Exploring CQA User Contributions and Their Influence on Answer Distribution

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***Abstract*—In community question answering (CQA) sites like Stack Overflow (SO), users provide contributions driven by community incentives and self-motivation, which gives rise to micro activities of individual user and macro emergence of community. According to our empirical research, the emergence of answer distribution in SO is of concern, about 90% questions have no more than two answers and almost 40% of questions have no accepted answer due to lack of alternative acceptable answers. In this paper, we explore CQA user contributions by considering both the external incentives of community and internal motivations of users, and study why CQA users contribute and how they influence the macro emergence of answer distribution. We present CQA community model based on normative multi-agent system approach, in which the users are modeled as agents and the community incentives as norms. The internal motivations are studied based on self-determination theory. The paper further analyzes how the internal and external factors together influence the activities of agents and ultimately the answer distribution of the whole community. We conduct experiments based on a simulation system and the SO dataset to validate the effectiveness of our proposed model. The results show that our model can reproduce the emergence that well matches up with the observation on real community.**

Keywords-NorMAS; BDI; User Contribution; Emergence; Incentive Mechanism; Self-Determination Theory

I. INTRODUCTION

Community Question Answering (CQA) sites such as *Stack Overflow* (SO), *Yahoo!Answers*, and *Quora* are a type of knowledge sharing communities, in which users contribute their knowledge in term of various activities such as asking, answering and voting [1]. These activities give rise to various macro phenomena, i.e. emergence [2]. For example, based on 2,509,027 SO questions from January 2018 to September 2019, we can observe the emergence of answer distribution to questions: about 90% SO questions have less than two answers and almost 40% of questions have no accepted answer. Such observation on the emergence is of great concern, as they may affect the prosperity of the community. It is significant for managers of CQA sites to understand why the macro emergence occurs and how to improve the emergence.

To address the issue, we need to explore the following three problems of CQA: user contribution motivation, user contribution decision, and the influence of user contribution on the emergence of CQA community. User contribution motivation refers to why users in CQA contribute their knowledge. Numerous scholars have conducted research on CQA user contribution motivations. For example, Lou [3], Jin [4], and Chen [5] used online surveys and statistical analysis to study the influence degree of various motivations to CQA user contributions. However, these researches lack of study and analysis on the factors that govern and drive users to contribute.

User contribution decision refers to how users select and take actions to participate in contributions in CQA community. Many of existing methods are equation-based to model user behavior. For example, Anderson [6], Gao [7] applied a game-theoretic model to analyze user behavior decision in CQA community. In essence, the equation-based methods are difficult to capture the autonomy feature of users [8][9] and the community incentives that govern users' decisions on their contributions.

For the influence of user contributions on the emergence of community, most of existing methods are normally based on the statistical analysis to explore what gives rise to the emergence. For example, Srba [10] applied statistical analysis based on the dataset of CQA community to conclude that low-quality user contributions lead to user churn. However, these studies can not naturally reveal the community emergence that results from the user contributions and their interactions.

In this paper we present an approach based on Normative Multi-Agent System (NorMAS) and Self-Determination Theory (SDT) to model CQA communities and examine how individual users in communities provide contributions and influence the answer distribution. The remaining sections are organized as following. The next section discusses the related works. Section III describes the NorMAS-based model of SO community. Thereafter, Section IV details contribution mechanism analysis of SO users based on BDI and SDT theory. Section V describes our experiment and result analysis. Finally, Section VI concludes the contributions of this paper and points out the future research direction.

II. RELATED WORK

NorMAS has been widely used to model complex social systems [11]. For example, Mao et al. [12] presented an adaptive casteship mechanism to model and design adaptive multi-agent systems. Mastio [13] et al. applied multi-agent system approach to simulate and tackle traffic management. As a classical architecture, BDI (belief-desire-intention) [14] is

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often applied to model and simulate the rule-based reasoning scenario. For instance, Yang et al. [15] considered a robot software as a multi-agent system and employed multiple interacting agents with different roles cooperate to achieve software functionalities. Yan et al. [16] proposed a BDI agent-based method to simulate suppliers' belief, reasoning processes, deception intention and their behavior. Moreover, they provided buyers with inspection suggestions to detect suppliers' falsified test results. In this work, we apply BDI model to describe CQA users and their reasoning.

