Modeling Multiple Fields of Collective Emotions with Brownian Agent-Based Model

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ABSTRACT

Understanding the emergence of collective emotions is critical to the analysis of online and offline societies. The agent-based simulation community has developed various social norm models to see the polarization of collective emotions. Yet, a few models have psychological background as fundamentals, as well as statistical validation, and this paper aims at resolving the two challenges. Particularly, this paper models agents as Brownian agents with different parameters of arousal, valence, and preference, which originates from the field of psychology. The Brownian agents enable the agents to become more heterogeneous, while they are simple enough to be understood and expanded. In the simulation, the agents influence and are influenced by multiple fields, or parts of community, of collective emotions. We designed two virtual experiments: one hypothetical setting to generate the emergence, and the other setting to validate the model with a real-world dataset. The first experiment identifies the scenario characteristics of extreme polarizations of collective emotions. The second experiment shows that the simple Brownian agent model is able to generate the real-world case with statistical significance.

Categories and Subject Descriptors

J.4 [**Social and Behavioral Sciences**]: Sociology

General Terms

Human Factors

Keywords

Social simulation, Artificial social systems, Social and organizational structure

1. INTRODUCTION

In recent years, online communities, such as web portal, online news media, and Social Networking Services (SNS), have emerged as new social discourse communities, and their influence is growing in the real world [23]. One source of the influences are the rapid emergence of collective emotions in those communities. To understand the emergence of the collective emotions, psychologists introduced various qualitative and quantitative models to explain the emergence with theoretical background [19, 35, 6]. Another venue of research on collective emotion has been the methodological approach with agent-based models [32, 2, 15]. Computational social scientists suggested a diverse generative model to explain social diffusion and norm emergence [11, 14]. The simulation studies focused on the interactions among agents and communities because the studies assume and prove that the interactions are the main source of emergence. While the *emergence* is fully appreciated in these simulations, the next step would be making the simulation model to adopt the existing theoretical studies from the psychology community, so the models have a better component in the *emotion*. In the collective emotion studies, one of the recent efforts to bridge the psychological background and the agent-based modeling is the Brownian agent model in [34]. A Brownian agent describes an agent's dynamics by a superposition of deterministic and stochastic elements [33]. In the rest of this paper, we used the term *agent* to denote Brownian agent for simplicity. This approach models an individual as an agent that determines the next state of its emotion with a linear sum of psychological factors, including the feedback from the community, and a Gaussian error. The timeline of an individual emotional state exhibits the Brownian motion, and the modeling assumption is that the collective emotion may emerge from the collective of the motions. However, the prior work does not support an environment with multiple sources of information. Recently, the technology-mediated interaction between people has become more popular [21]. This trend also includes emotional communication that occurs in the online environment, and it is mediated by the different media, which have different emotional tendencies. The motivation of adopting multiple fields is to provide a more comprehensive explanation about this realistic situation. From the basis of this prior work, we expand the model to have multiple fields of collective emotions, which means that the community would have multiple issues, represented as fields in our model, and collective emotions emerge for each field. This expansion requires: 1) modeling the field preference of agents, 2) modeling the feedback from multiple fields to agents, and 3) modeling the Brownian motion with feedbacks from the multiple fields. After expanding the model, we studied the emergence of collective emotions with

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two virtual experiment settings. The first virtual experiment explains the role of field preferences in the emergence of collective emotions. This experiment provides insight on how the emergence of collective emotions would alter if the population of agents are interacting with multiple subjects of the society, not just one subject as in the previous model. The second virtual experiment validates the model with a dataset from the real-world online community. We used an online community dataset, extracted emotions from the community posts, and validated the generative approach by comparing the generated intensity of collective emotions and the extracted collective emotion from the real world. This experiment validates that the simulation study is able to generate the real-world phenomena with simple agents of Brownian motion of *emotions* from the perspective of the generative social science.

