The Impact of Social Capital on Realizing a Trust-based Social Network

Research-in-Progress

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Abstract

How to build up trust has been a central topic of research in social networks. In this paper, we base on social capital theory to investigate what factors can influence an individual’s trust network in an online community. Specifically, we propose that three dimensions of social capital (1) opportunity, (2) motivation, and (3) ability have impacts on a user’s trust network formation in an online community. With the data from an online word-of-mouth community, we estimate a negative binomial regression model to test our hypotheses. As a result, all the hypotheses are supported. Future research directions are also discussed.

Keywords: social networks, online trust, social capital
Introduction

Both anecdotal evidence and literature have shown that, in deciding whether to buy a product online, a consumer not only cares about the usefulness of the product, but also concerns the value of it. More often than not, online reviews and comments are the major sources from which a potential customer can assess product value. With the rapid growth of the Word-of-Mouth campaigns, most online shoppers will make his/her purchase decisions after getting recommendations or reading online reviews. According to a recent study by Nelson (2013), “ninety-two percent of consumers around the world say they trust earned media, such as word-of-mouth or recommendations from friends and family, above all other forms of advertising.” These trusts undoubtedly play a central role in helping consumers overcome perceptions of uncertainty and make purchase decisions. Therefore, understanding the nature and antecedents of word-of-mouth trust is of great importance to both researchers and practitioners. Although a large number of studies have looked into the trust relationships in an e-commerce environment (such as the trusts in web vendors), the trust relationships built in an online word-of-mouth environment is much less investigated. Therefore, this study aims at filling this gap, based on social capital theory, by looking into how an individual can facilitate his/her trust network in an online community.

The rest of the paper is organized as follows. First, we introduce the concept of trusting behaviors and social capital and discuss the key elements in understanding trusts in a social network. Second, we develop a model based on social capital theory and identify the potential factors that might affect the online trust network. Finally, we present our preliminary empirical analysis and results, followed with a proposition of a dynamic network model for future research.

Literature Review

A steady stream of literature has examined trust in the Internet environment. Among previous studies, online trust has been defined in a variety of ways. Some researchers define online trust as a willingness to believe, while others define it as behavioral intentions that result from general beliefs regarding various attributes of the other party (Acemyan and Kortum 2012; Kim et al. 2009; Liu and Goodhue 2012). In other disciplines, trust has also been widely studied and has been defined with some other different perspectives. Therefore, some researchers have argued that the key to defining trust lies only indirectly in specific empirical context or in construct validation (McKnight and Chervany 2001).

As E-commerce and online shopping became prevalent, a good deal of research has contributed significantly to the understanding of consumer trusts in online vendors (Awad and Ragowsky 2008; Dellarocas 2003; Porter and Donthu 2008). Recently, with the emergence of word-of-mouth communication and the popularity of social media, a new trust form emerged among users in online social media. A good amount of studies have discussed consumer behaviors through social ties within those online social media. However, not many have focused on the trust-based online social networks. Understanding trust-based social network is crucial, as many anecdotal studies have shown that trust in either online or offline networks encourages word-of-mouth flow (e.g., Moldoveanu and Baum 2011). Extant research has already extensively studied the offline trusting behaviors (Ho and Weigelt 2005; Mortensen and Neeley 2012), while little attention has been paid to the impact of social capital on the user trust relations within an online social network. In online social networks, the dyadic trust-engendering effects of familiarity, reputation, similarity to self, and previous satisfactory interaction may not apply (Pavlou and Gefen 2004). Similar to the formation of offline initial trusts, trusts established among users within one social network are not based on any kind of experience or knowledge of the other party. Rather, they are based on an individual’s disposition to trust or on intuitional cues that enable one person to trust another without firsthand knowledge (McKnight et al. 1998). Therefore, we argue that this kind of trusts is a weak tie relation, which is not limited to the close social circle of the consumer. As a result, these trusts are more numerous and varied. Other research has provided evidence that customers more likely to find more and better information regarding the product from weak-tie recommendation sources (Duhan et al. 1997). Drawing on Coleman’s social network theory (Coleman 1988), research has found that the structural dimension of social capital, manifested as social interaction ties, stimulates trust and perceived trustworthiness, which represent the relational dimension of social capital (Tsai and Ghoshal 1998). Therefore, it is of our interests to find out what social capital factors contribute a customer’s building weak-tie trusts in an online social network.
Trust-based Social Network