III. NorMAS model of CQA communities

In this section, we present the normative MAS model of CQA communities, and illustrate the model with the sample of SO community. We define the NorMAS model of SO community as a 3-tuple

$$CQA\_MAS = < MAS, UGC, norm > . \quad (1)$$

- *MAS* represents a set of the agents.
- $UGC = UGC_q \bigcup UGC_a \bigcup UGCv$ represents the user generated contents (UGC), i.e. questions, answers, and votes. UGC_q , UGC_a , and UGC_v represent the sets of questions, answers, and votes, respectively. There exists three kinds of relations :

  (1) $R_1 = \{ < q, a > | \, q \in UGC_q \wedge a \in UGC_a \}$ represents the relation between questions and answers; (2) $R_2 = \{ < q, v > | \, q \in UGC_q \wedge v \in UGC_v \}$ represents the relation between questions and votes; (3) $R_3 = \{ < a, v > | \, a \in UGC_a \wedge v \in UGC_v \}$ represents the relation between answers and votes.
- *norm* represents the reputation incentive mechanism in the community.

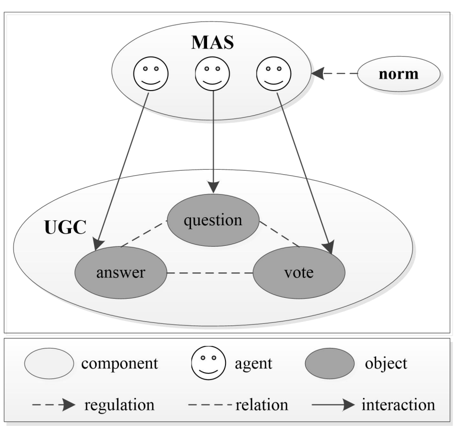

Figure 1. The NorMAS model of SO community

Fig. 1 depicts the NorMAS model of SO community. Governed by the norms in *norm*, agents in *MAS* autonomously ask, answer, or vote based on the current state of their contributed knowledge *UGC*, i.e. the number of questions, answers, votes, and their relations. In turn, their contribution behavior change the state of the contributed knowledge *UGC*.

A. The model of CQA user

In this paper, we employ BDI model to represent agents in *MAS*. Hence, we define agent as a 5-tuple

$$agent = < A, REP, BEL, DES, INT > . \quad (2)$$

- *A={ask, answer, upvote, downvote}* defines the action set of agents.
- *REP* is an agent's reputation point represented as integer.
- *BEL, DES, INT* are an agent's belief, desire, and intention, respectively.

B. The model of community incentives

To achieve system goals, CQA communities generally design and adopt incentive mechanisms to stimulate and govern users' behavior. For example, the reputation incentive mechanism in SO community (see Table I) describes how user can obtain their reputation points in SO. For example, the third row of Table I means that when an answer is upvoted, the answer contributor will be rewarded with 10 reputation points. In line with the incentive mechanism of SO, we do not take into account the rule "Upvote an answer".

TABLE I. Reputation rules in SO

Rule	Action	Reputation change
1	Question is upvoted	+5 (to asker)
2	Question is downvoted	-2 (to voter)
3	Answer is upvoted	+10 (to answerer)
4	Answer is downvoted	-2 (to answerer)
5	Downvote an answer	-1 (to voter)

We employ the norms of NorMAS to represent the reputation incentive mechanism of SO. Here, we define $UGC_o = UGC_q \bigcup UGC_a$ as the set of questions and answers. We define $A_v = \{upvote，downvote\}$ to represent *agents'* vote actions. The reputation incentive mechanism of SO can be defined as

$$norm：UGC_o \times A_v \rightarrow I \times I. \quad (3)$$

Here, *I* represents the reputation points. The function *norm* represents that when an agent votes another agent's question or answer, the two agents will be gave a certain reputation points, respectively.

