International Journal of u- and e- Service, Science and Technology
Vol.9, No. 7 (2016), pp.265-276
http://dx.doi.org/10.14257/ijunesst.2016.9.7.27

Relationships and Trust Modeling in Twitter Using Game Theory: The Supply Chain Perspective

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Abstract

Supply chain has been one of the most popular and efficient ways of exploring more benefits across businesses from the perspective of particular enterprise, with the objective of improving the long-term performance of individual companies. With the rapid development of social media platforms, such as Twitter, Facebook, LinkedIn, etc., social media has become one of the most valuable businesses due to largest user coverage, widest influential dissemination and highest commercial value. From the perspective of enterprises, leveraging social media for e-commerce are gradually being taken seriously. Indeed, social media helps compress the supply chain by eliminating unnecessary intermediate links. In this paper, we consider the roles in Twitter users (i.e., brands and audiences) as the nodes in supply chain, and simulate the social interactions between them as the collaboration decisions among supply chain members. Specifically, we consider social interactions as transactions, and sentiments as trust information. In this way, we tailor the traditional game model for modeling relationships among supply chain members in the context of Twitter, and propose a long-term game model based on trust.

Keywords: *Supply chain, social relationships, game model, Twitter*

1. Introduction

Supply chain has been the most popular and efficient way for enterprises to improve their competitiveness by making advantage of external resources, investing technology and key production, rebuilding and outsourcing business processes, establishing long-term contacts with upstream and downstream enterprises for complementary advantages and jointly participation in the competition, *etc.* The essential of Supply Chain Management (SCM) is the process of exploring more benefits across businesses from the perspective of particular enterprise, with the objective of improving the long-term performance of individual companies [1].

As shown in Figure 1, supply chain consists of many nodes with different roles, including suppliers, manufacturers, core enterprises, retailers, customers. Each node is independent with its own business objective and business conditions, and conflicts would be inevitable if collaboration happens among different nodes. The objective of SCM is to ensure supply chain collaboration operation and maximize the benefits of the whole supply chain.

E-commerce provides a more convenient platform for implementing SCM using Internet [2]. Typically, there are two main patterns in e-commerce. (1) B2B (business-to-business) refers to the information exchange and operation process integration between the upstream and downstream enterprises, in order to reduce the cost and improve the efficiency. (2) B2C (business-to-customer) is customer-oriented and typically realized as online stores.

With the rapid development of social media platforms, such as Twitter, Facebook, LinkedIn, etc, social media has become one of the most valuable businesses with largest user coverage, widest influential dissemination and highest commercial value [3]. As the

ISSN: 2005-4246 IJUNESST

number of social media users grows, investors, advertisers, program developers and other stakeholders are increasingly paying attentions to social networking sites. Social media and social networks construct a large network society with infinite business opportunities. From the perspective of enterprises, replacing traditional businesses with e-commerce and leveraging social media for e-commerce are gradually being taken seriously.

