

# Trust Agent-Based Behavior Induction in Social Networks

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**T**he fast development of social network applications, such as online social websites, blogs, and wikis, has dramatically changed how we deal with the Internet, to the point where Internet-based social networks have become the key channel for human social relationship maintenance and information

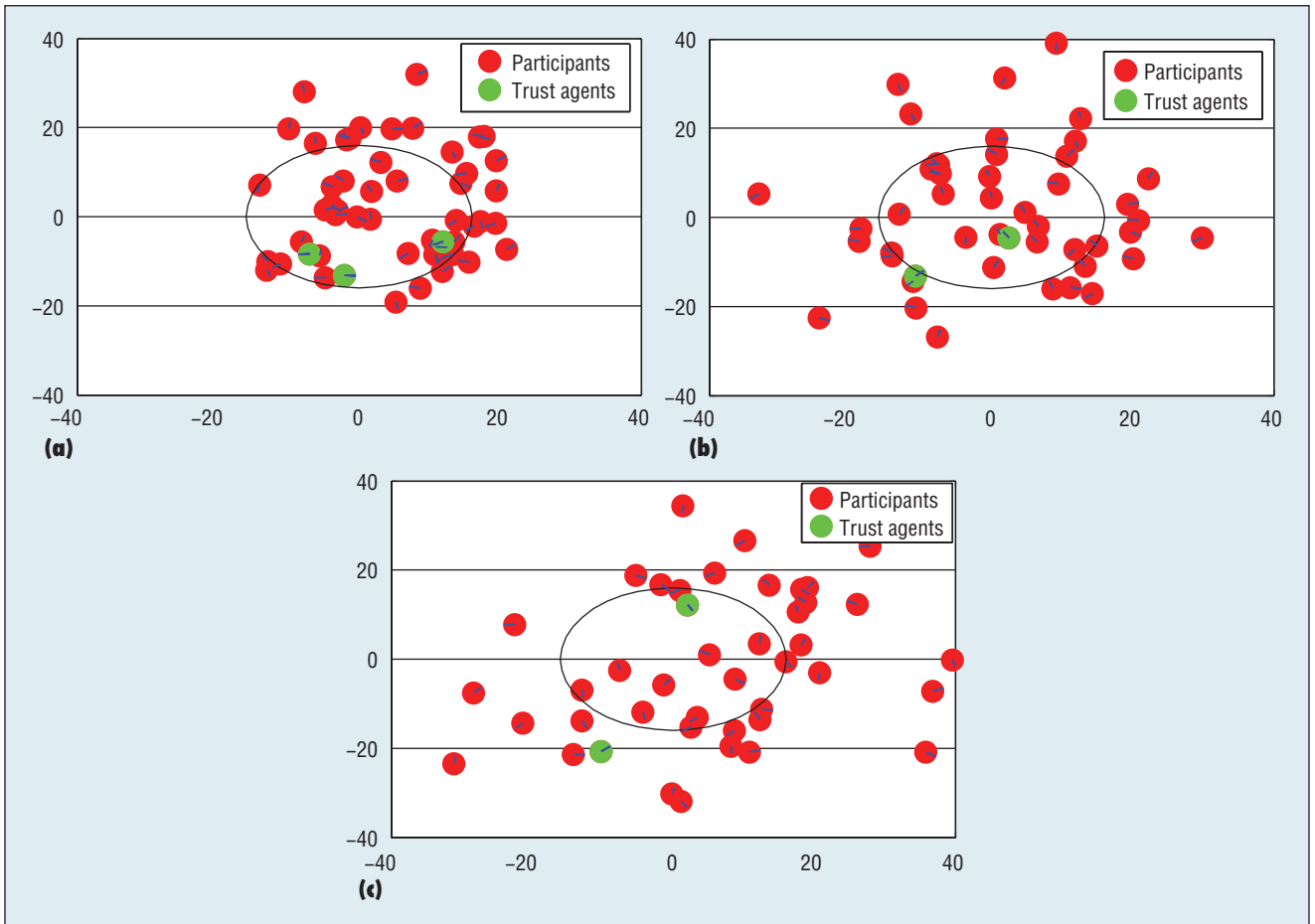
dissemination.<sup>1</sup> Generally, social networks are a kind of societal structure that consists of multiple nodes and the relationships among them. Through these relationships, social networks connect all kinds of participants, from casual speaking acquaintances to closely related family members. But while online social networks bring convenience to modern life, they can have negative effects as well.