IV. Contribution Mechanism Analysis of SO users

In this section, we analyze SO user contribution mechanism from two aspects: user contribution motivations and user contribution decision.

A. Contribution motivation analysis of SO users

Why do users contribute to CQA community? To answer this question, we adopt a combination of self-determination theory and online survey to analyze user contribution motivations. Self-determination theory [17] divides users behavioral motivations into five types of regulations: external regulation, introjected regulation, identified regulation, integrated regulation, and intrinsic regulation. Moreover, to obtain the contribution motivations of SO users, we investigated some SO users in January 2018. A total of 656 valid feedback samples were obtained. The questionnaire is in the form of five-level Likert scale. The respondents can choose one of the five answers: strongly disagree, disagree, indifferent, agree and strongly agree. The weights of the answers are 5, 4, 3, 2, 1, respectively. Based on the characteristics of the five motivations summarized by Ryan et al. [18] and our survey result, the motivations of SO users are classified into four types:

- Gaining reputation is an introjected regulation. When SO users ask or answer questions, they have a chance to gain their reputation points through received votes.
- Gaining privilege is an identified regulation desire for personal importance in the community. SO users are gave some privilege to manage the affairs of the community based on their reputation points. Privileges have an incentive effect on users' behavior.
- Returning favor is an integrated regulation to be competent or synthesis with self, which is a motivation not related to external reward. For SO users, if their questions have been answered by other users, they may have the motivation of giving back to community.
- Helping others is an intrinsic regulation for inner satisfaction. For SO users, when the questions of other users are not answered, they have the motivation to help others.

The first two desires are from the external incentives of community and the last two are internal motivations of individual users. Here, we do not consider the external regulation and the desire related to money and material.

B. Contribution decision of SO users

Here, we apply BDI model to analyze the contribution decision of SO users. The contribution decision process consists of four steps: belief update, desire generation, intention filter, and intention selection. Agent first updates its belief according to current belief and contributed knowledge information. Then agent generates its desire based on current belief related to current contributed knowledge and intention. Thereafter, agent filters intention based on current belief and desire. Finally, it selects the intention with the maximum of intensity to execute.

1) The update of agent's belief

In the context of CQA, an agent's belief is the cognition of self, the state of contributed knowledge, and norms. Combining the above analysis of user contribution motivation, we consider four types of cognition and define the belief of agent as

$$BEL = < RREP, PRI, RF, HO > . \tag{4}$$

- *RREP* is agents' cognition of probably obtained reputation points.
- *PRI* is agents' cognition of privilege corresponding to reputation points. There is a simple correspondence between privilege and reputation points.
- *RF* is agents' cognition of giving back to community.
- *HO* is agents' cognition of helping others.

Based on the perception of community information and their current belief, SO users update their belief. The belief update function can be defined as

$$brf\colon\ BEL \times UGC \to BEL'. \tag{5}$$

Here, *UGC* is the information of the contributed knowledge. The updated rules for each belief component are as follows.

- *RREP* can be updated by the probably received upvotes *VOTE* and the action *A*.

  $$fr: VOTE \times A \to RREP. \tag{6}$$

  We divide SO users into four groups based on their reputation points: newcomer (points<10), normal (10≤points≤999), established (1000≤points≤19999), and trusted (points≥20000). SO users with more reputation points usually have a stronger capability to gain upvotes.

- PRI represents the probably obtained privilege. Because privilege are described by some words, we employ a reputation point transform function γ to get the intensity of privileges.

  $$\gamma\colon\ REP \to PRI. \tag{7}$$

- RF can be updated by the equation

  $$RF = \begin{cases} 1, & iff\ na = true. \\ 0, & iff\ na = false. \end{cases} \tag{8}$$

  Here, *na* indicates whether an agent's questions have been answered by a community. If answered, it will give back to the community.

