e., $a_{ij}^t = 0(i \neq j)$, $b_{ij}^t = 0(i \neq j)$), the model deteriorates to traditional time series models that trade each temporal sequence in isolation, such as Auto-regression (AR), Autoregressive integrated moving average (ARIMA) and Kalman filters (KF).

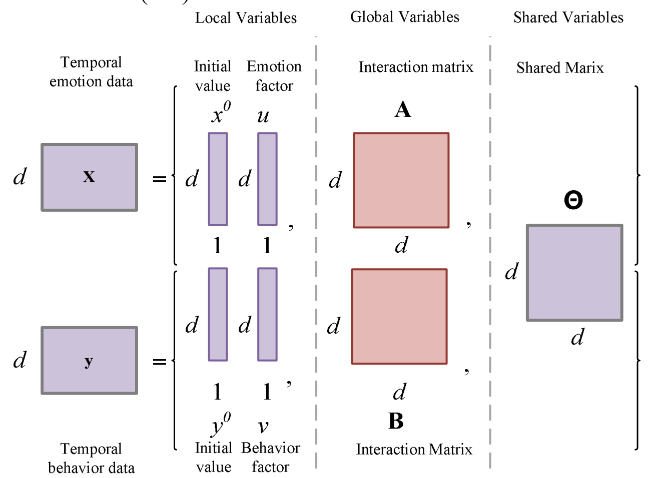


Fig. 1. Model illustration. Given two sets of *d* sequences **X** and **Y**, we depict local properties of each group, i.e., initial volume: x^0, y^0, modality factors *u* and *v*; global interaction matrix **A** and **B**; and shared structure Θ .

In the proposed model, $u_i \in [0,1]$ and $v_i \in [0,1]$ are modality factors, which respectively correspond to the ratio of effection caused by the same modality and different modalities, i.e., the degree of user emotions affected by user behaviors are depicted by u_i . Θ is the interaction matrix shared by the dynamics of user emotions and behaviors, which encodes knowledge transfer between emotions and behaviors. If there is no knowledge transfer, then $\theta_i = 0$; if two modalities benefit each other, then $\theta_i > 0$; if two modalities inhibit each other, then $\theta_i < 0$. The full model is illustrated in Fig. 1. The full parameter set to be learned is $S = \{x^0, y^0, u, v, \mathbf{A}, \mathbf{B}, \Theta\}$.

III. Experimental Setup

A. Data Description

The 2014 FIFA World Cup Brazil is a globally anticipated sports event. In social media, users discussed fiercely along the proceeding of the matches, which manifests abundant emotional and behavioral information. This characteristic makes online social media platforms suitable for investigating massive online emotion and behavior interactions.

To investigate massive emotion and behavior interactions, we have trained a Naive Bayes classifier [3] to determine the emotion charge of each message from Sina Weibo as positive (POS), Neutral (NEU), or Negative (NEG). The training dataset is provided by Zhao et al. [4], which contains 3.5 million emotion tagged messages from Sina Weibo. To tackle with polarity shifting and the emergences of neologisms, a self-learning scheme [5] is implemented in the classifier.

B. Settings

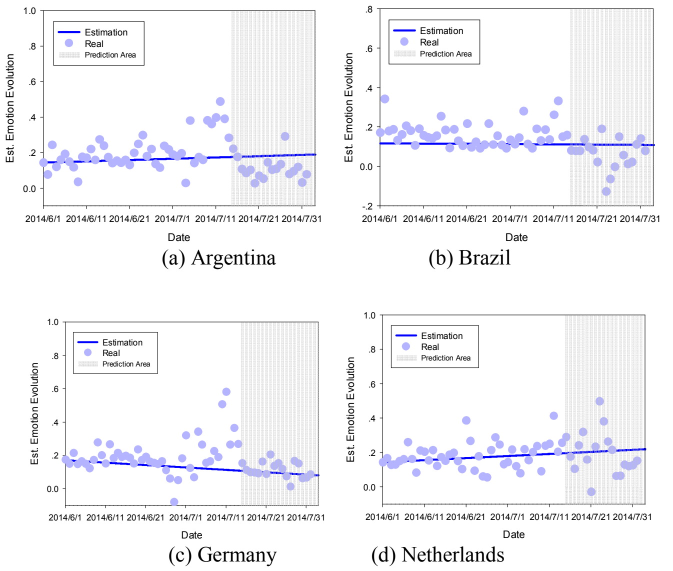
In the following experiments, we consider all users engaged in a fans club in Sina Weibo as a group. Thus, each emotion groups is represented by the time sequence of its average emotion charge, and each behavior group is represented by the time sequence of its posting number. Here, each day corresponds to a time tick.