2. PREVIOUS RESEARCH

2.1 Computational Models of Emotions

While we survey the computational models, we identified that the models inherit two theoretical backgrounds of emotions: the appraisal theory and the dimensional theory. The appraisal theory regards that emotions are the results of personal evaluations on events; personal characteristics, such as beliefs, desires, and intentions, are closely related to the personal evaluations. This theory becomes the basis of understanding why people react differently in the same situation [22]. In the dimensional theory, emotion is a point of the continuous dimensional space of personal states [31, 40], i.e., pleasure, activation, etc. From our survey, we think that the computation models of emotions has so far been studied mainly within the appraisal theoretical context [20, 25, 8]. Gratch and Marsella [20, 25] suggested a computational framework, which is called EMA, focusing on appraisal processes and coping strategies. Their emotional eliciting conditions are represented by if-then rules in terms of qualitative values of appraisal variables. It provides detailed explanations of internal emotional processes. For example, when we encounter a certain proposition p, if the desirability of p is larger, and if the likelihood of p is smaller than its threshold, an agent's elicited emotional state is labeled as a certain emotion. Battaglino et al. [8] introduced a computational emotion model that considers moral values. In this model, value-sensitive agents will receive an adjusted emotional reward, given the trade-off between moral values and individual goals. Such features can be useful in modeling empathic agents. In computational models from the dimensional theory, emotions are represented in the continuous dimensional space. This representation is more interpretable than the discrete labeling approaches in appraisal theory [7] when we explain the dynamics of emotions over time [24]. Becker-Asano et al. [9, 10] introduced an affect simulation architecture which is based on three-dimensional emotion space [26]. Interestingly, their experimental result was able to replicate some concepts in psychological theories, i.e., secondary emotions require more cognitive reasoning abilities than primary emotions. For further information on the computational models of emotions, Marsella et al. [24] provide a good review on the field.

2.2 Agent-Based Models of Collective Emotions

To define the *collective emotions* in our context, we consider the difference between personal emotions and collective emotions. Scheve and Ismer [38] define a wide range of collective emotions as *synchronous convergence in affective responding across individuals towards a specific event or object*; and they emphasize the significance of shared appraisal structures to lead to the emergence of collective emotions. In this paper, collective emotions mean the shared emotions by individuals [6] as in [17]. Analyzing collective emotions provides critical insight into social phenomena [5], as well as the analysis is applicable to various studies on online collective emotions [29, 18, 16, 27, 39]. Recent examples of collective emotions [38] include the Arab Spring [1, 36] and the 2011 English riots [4]. The agent-based model is widely used to analyze the emergent pattern of collective emotions. This approach has been considered appropriate to describe various complex and dynamic phenomena [28, 13].

3. BACKGROUND THEORY AND BASELINE MODEL

Our model is an extended version of a collective emotion framework from [17, 34]. Though they left some psychology theory that supports certain aspects of the model, it has been provided that this framework can not only provide experimentally testable results [17], but also be applied to empirical online communities. Therefore, we briefly introduce the baseline model and the background theory of the baseline model. The baseline model defined human emotional state as two independent variables, *valence* and *arousal*. The background theory is the dimensional theory explained in the previous section. Specifically, Russell's circumplex model [31], in the dimensional theory community, is the rationale behind the model. Russell assumes human emotional states as two-dimensional continuous space. This framework simplifies individual emotional dynamics, and focuses on the interaction between individual agents, while previous computational appraisal models have concentrated on internal individual emotional processes. The first dimension, valence, indicates whether the pleasure associated with an emotion is positive or negative (attractiveness and aversiveness). The second dimension, arousal, indicates the activity level induced by the emotion. This two-dimensional modeling results in four different emotional states: 1) active and enthusiastic (positive valence and positive arousal), 2) afraid, nervous, and angry (negative valence and positive arousal), 3) relaxed (positive valence and negative arousal), and 4) depressed (negative valence and negative arousal). The agents in the baseline model have both valence and arousal state variables, and the variables are influenced by feedback from the online community which are the collection of agents' actions. The agents of the baseline model follows the specific structure that combines features of reactive and reflexive agent concepts [33]. Each agent has a set of state variables $u_i^{(k)}$, where the index $i = 1, \cdots, N$ indicates the index of the individual agent and k indicates the different variables. The state variables change over time according to the environment and the internal dynamics. The below is a formal expression of these agent state dynamics.