- HO can be updated by the equation

  $$HO = \begin{cases} 0, iff\ ad = true. \\ 1, iff\ ad = false. \end{cases} \tag{9}$$

  Here, *ad* indicates if a question of the community has been answered. If answered, agents will generate the belief that they don't need to help others.

In conclusion, the update rule of the intensity of the belief of SO users can be defined as an vector:

$$\varphi_{BEL} = < RREP, PRI, RF, HO > . \tag{10}$$

2) The generation of agent's contribution desire

According to the analysis of user contribution motivation, we believe that agents also have four types of desire: gaining reputation, gaining privilege, giving back to community, and helping others. Agent may be affected by all the four kinds of desires at the same time. According to our survey, the intensity of each desire for different types of users are different. Therefore agents need to update their desire intensity as their reputation points change. The update rule for the overall desire intensity of agent is defined as

$$\sigma_{Des} = \psi \times \sum_{i=1}^{4}(\mu_i \sigma_{Des_i}). \quad (11)$$

Here, ψ is the overall ability of agent desire to drive agent behavior ($\psi \in [0,1]$); μ represents the weight of each desire of agents; σ_{Des_i} is the intensity of the i-th desire ($i \in [1,4]$). The values of μ and σ_{Des} are from statistics of our questionnaires.

3) The filter of agent's intention

Intention represents the behavior decision made by agents based on their own belief to achieve their desire. Agents possess four candidate actions: ask, answer, upvote, and downvote. Agents can filter their intention based on their current belief, desire, and intention. For example, if an agent wants to answer questions to gain reputation, it will filter some questions whose answers are difficult to obtain upvotes. Thus the intention filter function can be defined as

$$filter: \ BEL \times DES \times INT \rightarrow INT'. \quad (12)$$

More specifically, an agent's choice of an action depends on the intensity of its intention. And the probability of choosing an intention is determined by the intensity of the desire and belief related to the intention. We define the filter rule of agents' intention as

$$p(a) = \sigma_{Des} \times \varphi_{Bel}. \quad (13)$$

Here, $p(a)$ represents the probability of the candidate action a ($a \in$ {*ask, answer, upvote, downvote*}).

4) The selection of agent intention

Agents select the intention with the maximum of $p(a)$ to perform. The selection rule of agent intention is defined as

$$a = \{int \mid max(P(int)), int \in INT\}. \quad (14)$$

V. EXPERIMENT AND RESULT ANALYSIS

In order to investigate the influence of CQA user contributions on the emergence of answer distribution, we develop a simulation system to simulate massive users' contribution behavior to reproduce the emergence. If our simulation system can reproduce the emergence of answer distribution well, it will show that the proposed approach can well explain CQA user contributions and their influence on the emergence of answer distribution.

To achieve this goal, we first design a set of criteria to evaluate the recurrence of community emergence. Then, we collect the data of SO and investigate user motivations to initialize SO users. Finally, we run the simulation system on the dataset to reproduce the emergence of answer distribution. We compare the reproduced emergence on our simulation system with the observation of SO community based on the proposed criteria. The results will show whether the proposed model can effectively explain the CQA user contributions and their influence on the emergence of answer distribution.

A. Evaluation criteria

In this work, we adopt *PCC* (Pearson Correlation Coefficient) [19] and *MRE* (Mean Relative Error) [20] to evaluate the emergence recurrence effect of the simulation system. Given X and Y represent a real data and a simulation data, respectively. $\overline{X}$ and $\overline{Y}$ are the averaged value of X and Y, respectively. n is the number of samples. The *PCC* of X and Y is defined as

$$\rho_{X,Y} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}}. \quad (15)$$

And, *MRE* is defined as

$$MRE = \frac{\left|\overline{Y} - \overline{X}\right|}{\overline{X}}. \quad (16)$$

The greater the value of *PCC*, the better the emergence trend consistency between real SO community (X) and the simulation system (Y). The smaller the value of *MRE*, the smaller the value deviation between X and Y. According to the experience from statistics, when *PCC* is greater than 0.5, there exists a strong positive correlation between subjects.