The relationship between trust and social capital in a network has gone through a series of debates. Early literature mostly employed trust as a component of social capital. Over the last decade, an increasing number of researchers have contended that trust should be treated as a distinguishable factor from social capital. However, a new debate emerged as to whether trust is an antecedent of social capital or the other way around (e.g., Cook 2005; Lin 2005). Those researchers who favor the former view emphasize that trust can increase the credibility of information, which in turn will facilitate the use of it (Nahapiet and Ghoshal 1998). In a trust-based network, members are more likely to accept information that is shared by others. Specifically, trust will not only encourage more information sharing among members in the social network, but also ensure the use of that information (Robert et al. 2008). In comparison, other researchers believe that trust can serve as an important mediating factor through which social capital generates effects in times or situations of uncertainty and high risk (e.g., Cook 2005). It should be noted that this disagreement is in part due to the different levels of conceptualizations of social capital. While Putnam focused on social capital accrued in a certain community (i.e., a network level) (Putnam 1995), Coleman and Bourdieu conceptualized social capital on individual level (Bourdieu 1986; Coleman 1988). The underlying reasoning of trusts as antecedents of social capital mostly lies in the network context, whereas the notion that social capital can promote trust is more applicable at the individual level. In the present paper, we are interested in how a certain member can establish his/her trust network by engaging in community activities. With a focus at individual level, we follow the theory that trust is a potential outcome of social capital. In particular, we contend that Internet users’ activities in a certain community can facilitate their trust network by accumulating social capital.

Echoing social network theory, Coleman identified social capital as something inherent in the structure of relations between actors (Coleman 1988). The existence of social capital can be identified in terms of the influence that a focal individual exerts on others in a social system. Social influence occurs when a person adapts attitudes or beliefs of someone else in the social system. Also, the flow and reception of information is facilitated by the social capital, which is especially true in an online social network. In a contemporary online social network such as a word-of-mouth community, each individual can access extensive information and spread the information widely through their incoming and outgoing ties respectively. Deciding which information to adopt and which to screen off will be largely dependent on the social capital of the information source.

Some researchers contended that social capital would be difficult to establish in an online network, because social capital is more likely to accumulate in collectives characterized by a shared history, high interdependence, frequent interaction, and closed structures (e.g., Wasko and Faraj 2005). However, accumulated evidence consistently shows that Internet users can enhance their social capital by investing in online social activities (Huysman and Wulf 2004; Pénard and Poussing 2010; Robert et al. 2008). Influence does not necessarily require face-to-face interaction but rather is based on information about other people (Robins et al. 2001). In an online community, social influence is passed among users in the form of digital content (Trusov et al. 2010) and the nature of digital network allows information reach to users in a very quick fashion.

Although the relationship between trust and social capital has been intensively discussed in the real life network, such relationship remains largely unexplored in the context of network-based web. Based on Adler and Kwon’s three distinguishable dimensions of social capital (Adler and Kwon 2002), our model propose that the three key strands of social capital, “opportunity” (member impression, in our study), “motivation” (member posting frequency, in our study), and “ability” (review quality, in our study), should be considered in modeling online trusts at the dyadic level. We believe this multidimensional view of social capital provides a pliable theoretical lens for explicating the formation of online trusts. Given the prevalence of online user-generated content, how the dynamic of online opinions affect the structure or the web of trust network has become a very interesting topic. More specifically, we are interested in what posting pattern over time can lead a reviewer to an opinion leader in the community. Does review quality influence the status of opinion leader? Does review rating or variance have relations with the fact that node in the trust network is a central node? In this study, we contend that the social capital developed in online social network sites can significantly enhance the trusts that an individual can win, and the accumulation of social capital will lead to the emergence of opinion leader in a certain online community.
Theoretical Development and Hypothesis

Following the theoretical model of Adler and Kwon (Adler and Kwon 2002), we examine the three key aspects of social capital and their impacts on trusting behaviors, so as to develop a more nuanced view of the impact on trustworthiness in social networks.

Opportunity

In an online social network, the attentions users receive give them the opportunity to leverage resources and further grow the network. We use the term Member Impression to denote the perceived attention that each user receives. Specifically, a reviewer's member impression is defined as the number of members who have visited the reviewer’s personal page. Member impression to some extent indicates the reviewer's popularity among the members of the community and the opportunity of a reviewer to bring even more attention. Such opportunity in turn reflects the potential for the focal reviewer to influence other members, which represents the amount of social capital in the network. When new visitors of the personal page get to see the reviewer's member impression, they are likely to attribute more social capital to the focal reviewer, which encourages them to trust on the focal reviewer. Therefore, we propose the following hypothesis.