$$\frac{du_i^{(k)}}{dt} = f_i^{(k)} + F_i^{stochastic} \quad (1)$$

In the above formula, $F_i^{stochastic}$ is a stochastic term and $f_i^{(k)}$ is a deterministic term. This formulation is based on the concept of Brownian motion. Temporal change of the k^{th} variable of state u can be specified by the combination of deterministic and stochastic effects. From the background theory, an individual emotion can be described as a pair of valence and arousal, so the baseline model describes an agent emotional state as $e_i(t) =< v_i(t), a_i(t) >$, where $v_i(t)$ is valence of agent i and $a_i(t)$ is arousal of agent i at time t. Now, the agent model with the emotional state is described in the below formula.

$$\frac{dv_i(t)}{dt} = -\gamma_{v,i} v_i(t) + F_v + A_{v,i}\xi_v(t) \tag{2}$$

$$\frac{da_i(t)}{dt} = -\gamma_{a,i} a_i(t) + F_a + A_{a,i}\xi_a(t) \tag{3}$$

the first term of the right-hand side of each equation is a deterministic term to express an exponential decay, which forces both arousal and valence to reach an equilibrium state without any internal or external excitation. Valence and arousal have decreasing rates which are $\gamma_{v,i}$ and $\gamma_{a,i}$. These can be different in general; however, we used the same values for these rates. The second terms, F_v and F_a, are also deterministic terms from the feedback of environment, and this is the main source of complexity and emergence. Since we expand on the second term further, we explain the second term in more detail in the next section. The third term is the Gaussian stochastic element. $A_{v,i}$ and $A_{a,i}$ are weights of the stochasticity, and $\xi_v(t)$ and $\xi_a(t)$ are stochasticity itself. Whereas the above is the perception and the internal dynamics of the emotional agent, the action of emotional agents is modeled as follows. Each agent expresses its emotion when its arousal is high enough. For simplicity, the baseline model assumes that the expression is a simple polarity value that is either good(+1), neutral (0), or bad(−1). These settings are identical with the baseline model because our model ultimately aims at the estimation of emotional dynamics of population, not the detailed prediction of the personal emotion. The below is a formal definition of the expression s_i of agent i.

$$s_i(t + \delta t) = sign(v_i(t))\Theta[a_i(t) - \tau_i] \tag{4}$$

In the above, τ_i is the expression threshold of agent i by defining $\Theta[x] = 1$ when $x \geq 0$, and $\Theta[x] = 0$ otherwise. We fixed the value of δt as 1 in the rest of this paper.

4. MODEL OF COLLECTIVE EMOTIONS WITH MULTIPLE FIELDS

The baseline model has only one source of feedback, a single field, from a community. However, in the real world, agents might have multiple feedback loops from a community. For instance, if a user of an online bulletin board reads only articles of preferred topics, the emotional feedback from the bulletin board to the user should be multiple, rather than a single feedback as a whole. Therefore, we divided an online community into multiple fields, and we modeled that agents interact with preferred fields. Because of this additional feature, we added multiple field dynamics and preference model of interactions. Additionally, the emotional state dynamics are updated to cooperate with multiple fields.

4.1 Emotional and Preference States

Each agent has an emotional state, $e_i(t) =< v_i(t), a_i(t) >$, which is the same as before. Now, each agent has a preference state, $p_i(t) =< p_i^{(1)}(t), \cdots, p_i^{(K)}(t) >$ when K is the number of fields, $p_i^{(k)}(t) \geq 0, \forall k$ and $\sum_k p_i^{(k)}(t) = 1$, which is a vector of proportions that indicates the agent's preference of a certain field. The preference of each agent refers the likelihood that an agent selects a field, such as SNS, blogs, fora, etc., where the agent potentially expresses its emotion by its arousal level. Also, the field can store and distribute emotional information of agents [17]. We do not distinguish the strength of the expression among agents. The initial state of the preference per agent is equally instantiated. After the initiation, the model dynamically changes the preference of agents over the course of simulations. Once an agent selects a field, the agent updates its emotional states utilizing the value of the chosen field, and the agent influences the field by its emotional expression if the arousal is higher than its threshold. The following subsections explains the updates of the emotional states and the influence to the fields in turn.