In politics, for example, rumors could be produced and spread on social networks that lead to incidents affecting societal stability; similarly, in e-commerce, false information can be spread over social networks that deceive customers in online shopping platforms. Porn is often distributed via social video sharing and instant messaging platforms, and terrorists have adopted social networks to persuade teenagers to take part in their illicit activities. One way to counter these malicious behaviors is to introduce *behavior induction*, a process in which a person or group influences the behavior of another person or group through the induction of behavioral attitudes. Popular behavior-induction

approaches adopted in social networks include political restriction and employing people to publish positive information. However, most of these approaches are too simple and inefficient, easily leading to reverse recognition, a state in which the induced recognition is the reverse of the intended induction; feeling offensive, a state that the induced participants feel offensive; political negligence, a state in which the induced participants become negligent to politics; and more (for “Related Work in Behavior Induction,” see the sidebar). Ideally, we can use the relationship of participants and modern computational techniques to automatically induct behaviors in social networks.

To address these issues, we propose a novel trust agent-based behavior-induction approach for social network environments. Given a specified restricted negative behavior, the agent how to induct, persuade, encourage, or induce social network participants to avoid this kind of negative behavior as much as possible. Specifically, we introduce a trust agent (whose behavior is designed according to the corresponding

*To automatically and efficiently induct social network behavior, trust agents designed according to group behavior features can coordinate to maximally avoid restricted negative behavior.*



**Figure 1.** The general social behavior-induction process: (a)  $T = 6$ , (b)  $T = 148$ , and (c)  $T = 594$ . The number of participants  $NoP = 50$  and the number of trust agents  $NoA = 3$ . The circle represents the restricted behavior area, the red dots represent the participants in social networks, and the green dots represent the trust agents in social networks.

participants) aimed at eliciting maximized trust from other social network participants. In addition, we generate a dynamic control mechanism to coordinate participant behavior in social networks and avoid a restricted negative behavior.

### Behavior Induction in Social Networks

The core problem of behavior induction in this article is as follows: with some restricted behaviors predetermined, how to induct participants in social networks to avoid these behaviors?

Conceptually, as for restricted behaviors, the set of restricted behaviors can be labeled as  $\{b_{r_1}, b_{r_2}, \dots, b_{r_l}\}$ ,

where  $b_{r_i}$  ( $i \in [1, l]$ ) is a restricted behavior. A participant's behaviors can be mined from what he or she has posted on various social networks such as Twitter.<sup>3,5</sup> For example, by focusing on short texts published on social networks, one group of researchers proposed a bi-term topic model that learns behavior topics by directly modeling the generation of word co-occurrence patterns (that is, biterms) in the corpus.<sup>2</sup> Without a loss of generality, we only take one behavior  $b_r$  as the element in the set of restricted behaviors as an example to illustrate our induction approach.

Next, we introduce the similarity of behaviors  $b_{k_1}$  of participant  $p_{k_1}$

and behaviors  $b_{k_2}$  of participant  $p_{k_2}$ . If  $S(b_{k_1}, b_{k_2}) > \lambda$ , then behaviors  $b_{k_1}$  and  $b_{k_2}$  are similar to each other. Due to homogeneity, there should be a link between  $p_{k_1}$  and  $p_{k_2}$  in social networks. Otherwise, if  $S(b_{k_1}, b_{k_2}) < \lambda$ , there's no link between  $p_{k_1}$  and  $p_{k_2}$ . As introduced elsewhere,<sup>6</sup> a similarity function between behaviors can be defined by KL-divergence and evaluated.