Hypothesis 1. Member impression is positively related to the number of trusts that a member receives.

Motivation

Social capital theory suggests that social capital can be accumulated through social activities such as promoting themselves, building social status, etc. This type of social capital can facilitate the information exchange and develop the motivation to engage in the value creation. The effect of motivation on user trusts can be captured both posting frequency and timeliness. The more motivated that people engage in these social activities, the more likely they can accumulate social capital over time. Therefore, we argue that users who are more motivated or active in an online community will make them standout of the crowds and become an influential user. In our context, we assess a user’s motivation in the community by looking at the posting frequency (the number of reviews divided by the number of days) and the number of days between first post and registration. We argue that those users with higher posting frequency and fewer days between first post and registration are likely to be more enthusiastic and motivated in the community. Therefore, the likelihood to accumulate more social capital over time is higher for those reviewers, who can in turn win more trusts from other users. Given the above reasoning, we proposed that:

Hypothesis 2a. Posting frequency has a positive influence on the number of trusts that a member receives.

Hypothesis 2b. The number of days between first post and registration has a negative relation with the number of trusts that a member receives.

Ability

The importance of ability in the theory of social capital can be easily understood. In this context of Epinions, a member will choose to trust a reviewer when he/she wants to follow the reviews from the specific reviewer. In this case, trust reveals a member’s general confidence in the competence (ability) of the reviewer. Such competence may trigger those members’ confidence in the other information provided by the same reviewer. Therefore, the accumulated review helpfulness rating can be treated as an index of the focal reviewer’s competence in the online community. With high rating of review helpfulness, a reviewer’s opinions can exert significant influences on other’s decisions. For those who haven’t directly experienced the usefulness of the information provided by the reviewer, the review helpfulness index can be a strong and valid indicator of the reviewer’s social capital, and thereby trustworthiness.

On the other hand, when the users are choosing whom to trust, they are actually doing the same thing as buying a product. As we know, when customers lack of concrete information about the product, they rely much on the review ratings of the product. As is shown by many studies, the average review rating of a product can enhance the product sales significantly (Archak et al. 2011; Chevalier and Mayzlin 2006). The
review helpfulness for a reviewer works exactly as the ratings of a product. When it is higher, people tend to have more confidence in the reviewer and therefore are more willingly to trust him/her. With the above reasoning, we propose the following hypothesis:

**Hypothesis 3.** Review helpfulness is positively related to the number of trusts that a member receives.

**Model**

For empirical evidence, we capture the data from Epinions.com, where the statistics of trust votes are listed on each member’s personal page. At the individual level, we examine the number of trust votes each node has received since he/she became a member of Epinions. Noted that the number of trusts received, which is count data, presumably follows a Poisson distribution. Since we’ve found evidence of over-dispersion, we estimate a negative binomial regression model, which explicitly accommodate this over-dispersion by incorporating an individual unobserved effect into the conditional mean (Hausman et al. 1984).

\[
\begin{align*}
 f(y_i | X_i) &= \frac{e^{-\omega_i \alpha^2 y_i} y_i^{\omega_i}}{\Gamma(\omega_i)}, \quad y_i = 0, 1, 2, 3, \ldots \\
 E(y_i | X_i) &= \omega_i = \exp(X_i \beta + \epsilon_i) \\
 \epsilon_i &\sim \text{LogGamma}(\mu, \mu)
\end{align*}
\]

Formally, each observation, \( y_i \), represents the number of trust node \( i \) had received. \( X_i \) is a vector of independent variables, and \( \epsilon_i \) is the unobserved heterogeneity and is assume to follow a log-gamma distribution (Cameron and Trivedi 1998).

**Data**

The major purpose of this study is to investigate the significant social capital factors that promote trust network in a social network community. We test the proposed hypotheses with a cross sectional data from Epinions.com, an online consumer-review platform that provides user-generated content (UGC) of product reviews. Different from major online WOM sites such as Amazon or Yelp, where review information has a close ongoing relationship with consumer spending, Epinions is also a social network community where members are able to indicate their trusts on other members based on the reviews they’ve read, thereby forming a network of trusts. This mechanism endows individual reviewers with greater influence than those reviewers on product sites. The focal reviewer may broaden the product search space of other users in the trust network, since the trusting behavior of those users indicates certain homophilious tie to the focal reviewer. Once they are in the same trust network, the information flow can increase the likelihood of users’ adopting the same products as people in their network. Besides obtaining information, an individual can also gain trusts and accumulate social capital in the community through posting reviews and interacting with other members. Those reviewers with a high in-degree centrality are served as opinion leaders because they have direct influences on those who trust them.