4.2 Emotion Dynamics

We expand the baseline model to the multiple-field model. In detail, we have four modeling assumptions of emotional dynamics listed in the rest of this section. The following assumptions are identical with the baseline model for emotional dynamics [17, 34], except for 3) arousal dynamics. To avoid the same direction of feedback loops of valence and arousal, we assume that the arousal of an agent is affected by the opposite valence information. 1) Agents with negative (positive) valence mostly respond to negative (positive) emotional content. In the below formula, $h_+^{(k)}(t)$ and $h_-^{k}(t)$ indicate the amount of positive and negative feedback in the kth field at time t, respectively. The dynamics of field is described in the next section.

$$F_v \propto h_+^{(k)},\ v_i(t) > 0, \quad F_v \propto h_-^{(k)},\ v_i(t) < 0 \tag{5}$$

2) Agents with high enough arousal perform emotional actions, and after the action, the arousal becomes 0 where τ_i is the threshold to express emotion of agent i.

$$F_a = 0,\ a_i(t) - \tau_i > 0 \tag{6}$$

3) Agents' arousal increases when the opposite emotional information is high in a certain field.

$$F_a \propto h_-^{(k)},\ v_i(t) > 0, \quad F_a \propto h_+^{(k)},\ v_i(t) < 0 \tag{7}$$

4) In valence, if agents are negative (positive), the agents become more negative (positive) when the agents receive negative (positive) feedback. This is the same to the arousal state change. In the below, b_q is a polynomial coefficient for the valence feedback, and d_q is a polynomial coefficient for the arousal feedback. Here, q is the degree of the polynomials in the update functions.

$$F_v \propto \sum_q b_q v_i(t)^q, \quad F_a \propto \sum_q d_q a_i(t)^q \tag{8}$$

This paper accepted cubic polynomial feedbacks for valence and square polynomial feedback for arousal. That the cubic polynomial functions without square terms means that the function exponentially increases with keeping the sign directions (either positive or negative) of the input, so we used it for modeling the valence. The opposite rationale

Table 1: Model Inputs, outputs, and parameters for virtual experiments

Type	Name	Implication
Input	Agent Initial State	300 agents are instantiated, valences of each agent i are randomly drawn from the $Uniform(-0.01, 0.01)$, arousals of each agent i are initialized by the value 0, preferences of each agent i are initialized by the value of 1/3 in the case of multi-fields.
	Field Initial State	3 fields are instantiated, $<h_+,h_->$ of three fields are $<0.6,0.4>$, $<0.5,0.5>$, and $<0.4,0.6>$.
Output	Emotional pattern	Each agent has their own valence and arousal. Collective emotional pattern as the average of agents.
Parameters	Simulation Time	The total simulation time is 500 tick.
	Valence Stochastic Weight	Strength of stochastic influence of the valence.The values of each agent i are randomly drawn from $Uniform(6, 7)$.
	Arousal Stochastic Weight	Strength of stochastic influence of the arousal.The values of each agent i are the same as 0.3.
	Preference Stochastic Weight	Strength of stochastic influence of the preference.The values of each agent i are the same as 0.3.
	Decay Rates	Decay rates of valence, arousal, and field feedback are initialized as 0.5., 0.5, and 0.7, respectively.
	Neutrality Rate	Returning strength to neutrality of each communication fields. The values of each field k are the same. The value is initialized by 0.2.
	Valence Noise	The stochastic influence distribution in valence.The value is randomly drawn from $Normal(0, 0.01^2)$.
	Arousal Noise	The stochastic influence distribution in arousal.The value is randomly drawn from $Normal(0, 0.01^2)$.
	Preference Noise	The stochastic influence distribution in preference.The value is randomly drawn from $Normal(0, 0.05^2)$.
	Field Selection Rules	In the case of multi-fields, each agent selects one field, and moved the field for each time tick. Varied by the virtual experiment settings.
	Extreme Agent Ratio	The ratio of extreme agents. Varied by the virtual experiment settings.

is applied when we choose the square polynomial functions to model the arousal. We assume that an arousal of an agent is influenced by the opposite valence of the agent. By putting Equations (5) and (8) together, we can get two results, Equations (9) and (10). Equations (6) and (7) also lead to the final Equations (11) and (12). The coefficients are determined as follows: $b_1 = 1.5$, $b_3 = -1.5$, $d_0 = 0$, $d_1 = 1$, and $d_2 = 1$. The full details and the condition of coefficients in the following equations are beyond the scope of this paper; interested readers are referred to [17].