Now, it's time to introduce the behavior-mapping space, which is where we can project the behaviors of participants in social networks. An algorithm called DeepWalk<sup>7</sup> learns the social representations of a network's vertices—that is, the participants who represent the vertices'

## Related Work in Behavior Induction

Although there has been some research into behavior induction in social networks, it's still an open problem.

### Group Behavior Tendency in Social Networks

Group behavior tendency—that is, public opinion—is a publicly released, generally agreed upon attitude or opinion about a certain social incident by the general public under a specified time and space.<sup>1</sup> Network group behavior tendency is a set of all attitude, affection, and behavior tendencies on a certain event that are spread over the Internet.

Current research on group behavior tendency mostly focuses on politics, sociology, journalism, and related social science disciplines. In politics, many studies on group behavior tendency focus on democratic elections. In 2005, James Fishkin and Robert Luskin<sup>2</sup> claimed that an election speech has a certain influence on ordinary voters' group behavior tendency. Specifically, no matter if the text is defeatist, reasonable, or alarmist, it won't polarize group behavior tendency—that is, group behavior tendency won't tilt heavily in favor of one side. In 2007, Dennis Chong and James Druckman<sup>3</sup> pointed out that during the process of voter group behavior tendency formation, the quality of election policies is much more important than the number of times it's presented.

In sociology and journalism, research on network group behavior tendency generally can be divided into two areas: negative tendencies and hot-issue tendencies. For a negative tendency in group behavior, Yiting Zhang<sup>4</sup> explained why violent behavior exists on the Internet and proposed countermeasure research to avoid it. The research on hot-issue group behavior tendencies includes network text analysis and topic detection techniques that cover topic tracking, hot-topic detection and retrieval, network property analysis, and public opinion propagation.<sup>1</sup> In addition, Guohua Wang and colleagues<sup>5</sup> analyzed the link between

group behavior tendency and multiple hot events, pointing out that it promotes how participants perceive events, which leads to negative influence as well. Similar approaches such as persuasive techniques also focus on group behavior tendency induction. For example, Sahiti Myneni and colleagues<sup>6</sup> developed a framework for identifying persuasive attributes in online social networks, which is useful for inducing changes in human behavior, and Peter Ruijten and colleagues<sup>7</sup> found that besides agent characteristics, social exclusion and gender also have strong influences on persuasive agents' effectiveness.

### Social Network Behavior Formation Analysis

In social network behavior formation analysis, traditional analysis approaches can't accurately describe features such as strong interaction evolution and public emotional drift in large-scale online social networks. In 2013, Peng Cui and colleagues<sup>8</sup> were the first to investigate the problem of cascading outbreak prediction and propose a novel data-driven approach to identify the key users whose behaviors were highly correlated with information outbreaks. In 2008 Kuanyu Chen and colleagues<sup>1</sup> studied the herd mentality of online shopping. They found that a book's ratings, sales volume, and other users' reviews affect buyer decisions. In 2011, Cui and colleagues<sup>9</sup> investigated fine-granular social influence, formally formulated the problem of item-level social influence modeling, and proposed a novel hybrid-factor matrix factorization method for item-level social influence prediction.

In 2015, Cui and colleagues<sup>10</sup> uncovered the relationship between collective behaviors and group themes, proposing a novel method to effectively model the characteristics of collective behaviors in social groups. In 2011, Johan Bollen and colleagues<sup>11</sup> analyzed Twitter data and found that users follow other users with similar connections, which makes them gradually share the same or similar subjective feelings.

latent features that capture neighborhood similarity—by modeling a stream of short random walks. These latent representations encode homogeneity in a continuous vector space with a relatively small number of dimensions. DeepWalk takes a network of participants with behaviors as input and produces a latent representation as an output; the resulting behavior-mapping space has two latent dimensions in this article.