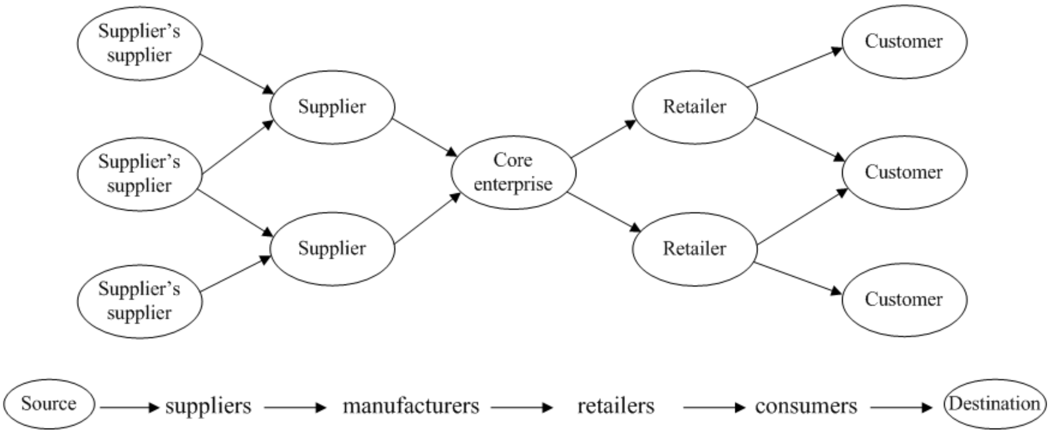

Figure1. Typical Traditional Pattern in the Supply Chain

Social commerce [4] means embedding social elements such as following, sharing, communicating and interacting into e-commerce, and it achieves the combination of social networking and e-commerce. For customers, social commerce helps to make the purchase decision and facilitate the communication and interactions after transactions. For enterprises, through the collaboration with social media tools and social networks, marketing, promotion and merchandise sales can be achieved more effectively.

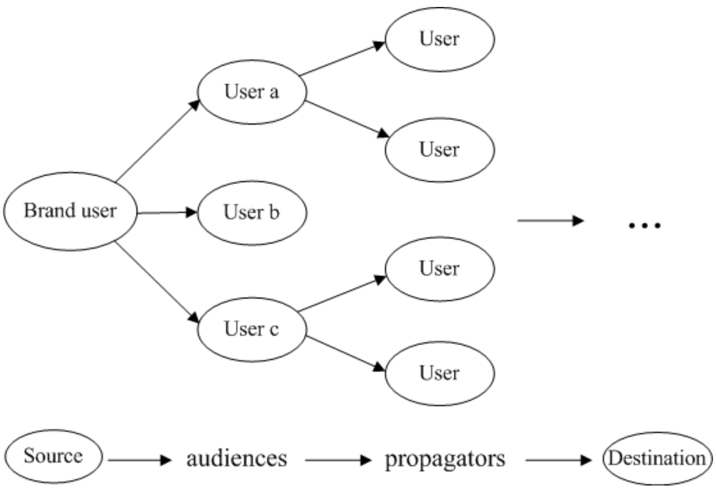

Figure 2. Typical Chain in Social Media

Indeed, social media helps compress the supply chain by eliminating unnecessary intermediate links. As shown in Figure 2, the typical chain from enterprises to customers in the context of social media include: (1) brand users: the social media account users of core enterprises, which is typically the official accounts of companies or brands; (2) audiences: the direct reachable user coverage for specific brand, including followers, friends, and users who interact with brand; (3) propagators: other users who contribute to information dissemination and make the brand visible to a wider coverage. Any user within audiences and propagators could communicate and interact with the brand if he/she is interested.

In this paper, we consider the roles in Twitter users (*i.e.*, brands, audiences) as the nodes in supply chain, and simulate the social interactions between them as the collaboration decisions among supply chain members. Indeed, we focus on analysis the relationships between Twitter users from the perspective of supply chain members collaboration. Inspired by the typical SCM, we consider social interactions as transactions, and the sentiment as trust information. In this way, we tailor the traditional game model for modeling relationships among supply chain members in the context of Twitter, and propose a long-term game model based on trust.

2. Related Work

Social commerce is the combination of social behaviors and business. Marsden [5] collected 22 definitions on social commerce, and summarized that the characteristics of social commerce include reputation, trusted recommendation and collaboration. Social commerce connects the purchase decisions with social interactions, and promotes customer interactions and participation, which would produce significant business results [6]. Many efforts have been made on social commerce. For example, Amblee *et al.* [7] investigated the reputation on Amazon book community using statistical hypothesis. Liang *et al.* [4] explored the influence of social connections on the purchase intentions based on Weibo. Olbrich *et al.* [8] investigated the factors of purchase behavior by analyzing clickstream data. Stephen *et al.* [9] studied on the implicit economic value in sellers social networks. Shin *et al.* [10] studied user behaviors in the context of social e-commerce sites based on a questionnaire survey. Lee *et al.* [11] explored the influence of opinion leaders on consumer behaviors through social network analysis technique. In this paper, we simulate social interactions as business transaction within the context of social media platform, and try to formulate the relationships between social users from the perspective of supply chain members.