$$F_v \propto h_+^{(k)}(b_1 v_i(t) + b_3 v_i(t)^3),\ v_i(t) > 0 \tag{9}$$

$$F_v \propto h_-^{(k)}(b_1 v_i(t) + b_3 v_i(t)^3),\ v_i(t) < 0 \tag{10}$$

$$F_a \propto h_-^{(k)}(d_0 + d_1 a_i(t) + d_2 a_i(t)^2),\ v_i(t) > 0 \tag{11}$$

$$F_a \propto h_+^{(k)}(d_0 + d_1 a_i(t) + d_2 a_i(t)^2),\ v_i(t) < 0 \tag{12}$$

4.3 Field Dynamics

Modeling multiple fields suggest that agents should decide which fields to visit at each timestep. We propose a proportional mechanism on the field dynamics. The below is the update formula of each negative and positive feedback of the field k at time t.

$$\frac{dh_\pm^{(k)}(t))}{dt} = -\gamma_h^{(k)} h_\pm^{(k)}(t) + c_h^{(k)} \frac{N_\pm^{(k)}}{N_+^{(k)} + N_-^{(k)}} + ne_h^{(k)}(\frac{1}{2}) \tag{13}$$

In the above, $\gamma_h^{(k)}$ is the exponential value decay of the field k. $c_h^{(k)}$ is an acceptance rate for new emotional information, which models the stability of the field. $ne_h^{(k)}$ is the neutrality rate, and $N_\pm^{(k)}$ is the number of expressed emotions that is either positive or negative. As a summary of this update, the first term is the decay of previous emotion in the field, the second term presents the acceptance degree of new influence freom agents, and the third term refers to the neutral adjustment. We maintain that the updates of field feedbacks to keep the sum of $h_\pm^{(k)}(t)$ as 1. To maintain this constraint, we hypothesize that $\gamma_h^{(k)} = c_h^{(k)} + ne_h^{(k)}$. This means $h_\pm^{(k)}(t)$ is always in [0,1].

4.4 Preference Dynamics

To model multiple fields, we need to describe both selection rule and interaction rule. Here, we assumed that an agent interacts with a field at a single timestep, which can be relaxed in the future models. Each agent can choose a field from the multinomial distribution whose parameters are the preference states of the agent. The preference dynamics of $p_i^{(k)}(t)$ are also modeled by the Brownian motion.

$$\frac{dp_i^{(k)}(t)}{dt} = F_p^{(k)} + A_{p_i}\xi_p(t) \tag{14}$$

In the above, $F_p^{(m)}$ is the deterministic term influenced by the feedback of the field. A_{p_i} is the weight for the stochasticity, and $\xi_p(t)$ is the stochastic term. The deterministic term of the field feedback increases proportionally more when the