Next, we can conceptually define the core problem: With the predetermined restricted behavior  $b_r$ , for any

participants  $p_i$  and their behaviors  $b_i$ , how do we induct  $s(b_i, b_r) > \lambda$  in the behavior-mapping space  $\Omega$ ?

### Trust Agent Feature Selection

Trust agents' social features can be selected according to participants' social features. This encourages participants to trust the agents, and then follow the agents' designed behaviors.

Social features describe context—in this case, a participant's social environment in a social network<sup>8–10</sup>—and can be classified into independent and dependent social features.

A participant's independent social features refer to the personal characteristics that influence his or her interactions, trust, and recommendations; they typically include a role impact factor and preference.<sup>11</sup> Participant activities in social networks can be categorized into different domains based on their characteristics, which we consider the role impact factor. For example, the behavior of a person who has expertise in a particular domain is deemed more trustworthy than that of someone who has no knowledge in it.<sup>12</sup> Let  $RIF_{R_i} \in [0, 1]$  denote participant

## Social Network Behavior Interaction Analysis

There are all kinds of interaction relations between participants in social networks, but the most important one is trust. Abstractly, trust is the measure taken by one party about the willingness and ability of another party to act in the interest of the former party in a certain situation.<sup>12</sup> If the trust value is in the range of  $[0, 1]$ , it can be taken as the subjective probability with which one party expects that another party performs a given action.<sup>13</sup> Since the pioneering work by Stephen Marsh,<sup>14</sup> the issue of trust has attracted much attention in the field of information technology, where researches mostly focus on a target entity's security, the relation between participants, and the influence on trust relations. The ultimate goal is to obtain objective results about effective approaches.<sup>15,16</sup>

Early research on social network-oriented trust inference is mostly based on the trust values between neighboring participants (average,<sup>17</sup> multiplication,<sup>18,19</sup> or probability<sup>20,21</sup>). However, there's still no research on trust related to behavior induction in social networks—in particular, how to design features that make trust agents trusted by participants, maximize the effect of participant behaviors, and enhance the effectiveness of behavior induction.

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$R_1$ 's role impact factor, illustrating the impact of  $R_1$ 's social position and expertise on the trustworthiness of  $R_1$ 's behaviors. The higher the  $RIF_{R_1}$ , the more the influence of  $R_1$ 's behaviors on adjacent participants, those with prior interactions or similar behaviors.<sup>11</sup> Preference can be thought of as an individual's attitude toward a set of objects, typically reflected in an explicit decision-making process.<sup>13</sup> The more preferences someone shares with someone else, the more likely they will trust each other.<sup>14</sup> Let  $PS_{R_1, R_2} \in [0, 1]$  denote the preference similarity

between  $R_1$  and  $R_2$ . The higher the  $PS_{R_1, R_2}$ , the higher similarity of the preferences between  $R_1$  and  $R_2$ .

Dependent social features refer to the context between adjacent participants, which typically includes a behavior similarity degree. As introduced elsewhere,<sup>15</sup> the behavior similarity degree between participants can be defined and evaluated by KL-divergence.