The development of information technology and social commerce makes it possible to virtualize the whole supply chain. Anderson *et al.* [12] indicates that collaborative supply chain is the trend for SCM. Currently, with the integration of social commerce and supply chain, many efforts have been made on the integration management of e-commerce and supply chain collaboration [13-14]. Hansen [15] proposed that sharing business resources helps to improve the overall performance of the supply chain. Manthou *et al.* [16] simulated the collaborative process to analyze factors and roles in the virtual e-supply chain. Dustdar *et al.* [17] defined the collaboration and operations rules in virtualized collaborative supply chain. Gunasekaran *et al.* [18] provided insights on the trend of collaborative supply chain based on IT. Singh *et al.* [19] believed that the key element of successfully established collaborative supply chain is the collaborative relationships between supply chain members. In this paper, we focus on the collaborative relationships modeling.

There are existing works on trust in supply chain. In SCM, trust means one side believes that the other is able and willing to fulfill commitments, and trust is closely related to the mutually beneficial behaviors between two sides [20]. Kwon *et al.* [21] investigated the factors that affect the trust and commitment among supply chain members. Handfield *et al.* [22] analyzed the trust and relationship from the perspective of improving cupply chain responsiveness. Laeequddini *et al.* [23] built a conceptual model for supply chain partners relationships. Ouyang *et al.* [24] proposed to model trust relationships among supply chain members using game model. In this paper, we tailor the supply chain members relationship modeling into the context of Twitter users using game model.

3. Problem Formulation and Basic Model

In this paper, we propose to formulate the relationship modeling among Twitter users as the problem of relationship management among supply chain members. The intuition behind is that social media platforms such as Twitter have become a new channel in the supply chain, and compress the traditional supply chain flows, and therefore the concept and problem spaces can be mapped between social media and SCM. In this study, we provide a preliminary attempt along this line. Specifically, we focus on measuring relationships among Twitter users by viewing brand oriented users as suppliers, and their audiences as customers.

3.1. Problem Formulation

First of all, we define some terms that are used throughout the paper.

Definition 1 (brands, audiences) Twitter accounts that are operated by enterprises or companies or specific brands are unified as *brands*, and their *audiences* include: a) followers that follow the brand, b) friends that are followed by the brand, c) *mentioners* that mention the brand in specific tweet by using @username format, and d) *hashtagers* that use hashtags in specific tweet where #hashtag = #brand.

Definition 2 (suppliers, customers) Inspired by SCM, we differentiate roles in Twitter as suppliers and customers since social media shrinks the traditional supply chain link as two nodes. That is, suppliers are brands, and *customers* are their audiences.

Definition 3 (Twitter based Supply Chain, TSC) TSC is derived from Twitter users, where the supply chain members mapping is as follows: suppliers correspond to brands (notated as B), and customers correspond to audiences (notated as A). TSC has the following assumptions:

(1) TSC members have the learning and analysis abilities with limited rationality even though they cannot precisely and comprehensively make the decisions;

(2) The benefits in TSC are gained through interactions among members. During each interaction, TSC members are sharing information in a fair and open manner, and at the same time, they would like to take the risk of the interaction;

(3) Interactions are built upon trust, that is, TSC members are willing to participate in the interactions because they trust each other.

3.2. Basic Game Model

We formulate the interaction decisions among brands and audiences using game theory based on trust. That is, if TSC members trust each other, they would like to interact with each other. The basic game model is:

Players: brands and audiences, *i.e.*, $\{B, A\}$;

Strategies: trust or not, *i.e.*, $S = \{T, \overline{T}\}$.