We obtain a cross-sectional dataset of user review information and trust votes activities on Epinions. Epinions was established since 1999. The review information collected in our dataset is dated from 1999 to 2010. After eliminating incomplete and error data, we have a sample of 61587 users. The time stamp on each review provides us with an opportunity to investigate the importance of posting frequency and member activities in determining user involvements. Social capitals are developed by each user in this community through activities such as posting reviews and giving ratings. There are several reasons why Epinions serves as a good platform for the trust network. First, it includes a vast scope of products to be reviewed, so that it allows any user to possibly involve themselves in the community. Second, it requires no access fee for either posting or searching for contents. After reading the product reviews, users can indicate their trusts of the reviewers and establish network ties between themselves and the reviewers. Moreover, Epinions is different from Facebook or Linkedin, where people have strong ties and weak ties.
in the same network. In comparison, the trust network in Epinions is solely built upon the reviews people post and read, exhibiting weak-tie network characteristics.

Since Epinions is an online social network community, members can form relationships by selecting the right person to trust and/or gaining trusts by writing unbiased reviews. In the trust network, each person is a node, and has direct ties connected to other people in the network. At the node level, we gather node-specific variables such as activity frequency, review helpfulness, member impressions, as well as control variables such as average product ratings, standard deviation of ratings, total impressions, etc. Review helpfulness is measured with the composite “helpfulness” ratings each review receives. Similar to Amazon and many other review websites, Epinions allows members to rate the helpfulness of each review in a 4-point Likert scale (1. Very Helpful; 2. Helpful; 3. Somewhat Helpful; 4. Not Helpful). This rating shows the competence of the reviewer providing useful review, thus it serves as a good indicator of reviewer’s ability. One objective of this research is to understand how frequent the posting activities influence the trusting votes a reviewer can obtain. We characterize the posting activities by using the time stamp on each review to measure the activity frequency of each user. We believe that frequency is a better measurement than the total number of review posts since it captures both review quantity and activity history of each member. Besides frequency, FirstPost is another time related variable indicating the days since a member’s first post. We define MemberImpressions as the total number of members who has visited the focal reviewer’s personal page. Similarly, TotalImpressions refers to the total number of people who has visited the reviewer’s personal page, and it serves as an necessary control variable. In this particular community, trusts can be established mutually. The number of in-degree trusts maybe in part due to the number of out-degree trusts that a user send out. Therefore, the number of trusting votes each user sends out is also considered an important control variable in our model. While we focus on the effects of AvgHelpfulness, FirstPost, Frequency, and MemberImpression on the trusting votes that a member receives, we also include the control variables along with the major variables and their respective descriptions in table 1.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>NumTrust</td>
<td>The number of trusts each node receives</td>
</tr>
<tr>
<td>Frequency</td>
<td>Average number of reviews/(last time stamp-first time stamp+1)</td>
</tr>
<tr>
<td>FirstPost</td>
<td>Days of first review post since the user’s registration date</td>
</tr>
<tr>
<td>AvgHelpfulness</td>
<td>Average helpfulness ratings node i receives for all the reviews written</td>
</tr>
<tr>
<td>MemberImpression</td>
<td>Total number of member visits each node receives at current network structure</td>
</tr>
<tr>
<td>Sd_Helpfulness</td>
<td>Standard deviation of helpfulness ratings node i receives for all reviews written</td>
</tr>
<tr>
<td>TotalImpression</td>
<td>Total number of visits each node receives at current network structure</td>
</tr>
<tr>
<td>AvgRating</td>
<td>Average rating score on all the products node i have reviewed</td>
</tr>
<tr>
<td>Sd_Rating</td>
<td>Standard deviation of product ratings given by node i</td>
</tr>
<tr>
<td>OutdegreeTrust</td>
<td>Total number of trusts each node sends out</td>
</tr>
</tbody>
</table>

Results

Figure 1 presents the distribution of the dependent variable NumTrust. The left panel shows that the distribution of NumTrust is a long tail distribution, and the linear relations presented in the right panel reveals that the long tail distribution is actually a power law distribution. The average number of trusts people received is about 9. Although most nodes have a small number of trusts received, there are a few nodes with more than 1000 trusts; those nodes undoubtedly act as influential users or opinion leaders in this community.
Tables 2 and 3 list the descriptive statistics and regression output respectively. Several independent variables have the problems of inflated standard errors and skewed distributions. Therefore, in order to make those positively skewed distributions more approximate to normal ones, we have taken logarithm transformation of those variables.