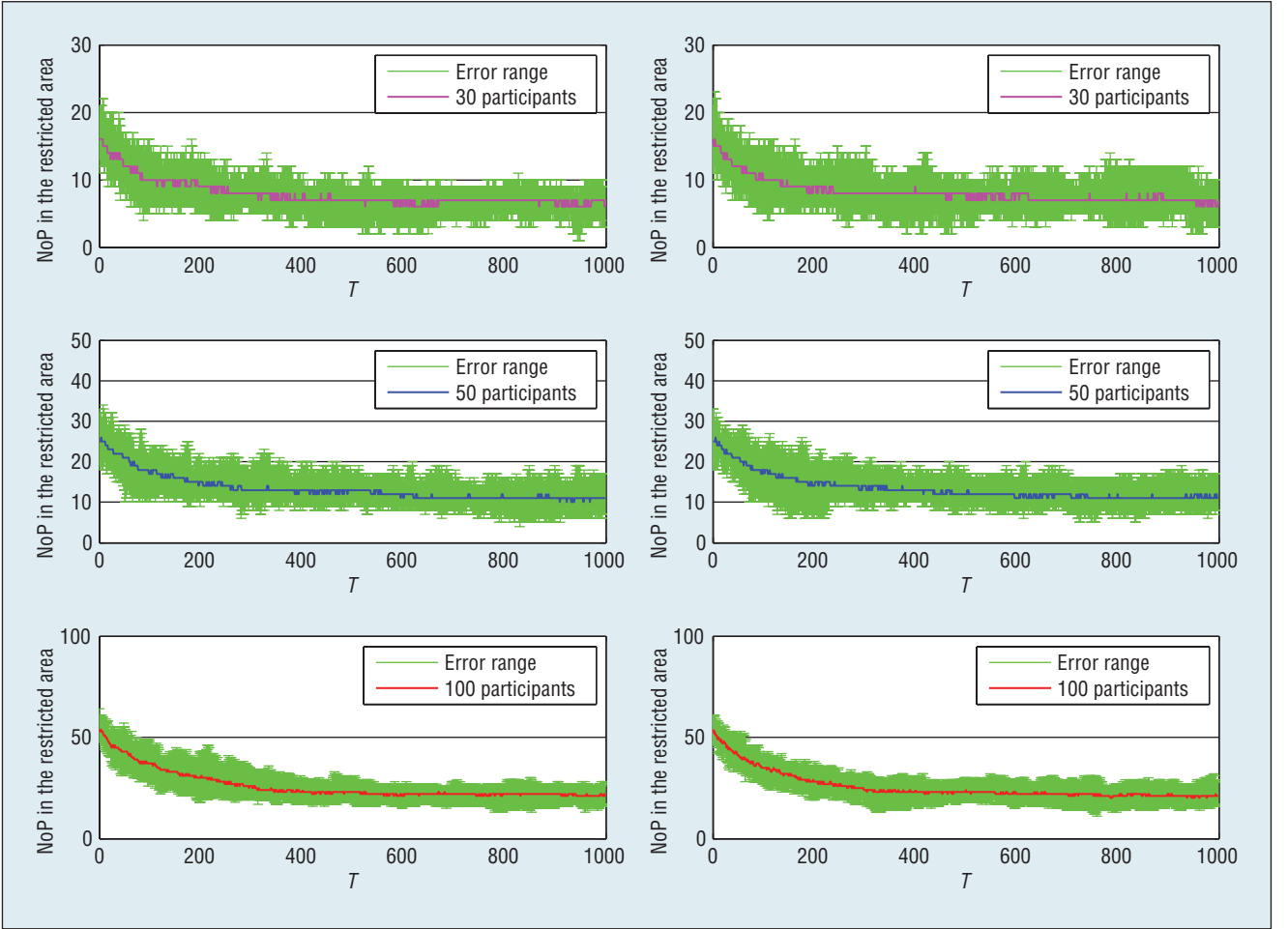
Some social networks only consider dependent social features, such as anonymous social networks, which can be called behavior feature-driven social net-

works, whereas some social networks consider both independent and dependent social features, which can be called mixed feature-driven social networks.

## Trust Agent-Based Behavior Induction

After trust agents' social features are selected to make participants trust the agent, the agent's designed behaviors can effectively induct participant behaviors through the following steps:

1. Initialize the average probability  $R_{Agt}$  of all trust agents entering the



**Figure 2.** Changing the number of participants in the restricted area. Pink dots represent the average number of participants in the restricted area corresponding to 30 participants in total, blue dots correspond to 50 participants in total, and red dots to 100 participants in total. In addition, green dots represent the number of participants in the restricted area during the experiments.

restricted behavior area in a behavior-mapping space as the average probability  $R$  of all participants entering the restricted behavior area. Initialize the average probability  $Q_{Agt}$  of all trust agents leaving the restricted behavior area in the behavior-mapping space as the average probability  $Q$  of all participants leaving the restricted behavior area.