Table 1. Gain Matrix Between Brands and Audiences

B A	T	$\overline{T}$
T	(π^{b*}, π^{a*})	$(\underline{\pi^{b}}, \overline{\pi^{a}})$
$\overline{T}$	$(\overline{\pi^{b}}, \underline{\pi^{a}})$	$(0, 0)$

Table 1 illustrates the gain matrix, where π^{b*}, π^{a*} are the gains of B, A when A, B choose to trust respectively; $\underline{\pi}^{b}$, $\overline{\pi}^{a}$ are the gains of B, A when B chooses to trust but A doesn't trust respectively; $\overline{\pi}^{b}$, $\underline{\pi}^{a}$ are the gains of B, A when A chooses to trust but B doesn't respectively; and if A, B doesn't trust, the gains of B, A are 0. Typically, the gain matrix satisfies:

$$\overline{\pi}^{b} > \pi^{b*} > \underline{\pi}^{b}, \overline{\pi}^{a} > \pi^{a*} > \underline{\pi}^{a}, \tag{1}$$

$$\pi^{b*} + \pi^{a*} > \overline{\pi}^{b} + \underline{\pi}^{a}, \pi^{b*} + \pi^{a*} > \underline{\pi}^{b} + \overline{\pi}^{a}. \tag{2}$$

If B, A trust each other, the gains of cooperate are π^{b*}, π^{a*} respectively. If B trusts A but A doesn't trust B, the opportunism of A leads to more gain ($\overline{\pi}^{a}$) than the collaboration(π^{a*}), and the gain of B ($\underline{\pi}^{b} < 0$) is damaged because the trust of B is used by A. The situation is the same if A trusts B but B doesn't trust A. Indeed, if one player doesn't trust, the other player would choose not to trust as well. Therefore, the Nash equilibrium of one round gaming is $(\overline{T}, \overline{T})$, and the gains are 0 for both.

Suppose A believes the probability of B to trust in the first round is $p_1^a \in [0,1]$, which is actually the trust of A in B. Therefore, the expect gain of A choosing to trust is:

$$G^a(T) = p_1^a \pi^{a*} + (1 - p_1^a)\underline{\pi}^{a}, \tag{3}$$

and the expect gain of A choosing not to trust is:

$$G^a(\overline{T}) = p_1^a \overline{\pi}^{a}. \tag{4}$$

Therefore, the net expect gain of A is:

$$G^a(T) - G^a(\overline{T}) = \underline{\pi}^{a} + p_1^a(\pi^{a*} - \overline{\pi}^{a} - \underline{\pi}^{a}) > 0. \tag{5}$$

Thus, the trust threshold of A in B is:

$$p_1^{a*} = \frac{\underline{\pi}^{a}}{\overline{\pi}^{a} + \underline{\pi}^{a} - \pi^{a*}}. \tag{6}$$

Similarly, the trust threshold of B in A is:

$$p_1^{b*} = \frac{\underline{\pi}^{b}}{\overline{\pi}^{b} + \underline{\pi}^{b} - \pi^{b*}}. \tag{7}$$

The condition of A, B collaboration is:

$$p_1^a > p_1^{a*}, p_1^b > p_1^{b*}. \tag{8}$$

4. The Long-Term Game Model

Typically, the interactions between brands and audiences are long-term collaboration based on trust, and the trust affects the repeated gaming process.

Repeated gaming refers to repetitions of stage game. If the gaming is single stage game, each player only cares about the one-time gain. If the gaming is repeated games, player could give up the decision with maximum one-time gain for long-term interests.