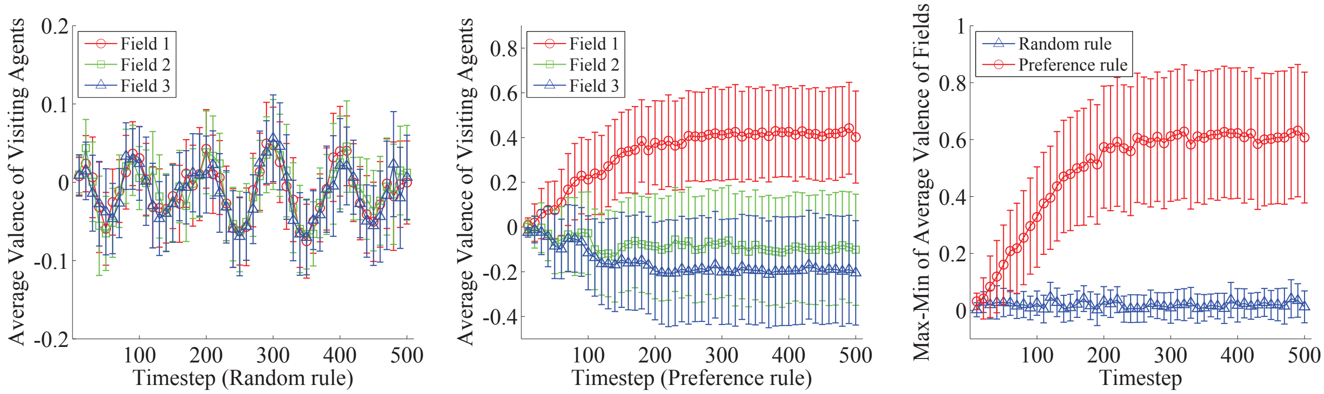

Figure 1: (Left and Middle) Trajectories of the number of visiting agents when using either random selection or preference selection in the interaction field selection. (Right) Divergence of valence by the field selection rules.

Table 2: Virtual experiment design for sensitivity analysis

Experiment Variable Name	**Experiment Design**	**Implication**
Field Selection Rules	Random or Preference States (2 cases)	Sensitivity analysis of different interaction field selection rules
Percentage of extreme agents	0%, 1%, 2%, or 3% (4 cases)	Sensitivity analysis of rates of extreme agent in populations. Extreme agents have <-1,1> as <valence,arousal>.
Total Number of Experiment Cells	12 experiment cells (=24 + 4 cases of single field as baseline)	Each cell is replicated 30 times.

agent's valence matches the field's feedback direction, and decreasing otherwise.

$$F_p^{(k)} \propto \begin{cases} (h_+^{(k)} - 0.5)|v_i(t)| & \text{if } v_i(t) > 0 \\ (h_-^{(k)} - 0.5)|v_i(t)| & \text{if } v_i(t) < 0 \end{cases} \tag{15}$$

Following the above equation, $p_i^{(m)}(t+\delta t)$ may not satisfy the probability distribution assumption, $\sum_k p_i^{(k)}(t+\delta t) = 1$. Hence we normalized $p_i^{(m)}(t+\delta t)$ when an agent selects a field.

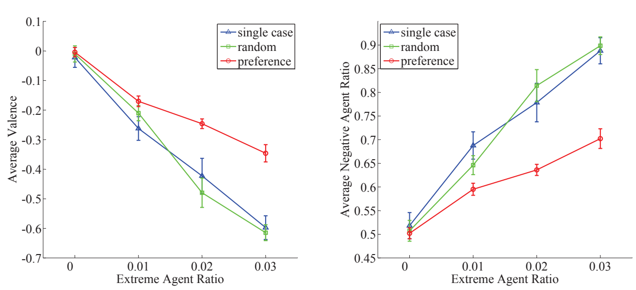

Figure 2: (Left) The level of valence as the degree of negative emotion in population. (Right) The average number of agents with negative valence.

5. VIRTUAL EXPERIMENTS

After implementing the agent-based model described in the previous section, two questions arise. The first question is the simulation results with the model. The model lays out critical factors of collective emotions from the perspective of the dimensional theory from psychology, and we expect to see the emergence of the emotions in multiple fields. The second question is whether or not the model can replicate the dynamics of collective emotions observed in the real world. The following subsections answer these questions in turn.

5.1 Sensitivity Analysis

Before we present the simulation result, Table 1 shows the summary of our agent-based model and its initial setting for the experiments. We varied two input variables to analyze the sensitivity of the simulation result, and this virtual experiment setting for the sensitivity analysis is enumerated in Table 2. The combination of 1 and 2 enumerates the complete list of parameters that we used in the virtual experiments. Figure 1, which is not under the experiment design, is a simple replication of models with default settings and varying field selection rule, either random or preference. Figure 1 shows the impact of the field selection rules. Without assuming the preference field selection, the model cannot generate the divergence of collective emotions over time. This suggests the polarized collective emotions that we see in the real world might come from the agent's preference-based interactions. Figure 2 illustrates the influence of the extreme agents. The extreme agents are initialized to have -1 as valence and 1 as arousal, so the agents are very eager to influence the field with negative emotion. As expected, the level of valence quickly decreases when we add more extreme agents, which means the population becomes

Table 3: Standardized coefficients for meta-model regression for average valence and average negative agent ratio. We used two dummy variables for three categorical variables: multi-fields with preference rule, multi-fields with random selection, and single-field. *:p-value<0.01