2. Define the initial induction time as  $t_0$ , when participants in the restricted behavior area reach the threshold  $Z$ . Define  $q$  time units as  $q\tau$ . Initialize  $q = 1$ .
3. With Equations 1 and 2, at time  $T = t_0 + q\tau$ , the probability of all

trust agents entering and leaving the restricted behavior area is  $R_{Agt}^{t_0+q\tau}$  and  $Q_{Agt}^{t_0+q\tau}$ :

$$R_{Agt}^{t_0+q\tau} = (1 - \gamma)^q \times R \quad (1)$$

$$Q_{Agt}^{t_0+q\tau} = \begin{cases} (1 + \gamma)^q \times Q & (1 + \gamma)^q \times Q < 1 \\ 1 & (1 + \gamma)^q \times Q \geq 1 \end{cases} \quad (2)$$

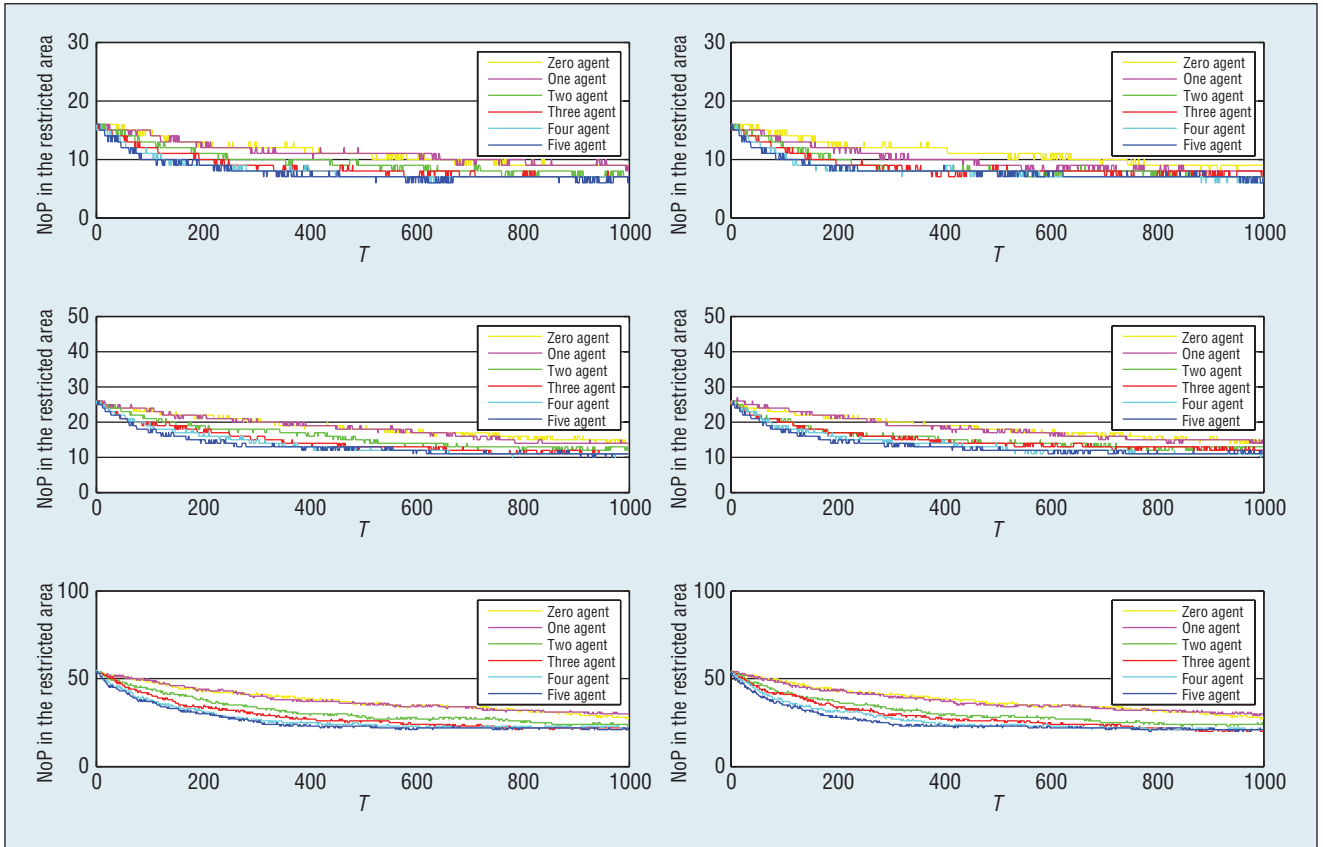
where  $\gamma$  is the induction factor, which is specified in the system users' preferences or fulfilled by domain experts.