For audience A, let the influence of trust in previous interaction on subsequent interaction be $\delta^a \in [0,1]$ and discount factor be α. If brands and audiences interact before, $p_1^a = 1$. If repeated gaming happens between A, B, the best strategy is to cooperate [25]. The gains of A, B for repeated collaboration are:

$$\begin{cases} \pi^{a*} + \sum_{n=1}^{\infty} \alpha^n \pi^{a*} \\ \pi^{b*} + \sum_{n=1}^{\infty} \alpha^n \pi^{b*} \end{cases} . \tag{9}$$

Eventually, the following would be true:

$$\begin{cases} \pi^{a*} + \sum_{n=1}^{\infty} \alpha^n \pi^{a*} > \overline{\pi^a} \\ \pi^{b*} + \sum_{n=1}^{\infty} \alpha^n \pi^{b*} > \overline{\pi^b} \end{cases} . \tag{10}$$

Let the initial trust of A be $\beta (\beta = p_0^a) \in [0,1]$. During repeated gaming, the trust of A is:

$$p_{i+1}^a = \delta^a p_i^a + (1 - \delta^a)\beta . \tag{11}$$

Suppose the probability of collaboration is p, and thus the expect of trust is:

$$Ep_{i+1}^a = \beta(1 - \delta^a) + Ep_i^a \left[1 - (\beta + 1 - p)(1 - \delta^a)\right]. \tag{12}$$

The limit of Equation (12) is:

$$\lim_{i \to \infty} Ep_i^a = \frac{\beta}{\beta + 1 - p} . \tag{13}$$

That is, A believes B would cooperate with the probability of $\frac{\beta}{(\beta + 1 - p)}$. If $p \to 1$, $\frac{\beta}{\beta + 1 - p} \to 1$.

From above analysis, we have the following observations:

(1) Consistent collaboration is dependent on the initial trust and the cooperate decision every round, which would enhance the trust between players.

(2) The first collaboration is determined by the initial trust.

(3) Current trust is accumulated by individual game strategy at the rate of $(1 - p_i^a)$, and the increase of trust reduces as the times of collaboration grow.

(4) Opportunism reduces the trust between players, and consistent repeated opportunism brings the trust down to β.

Therefore, trust is prerequisite for collaboration or interactions between players, and the collaboration is successful only when the trust threshold is satisfied. On the other hand, if one player chooses to cooperate, the trust of its own would be enhanced, and the threshold of future collaboration is reduced. Along this line, we claim that trust is essential for interactions among players in social media.

5. Trust Modeling

Now that trust is essential for supply chain members cooperation, it is necessary to establish a trust model. Besides, we introduce a penalty mechanism to punish the opportunism during the long-term interaction games.

5.1. Trust Modeling

As mentioned before, the decisions of players to interact or not are made upon the trust. In this section, we consider the trust between players (*i.e.*, Twitter users) as (1) direct trust if there exist interactions between them, and (2) indirect trust if they have no direct interactions.

5.2.1. Direct Trust: Given players A, B, direct trust is calculated from the sentiment of all historical interactions. The intuition is that the more positive the interaction is, the higher the trust is. Suppose there are n interactions between A, B, and each interaction is represented as a tweet with @ symbol. Denote the sentiment associated with interaction i as s_i, and we define the direct trust between A, B as:

$$DT(A,B) = \sum_{i=1}^{n} s_i(A,B). \tag{14}$$

Suppose we have a set of labels $L = \{-1, 0, 1\}$, denoting negative, neutral and positive sentiment respectively, and $s_i \in L$. After pre-processing on the corpus of mention tweets, including converting to lower case, eliminating URLs and @username, replacing #hashtags and removing punctuation and additional white spaces, we perform a support vector machine (SVM) based method to train the sentiment classifier [26].

Consider the time factor, that is, the more recent the interaction is, the more contribute it makes to the trust calculation. Suppose $\lambda \in (0,1)$ is the average weight of each interaction and Equation (26) can be rewritten as:

$$\begin{aligned} DT(A,B) = \lambda[& s_1(A,B) + (1-\lambda)s_2(A,B) + (1-\lambda)^2 s_3(A,B) \\ & + \dots + (1-\lambda)^{n-2} s_{n-1}(A,B) + (1-\lambda)^{n-1} s_n(A,B)] \end{aligned}, \tag{15}$$

Where $s_1(A,B)$ is the most recent interaction, and $s_n(A,B)$ is the oldest historical interaction. The larger λ is, the less important the historical interactions are.