Dependent Variable	Average Valence	Average Negative Agent Ratio
Dummy (Multi-random)	-0.285*	0.337*
Dummy (Single)	-0.279*	0.342*
Extreme agent rate	-0.833*	0.788*
Adjusted R-square	0.771	0.734

very negative. However, when agents chooses the field with preference, the impact is limited when we compare the case to the random selection and the single-field case. This illustrates that the extreme agents were caged in a certain field and failed to influence the bigger portion of the population. To investigate details of them, we computed the meta-model regression. Table 3 shows that the meta-model regression is consistent with Figures 1 and 2. We used two dummy variables, D1 and D2, to represent three categorical variables. The categorical variables are 1) multi-fields with preference rule (D1 = 0, D2 = 0), 2) multi-fields with random selection (D1 = 1, D2 = 0), and 3) single-field (D1 = 0, D2 = 1). The regression shows that the number of extreme agents is the twice stronger contributor in making the community more negative compared to the field selection rules. At the same time, the regression also indicates that the field selection rule significantly influences the level of valence in collective emotions. Adjusted R-squares shows that the average valence is easier to represent than the average negative agent ratio. In addition, we observed the following results in the virtual experiment. When extreme agents are exist, all other agents finally reached a negative valence in the single-field case while all agents did not reach a negative valence in the two multi-field cases. In practice, the confrontation with different people has always existed in online communication. Therefore, it is not practical that all agents have an equal directional emotion (negative valence), even if extreme agents manipulate emotional feedback at a certain field.

5.2 Model Validation

We validated the presented model with an online community, Digg. The community stores the positive and the negative posts from Internet users, and the community has categories that we see as fields. Table 4 shows the descriptive statistics of the Digg dataset in [30]. From the dataset, we selected three categories as fields, and they were *gaming*, *world and business*, and *science*. After the dataset filtering, we measured the daily collective emotions. Each post is analyzed by counting words that also appear in SentiWordNet [3] and ANEW [12] which are sentiment lexicons that label words as either positive or negative. While we prepared the dataset, we ran simulations by varying two parameters: the number of extreme agents and the field selection rules. To determine the appropriate number of extreme agents, we performed two correlation analyses. Firstly, we computed the Pearson correlations between the collective emotions of simulation results and the collective emotions of Digg. The Pearson correlation was maximized when we set the number of extreme agents as 12 and when the agents choose the field based on their preference, and at the specific setting, the correlation value was 0.676 with $p - value < 0.01$. This

Table 4: Descriptive Statistics of Validation Dataset

Dataset	Values
Time period	Feb. 2009 ∼ April. 2009 (89 days)
Num. of Posts	1,195,808
Num. of Comments	1,646,153
Num. of Users	877,841
Gaming category	51,847
World and business category	279,491
Science category	41,122

Pearson correlation does not consider the temporal mapping from one time series to another which means that the time flow in Digg and the time flow of the simulation do not match. Therefore, we performed the correlation analysis of dynamic time warping [37] which corrects the time flow by finding the best fit of two time series. This particular correlation measure produces lower value if two time series correlates higher, and the zero value of this measure suggests the perfect match. Figure 3 shows the dynamic time warping analysis result. The measure becomes the lowest when the simulation setting becomes 12 extreme agents and preference-based field selection, which is the identical result of the Pearson correlation analysis. The number of 12 extreme agents should not be regarded as a certain underlying truth value of the real-world dataset, but it should be regarded as an estimation where we can start more statistical investigation of the given dataset. At the moment, we cannot add more rationale about the calibration result.

Figure 4 shows the plot of daily collective emotion changes from Digg and the optimal simulations of the last 89 timesteps. The rationale behind choosing the last time step of the simulation is that we assumed the collective emotions will converge at the last part of the simulation. The daily collective emotion oscillates daily, so the agent modeling would be an appropriate approach to model this phenomenon. Figure 5 suggests that the science category of Digg has the most negative collective emotion compared to the gaming and the world & business categories. The simulation models have three fields that differ at the levels of valence, and as in the Digg dataset, these fields have negative collective emotions, as well.