As the match proceeds, some seed teams were gradually eliminated and their posting behaviors may be quite different hereafter. With regard to this change, we only focus on the top eight seed teams, i.e., Brazil, Columbia, France, Germany, Netherlands, Costarica, Argentina and Belgium. During this period, posting number are positively correlated with positive emotions, with Pearson's Correlation Coefficient of 0.169, 0.377, 0.225 and 0.256 respectively for Argentina, Brazil, Germany and Netherlands. These correlations suggest that fans' emotions interactions with behaviors, thus underpinning the multi-modality assumption in the proposed model.

IV. Results

A. Prediction Performance

Fig. 2 shows the fit of our model to the dataset (white parts). The good agreement supports for the model. In addition, the proposed model could accurately predict future emotion dynamics (blue parts in Fig. 2). It is noticeable that Brazil is the only team with average negairve emotions (Fig. 2-b, after Jul 20th 2014). This is largely attibuted to the fans' exteremly angry with Brazil's humiliating defeat by Germany. Our model subtly captures this emtion trend.



(a) Argentina (b) Brazil

(c) Germany (d) Netherlands

Fig. 2. Predicting future evolutions (Top 4 teams). Emotion predictions are colored in blue .

B. Fitting Error

To further examine the rationale of the proposed model, we compare the performance before and after behavior information involved in the model. Results indicates that when behavior information is encoded through knowledge transfer, prediction error rate is reduced by 69.28 (±12.80) percent. This result supports the assumption of emotion and behavior joint modeling. We notice that the error rate reductions are more significant for Argentina (75.47 percent) and (84.24 percent), who enter the final for championship. This results suggest that the interaction between fans' emotions and behaviors are stronger in these two teams, thus more knowledge can be transferred to depict emotion dynamics. To quantify how fans' emotions interact with behaviors, we turn to examine modality factors in the next subsection.

C. Modality Factors

If the proposed model and its interpretation are correct, then we expect that the fitted modality factors (u and v) will capture something meaningful about the interaction mechanism about fans' emotions and behaviors. Table I shows the values of u and v for different teams.

Modality factors quantifies how the current modality (emotion/behavior) is influenced by the other modality (behavior/emotion), and smaller values suggest that the current modality is more influenced by the other modality. By comparing the last two columns in Table I, we find that emotion modality factor (u) and behavior modality factor (v) are both less than 0.5. This result means that fans' emotions and behaviors are mutually influenced during the World Cup. As the values of u are generally larger than that of v, it suggest that fans' behaviors are more influenced by their emotions, i.e., changes in fans' emotions determine how they behave consequently. Compared with those of the final four teams, behaviors of the final eight teams are more likely to be influenced by their emotions (v is smaller, $p<0.05$ according to a one-tailed t-test).

TABLE I. EFFECTS OF MODALITY FACTORS.

Group ID	Team Name	Last Ranking	u	v
G1	Germany	1	0.349	0.026
F1	Argentina	2	0.327	0.034
B2	Netherlands	3	0.286	0.065
A1	Brazil	4	0.188	0.049
H1	Belgium	8	0.224	0.077
C1	Columbia	8	0.293	0.093
D2	Costarica	8	0.284	0.038
E3	France	8	0.376	0.108

V. CONCLUSIONS AND FUTURE WORK

We have proposed an efficient modeling framework that promotes performance by leveraging multi-modality knowledge, and quantifies the interactions among different modalities. To scale up to large dataset, we propose a hierarchical optimization algorithm to accelerate the convergence of the model. Evaluation result suggests that the proposed model can lower prediction error rate by 69 percent. In addition, the model reveals that fans' emotions and behaviors are tightly correlated during the World Cup, yet behaviors are more influenced by emotions.

In our future work, we plan to study emotion dynamics in two directions. First, we attempt to explore whether time-varying interaction mechanism would further benefit emotion prediction. Second, we are interested in explore more knowledge from the aspects of sociology, psychology and game theory. We intend to elaborate a unified model to involve such knowledge to leverage emotion prediction.

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