5.2.2. Indirect Trust: If there are no direct interactions between A, B, the trust value can be inferred from other users connected to them. As shown in Figure 3, even though there are no direct connections between A, B (dashed line), there are two connected paths ($A \to c_1 \to c_2 \to B$ and $A \to d_1 \to d_2 \to B$). Therefore, the trust can be transmitted over intermediate nodes.

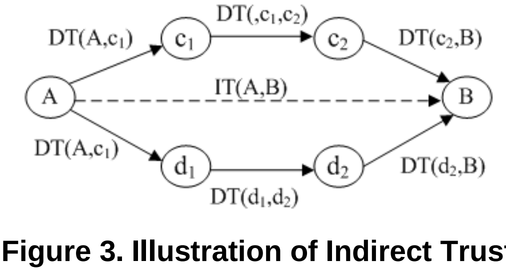

Figure 3. Illustration of Indirect Trust

Suppose there are l connected paths between A, B, and on path l_j, the intermediate nodes are $n_1, n_2, \dots n_{l_j}$. Therefore, the indirect trust is:

$$IT(A,B) = \frac{1}{l}\sum_{j=1}^{l} DT(A,n_1) \times \prod_{k=1}^{l_j - 1} DT(n_k, n_{k+1}) \times DT(n_{l_j}, B) . \tag{16}$$

Combine Equations (15) and (16), we have the trust between A, B:

$$T(A,B) = \omega_1 DT(A,B) + \omega_2 IT(A,B) , \tag{17}$$

where $\omega_1, \omega_2 \in (0,1), \omega_1 + \omega_2 = 1$.

5.2. Penalty Mechanism in Game Model

In order to shape the trusted reputation, we introduce a penalty mechanism to punish seduction and deception.

Table 2. Gain Matrix Between Brands and Audiences with Penalty

B / A	T	$\overline{T}$
T	(π^{b*}, π^{a*})	$(\underline{\pi}^{b}, \overline{\pi}^{a} - \tau\rho)$
$\overline{T}$	$(\overline{\pi}^{b}, \underline{\pi}^{a} - \tau\rho)$	$(0, 0)$

Suppose $\rho\,(\rho > 0)$ is the punishment of opportunism, and τ is the probability of being punished, $\tau \in [0,1]$. The gain matrix with penalty introduced can be updated in Table 2. The collaboration conditions are:

$$\begin{cases} \overline{\pi}^{a} - \tau\rho < \pi^{a*} \\ \overline{\pi}^{b} - \tau\rho < \pi^{b*} \end{cases} . \tag{18}$$

That is,

$$\begin{cases} \overline{\pi}^{a} - \pi^{a*} < \tau\rho \\ \overline{\pi}^{b} - \pi^{b*} < \tau\rho \end{cases} . \tag{19}$$

Therefore, one must consider the reputation penalty to avoid long-term cost.

6. Experimental Analysis

Our dataset was collected from Twitter from 16th September to 29th December 2011 using Twitter API[1]. There is rich information about users and tweets represented in JSON[1]. Figure 4 shows the number of audiences for each brand user, including followers and mentioners. We preprocess the dataset by extracting all interactions represented via @ symbol. Figure 5 demonstrates the distribution of interactions between users. From this figure, we observe that the number of interactions roughly follows the power law distribution in a log-log plot.