Each comparison of the emergence between SO and the simulation system is comprised of multiple parts. For example, answer distribution consists of four types of answer count: 0, 1, 2, and more than 2. Therefore, it is necessary to modify the above equations as

$$\rho_{overall} = \frac{\sum_{i=1}^{m} w_i \rho_i}{m}. \quad (17)$$

and

$$MRE_{overall} = \frac{\sum_{i=1}^{m} w_i MRE_i}{m}. \quad (18)$$

Here, m is the component number of an emergence. we represents the weight of the i-th component. In this way, we give an overall score for the comparison of a certain emergence.

B. Data collection

We downloaded three versions of Stack Overflow datasets between 2017 and 2019. Based on the difference of the reputation points, the question number, the answer number, and the vote number of the users in different periods, we compute out the capability of gaining upvotes of different types of users. In addition, as described in Section IV, we investigated some SO users in January 2018 to obtain the contribution motivations of SO users and their motivation intensity distributions.

C. Result Analysis

We analyze 2,509,027 SO questions from January 2018 to September 2019 and observe the emergence of answer distribution. As shown in Fig. 2, about 90% questions in SO have no more than two answers.

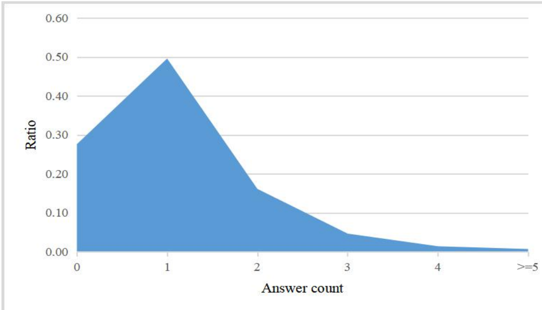

Figure 2. The emergence of answer distribution.

Why are users reluctant to provide more answers for a question? To explain the phenomenon, we run the simulation system on So dataset from January 2018 to September 2019. We first count the distribution of answers of 0, 1, 2 and more than 2. Then we compare the captured emergence on the simulation system with the observation of SO community.

TABLE II. THE SIMULATION EVALUATION OF ANSWER DISTRIBUTION

Index	PCC	MRE
0 answer	0.7653	0.0022
1 answer	0.9210	0.0013
2 answers	0.6901	0.0123
more than 2 answers	-0.9632	0.0956
overall	0.7729	0.0314

Table II presents our simulation performance of answer distribution. Except when the number of answers is more than 2, other simulation results are in line with our expectations. Other *PCC* of emergence simulation are greater than 0.65 and the overall *PCC* is 0.7729, which indicates that the simulation system successfully reflects the trend of the emergence of the real SO community. In addition, the deviations of the simulation is very small. The small deviation of the simulation indicates that the simulation system can accurately represent the real community's data. Moreover, Fig. 3 depicts the evolution of the trends of answer distribution in 12 months, which more intuitively illustrates a very good match between our simulation and observation of real SO community.

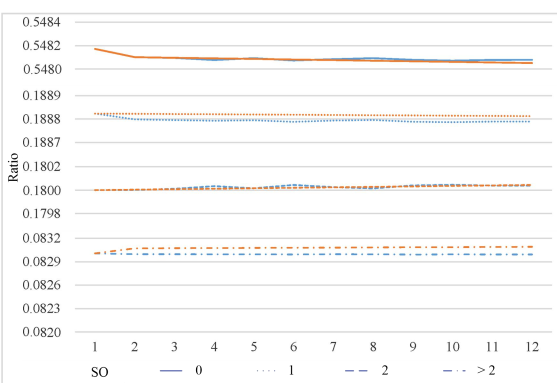

Figure 3. The evolution of the answer distribution in 12 months

To analyze the influence of external incentives of community and internal motivations of individuals on user contributions, we performed the influence analysis on answer distribution without the corresponding motivations. Fig. 4 depicts the evolution of answer distribution without external incentives in a year. We can observe that in the absence of external incentives from the community, the proportion of unanswered questions decreases, the proportion of questions with one answer does not almost change, and the proportions of questions with more than one answer increase. The result shows that in the absence of external incentives, users answer questions more based on the belief of helping others and giving back to the community. It leads to a decrease of the ratio of unanswered questions. Without the external incentives, users don't care about the influence of existing answer count to a question on their probably received upvotes. Hence, they will be willing to contribute more answers to the answered questions. This is why the proportions of answered questions increase.