4. If the number of participants in a restricted behavior area  $p_r$  is less

than a threshold  $L$ , the induction is completed; otherwise, assign the value of  $q + 1$  to  $q$  and go to step 3.

Figure 1 shows snapshots of the social behavior-induction process, where the number of participants  $NoP = 50$  and the number of trust agents  $NoA = 3$ . The circle represents the restricted behavior area, the red dots represent the participants in social networks, and the green dots represent the trust agents in social networks. In Figure 1a, when participants in the restricted behavior area reach the threshold  $\theta$ , the behavior-induction process begins,





**Figure 3.** Changing the number of trust agents in the restricted area. The dots with different colors represent the average number of participants in the restricted area corresponding to the different number of trust agents.

and trust agents are introduced with time  $T = 6$ . After the behavior-induction process depicted in Figure 1b with  $T = 148$ , the participants in the restricted behavior area can be inducted away from it (depicted in Figure 1c) with  $T = 594$ .

### Experimental Simulations

We designed two simulation systems to illustrate our trust agent-based social behavior-induction process, including a mixed feature-driven trust agent-based social behavior-induction (MFTABI; <http://pan.baidu.com/s/1i3pJnoD>, which is labeled as Behavior Induction1.0.mlappinstall) system and a behavior feature-driven trust agent-based social behavior-induction (BFTABI; <http://pan.baidu.com/s/1i3pJnoD>, which is labeled as Behavior Induction1.1.mlappinstall) system.

### Simulation of the Number of Participants in Social Networks

To examine the influence of the number of participants on behavior induction, we conducted 20 experiments with five trust agents for both MFTABI and BFTABI systems. In Figure 2, pink dots represent the average number of participants in the restricted area corresponding to 30 participants in total in social networks, blue dots correspond to 50 participants in total, and red dots to 100 participants in total. In addition, green dots represent the number of participants in the restricted area during the experiments.

From all the snapshots in Figure 2, we can observe that with different settings, the number of participants in the restricted area generally shrinks as time increases. In addition,

the upper and lower bounds of the number of participants in the restricted area generally shrink as well.

### Simulation of the Number of Trust Agents

To examine the influence of the number of trust agents on behavior induction, we conducted 20 experiments with five trust agents for both MFTABI and BFTABI systems. In Figure 3, the dots with different colors represent the average number of participants in the restricted area corresponding to the different number of trust agents.

As you can see, more trust agents can induct participant behavior more quickly. In addition, more participants in the restricted behavior area need more trust agents to achieve the same effect during the behavior induction.

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**N**ow that we've proposed and experimentally validated our trust agent-based social behavior induction approach. In future work we'll introduce Latent Dirichlet Allocation to abstract the behavior features of users in social networks, such as Twitter. We can construct links in behavior feature-driven social networks using the Pearson similarity of users' behavior features. ■

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