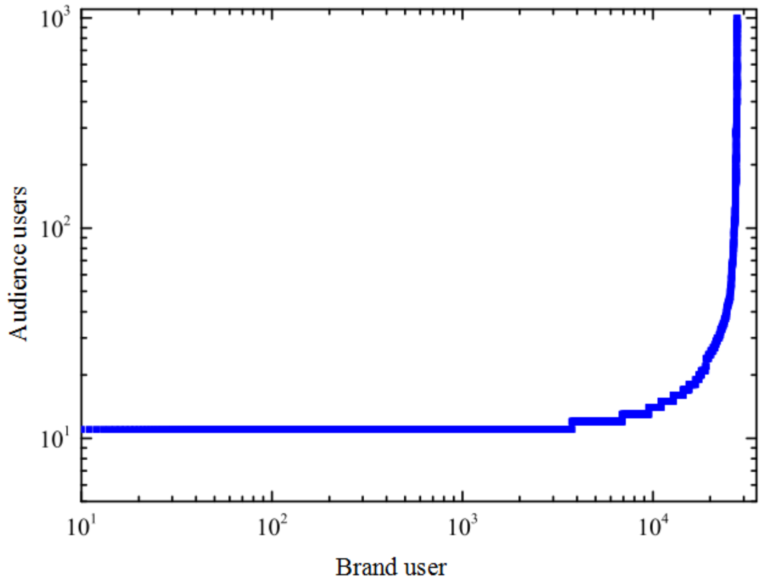

Figure 4. The Number of Audiences Per Brand User

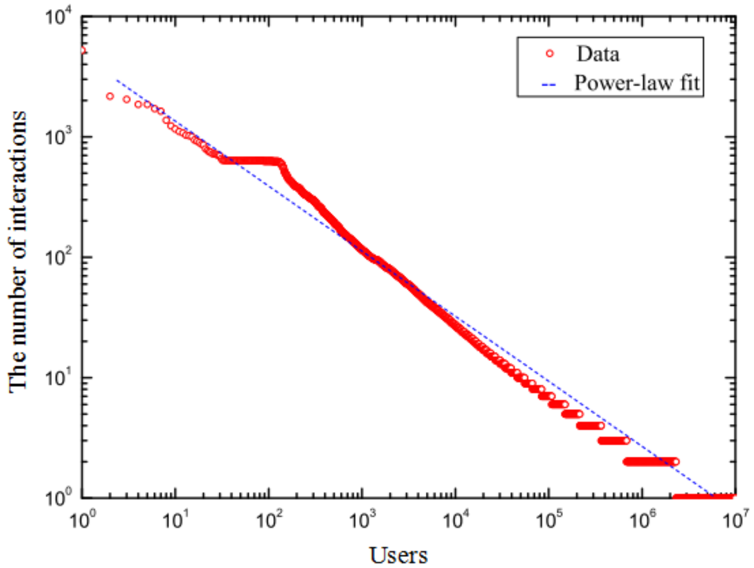

Figure 5. Distribution of Interaction Frequency Between Users

Figure 6 gives the trust results when interactions happen between users, where the x-axis is the number of interactions between users, and the trust values are normalized into [0,1]. We can observe that the trust value remains stable at 0.6~0.7, if the number of interactions between users is around 25. That is, when the number of interactions between users is approximately 25, the trust between them tends to be stable.