The regression output of alpha is significantly larger than zero, indicating that the negative binomial model fits data better than Poisson regression model. We have the model run for two sets of observations. While one set of observations only includes those nodes with more than one review, the other set covers all observations. Although the results turn out to be similar in the two tests, we believe that the result from observations with more than one review is more appropriate in understanding the network effect.

Specifically, the regression output shows that the average helpfulness of a reviewer does significantly increase his/her incoming trusts ($\beta = 0.35, p < 0.01$). Therefore, Hypothesis 1 is supported. Also, frequency has a significant and positive impact ($\beta = 0.063, p < 0.01$) on the number of trusts received. The positive coefficient supports our Hypothesis 2a. The negative coefficients of FirstPost ($\beta = 0.02, p < 0.01$) also supported our Hypothesis 2b, that is, the longer time people wait to post their first review, the
lower influence they can get in the future. Hypothesis 3 is supported, as MemberImpression is significantly related to the focal user’s received trusts ($\beta = 0.56, p < 0.01$).

On the other hand, TotalImpression has no significant impact on the incoming trusts. TotalImpression includes visits from not only Epinions users but also outside visitors. Although people can get attention from outside users as well, but those people cannot indicate their trusts in this network, therefore has no direct impact on the trusts people receive. Average product rating (AveRating) has no significant impact on the number of trusts people receive, while the significance of rating standard deviation (sd_Rating) shows that people who are more consistent in giving ratings are possibly getting higher number of trusts.

<table>
<thead>
<tr>
<th>Number of obs</th>
<th>47281</th>
<th>Number of obs</th>
<th>61587</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log pseudolikelihood</td>
<td>-103653.89</td>
<td>Wald $\chi^2$ (7)</td>
<td>134291.33</td>
</tr>
<tr>
<td>Wald $\chi^2$ (9)</td>
<td>128007.75</td>
<td>Log pseudolikelihood</td>
<td>-123789.36</td>
</tr>
<tr>
<td>Prob $&gt;\chi^2$</td>
<td>0.0000</td>
<td>Prob $&gt;\chi^2$</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

| NumTrust | Coef. | Robust Std. Err. | P>|z| | Coef. | Robust Std. Err. | P>|z| |
|----------|-------|------------------|------|-------|------------------|------|
| OutdegreeTrust | 0.4013 | 0.01 | 0.00 | 0.4169 | 0.01 | 0.00 |
| MemberImpression | 0.5619 | 0.01 | 0.00 | 0.5123 | 0.01 | 0.00 |
| TotalImpression | 0.0000 | 0.00 | 0.17 | 0.0000 | 0.00 | 0.00 |
| FirstPost | -0.0206 | 0.00 | 0.00 | -0.0257 | 0.00 | 0.00 |
| Frequency | 0.0630 | 0.00 | 0.00 | 0.0784 | 0.00 | 0.00 |
| AveRating | 0.0087 | 0.01 | 0.40 | 0.0017 | 0.01 | 0.79 |
| AvgHelpfulness | 0.3487 | 0.01 | 0.00 | 0.2511 | 0.01 | 0.00 |
| sd_Rating | -0.0291 | 0.01 | 0.02 | 0.1455 | 0.02 | 0.00 |
| sd_helpfulness | 0.3134 | 0.01 | 0.00 | 0.3294 | 0.01 | 0.00 |

### Future Work

The preliminary results of the proposed negative binomial model have provided us with a stepping-stone to further investigate the realization of trust networks in online communities. In order to have a better understanding of the relationships between the trust behavior and individual social capital, future research can look into the dynamics of trust network structure as a social process evolving over time, where individual activities and network ties mutually influence each other.

The actor-driven-modeling approach, proposed by (Snijders 2001; Snijders et al. 2007) suggested a statistical method to study the network structure while incorporating relevant actor attributes as a joint dependent variable in a longitudinal framework. In this model, the network structure and the individual attributes evolve simultaneously in a dynamic process, and the network evolution is regarded as the consequences of optimizing the network actors’ individual objective function. The change of ties in the
network is modeled as the stochastic result of nodal attributes and network effects, such as reciprocity or transitivity.

Based on the above model, a continuous time Markov chain can be defined by the model with the objective function. For our future research, we will obtain the estimated parameters from dynamic network analysis, together with latent space model (Sarkar and Moore 2005) and agent based simulation, to capture network dynamics across different time periods.

References


Trust-based Social Network