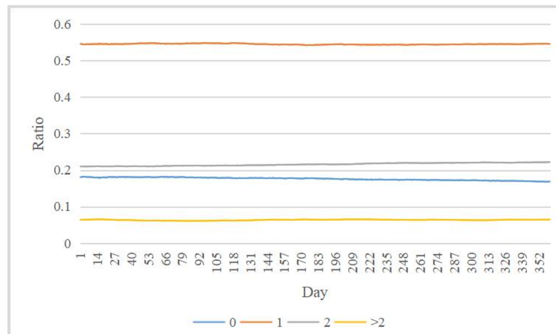

Figure 4. The evolution of the answer distribution without external incentives of community in a year

Fig. 5 depicts answer distribution without internal motivations of users. We can observe that the proportion of unanswered questions continues to increase, whereas the other proportions of questions continue to decrease. The result shows that in the absence of internal motivations, users lose willingness to give back to the community and help other users, which makes most of them reluctant to answer any questions that have an answer or not.

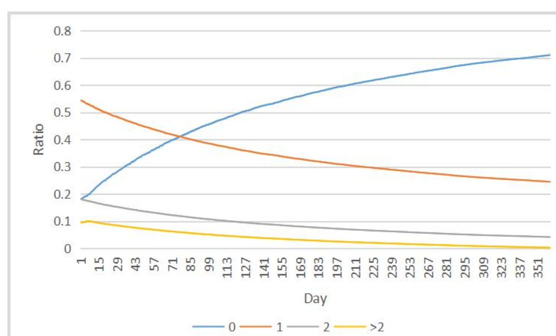

Figure 5. The evolution of the answer distribution without internal motivations of users in a year

In conclusion, the answer provision of SO users for community questions are motivated by external incentives of community and internal motivations of individuals. On the one hand, SO users behavior are affected by the community incentive mechanism. SO users answer questions based on the probably received upvotes. When a question has answers, SO users believe that their capability of gaining upvotes in answer will decrease. Thus they will be reluctant to provide more answers for a question that has answers. On the other hand, SO user behavior are affected by their internal motivations. If a question has been answered, SO users will not generate the desire to help others to answer the question. Both aspects may make users not to provide more answers for community questions. The similar behavior pattern of massive SO users eventually leads to the emergence of answer distribution. The result confirms that our approach can effectively explain CQA user contributions and their influence on answer distribution.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, we propose a NorMAS-based approach to explore CQA user contribution and their influence on answer distribution. The contributions of the paper are three-fold: (1) We put forward a NorMAS-based approach to model CQA communities under the governance of incentive mechanisms. The constructed model provides a natural description of CQA communities. (2) We apply self-determination theory and online survey to classify user contribution motivations. And we employ BDI theory to detail user contribution decision driven by community incentives and self-motivation to explain why users answer a question or not. (3) We develop a simulation system to simulate CQA communities and reproduce their emergence. Moreover, we design a set of criteria to examine the recurrence of the emergence in SO community. The results show that the proposed approach can effectively explain CQA user contributions and their influence on answer distribution.

The validity of our study may be threatened by the following aspects. First, we differentiate users' capability and desire based on the types of users grouped by their reputation points. The evaluation is not very accurate to some active users whose reputation points greatly fluctuate. Second, we only consider the individual behavior such as asking, answering, voting, and do not consider other behavior such as accepting an answer. Third, there is no consideration of the changes of SO reputation mechanism. Hence, the latter two may lead to a certain deviation in individual behavior analysis. In the future study, we will collect more data from CQA communities to improve the performance of our approach. More importantly, we will further consider how to use the proposed approach to improve community management and promote long-term prosperity of CQA communities.

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