6. CONCLUSION

The objective of this paper is providing an agent-based model of collective emotion with multiple fields. The model is an expanded version of Schweitzer's collective emotions framework with the dimensional theory from psychology. The model augments more details of the agent's internal dynamics of emotions, the interaction rules between agents

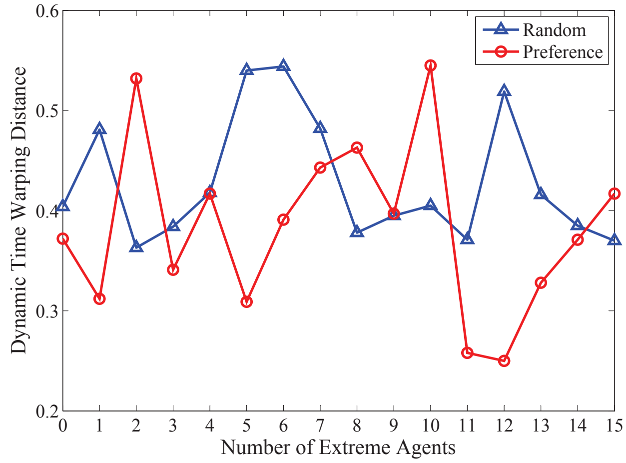

Figure 3: Dynamic time warping correlation analysis between Digg and simulation cases. The X-axis shows the number of extreme agents. Solid lines and dotted lines are preference field selection and random selection, respectively. Lower dynamic time warping means higher correlation.

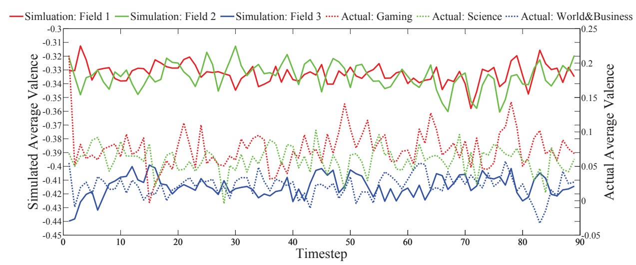

Figure 4: Daily changes of collective emotions in fields from Digg and the simulation. Solid lines are the daily sum of positive and negative feedbacks at three fields. Dotted lines are the daily sum of positive and negative posts at three categories.

and fields, the field emotional dynamics, and the preference mechanism. The proposed model was tested by two scenarios: a hypothetical scenario to see the result sensitivity and a real-world scenario to validate the model. In the sensitivity analysis, we could see some interesting patterns, such as the polarization of the fields and the divergence of the valence by different field selection rules. These sensitivity analyses illustrate how the model works and how the agents within the model behaves. Then, we used the crawled data to validate the model, and the objective of the validation was confirming the similarity of the polarization of agents' emotions in the virtual simulation and the real world. While the validation was statistically measured and resulted in positivity, we would emphasize that this model needs to be used to gain insights and pursue generative social science studies, not for exact predictions of the real world.

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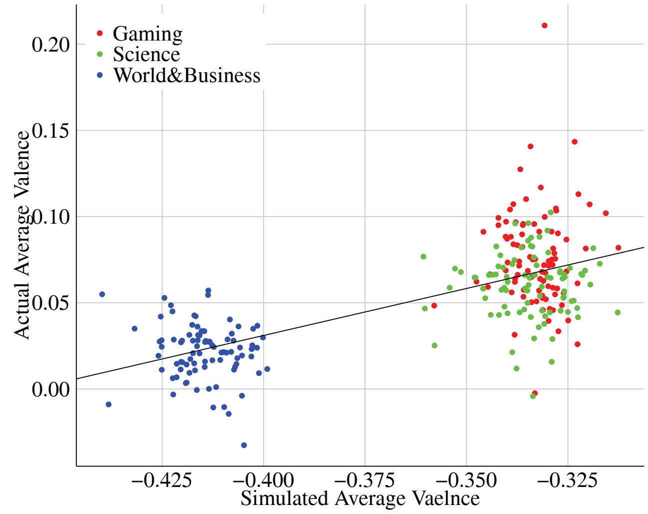

Figure 5: Scatter plots three sets of simulation-actual valence points. Each set has 89 points corresponding to the simulation period.

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