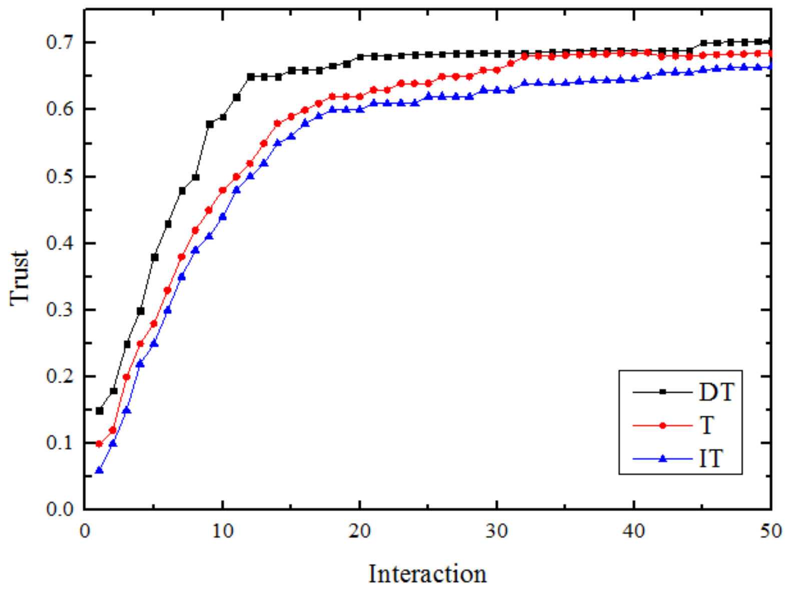

Figure 6. Trust Results of Interactions Between Users

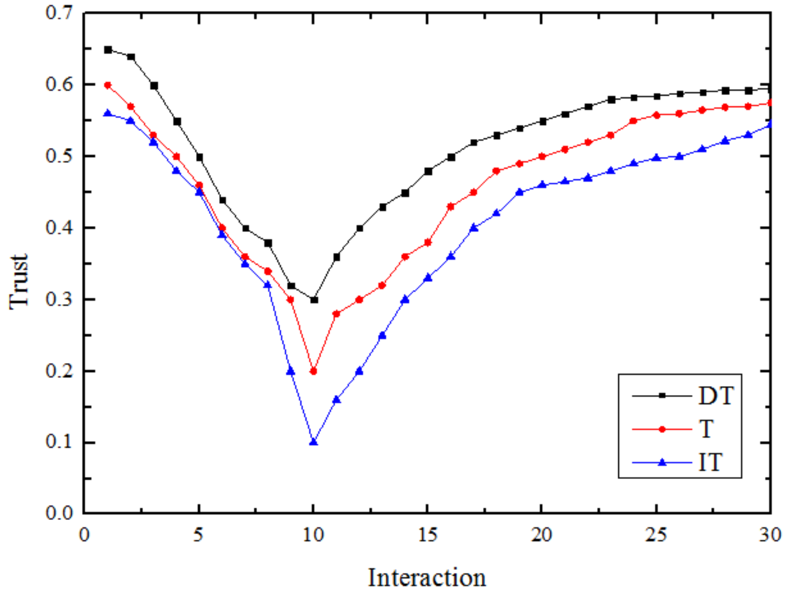

Figure 7. Trust Results with Negative Interactions

If the interactions are negative or there exist opportunism, the trust results are shown in Figure 7. In this experiment, we choose a brand user with initial trust 0.6, and analyze the interactions conducted by those audiences who negatively interact with the brand. We can see that, after 10 negative interactions, the trust value descends from 0.6 to approximately 0.2, that is, negative interactions do affect the credibility of brands. Then, during future 20 positive interactions, the trust value rises again but still lower that the initial trust. That means, reputation can be rebuilt if proper interaction strategy is used, but still, negative interactions could affect the credibility for a relatively long time. Therefore, brand users should pay attention to the negative opinions on social media and proper measures should be made for long-term interests.

7. Conclusion

In this paper, we model the social relationships between Twitter users from the perspective of supply chain using game model. Specifically, we differentiate Twitter users as brands and audiences, and simulate the social interactions between them as collaboration among supply chain members.

This paper provides a primary attempt on combining social media and supply chain. Indeed, it's believed that social media provides another perspective of SCM, and some theories in SCM can be transferred into social media based supply chain. In this work, we investigate the supply chain membership analysis on Twitter users using game model. Indeed, there are many other issues in SCM, such as information flow analysis, revenue analysis and distribution, dynamic supply and demand networks, *etc*. In future works, we would like to explore more fusion of social media and SCM, and aim to establish a supply chain for social media commerce.

Acknowledgment

Heilongjiang BaYi Agricultural university talent project: the development mechanism study on the industrialization of forestry carbon sink in Heilongjiang Province (Number: 2012DB-10); The project of science and technology bureau in Daqing: The marketing and logistics coordination model on stock market under the condition of online shopping "blow – outs" in Daqing (S2d -2012-01); Social Science Fund Project of Heilongjiang Province: Study on the game and evaluation of the interest subject of the new urbanization in Heilongjiang Province (Number: 15GLD06).

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