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Understanding suppliers' participation in business-to-government (B2G) electronic auction markets in the thai context

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KNOWLEDGE SHARING IN ONLINE COMMUNITIES

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Abstract

This paper investigates online knowledge sharing behaviour in Baidu Knows, a platform sponsored by the largest search engine company Baidu in China. We developed a spider engine to collect data from over 2 million questions posted at Baidu Knows. The data collected allows us to profile registered members, to answer questions such as who are the main driving force of those online communities and their attributes, and who are the free-riders seldom posting and answering questions. We also test several hypotheses in explaining the motivations of knowledge sharing, and the quality of such knowledge sharing. Our results indicate that there is a large proportion of users who seldom answer questions, but always ask questions. Although their behaviour seems selfish at the surface, they are actually the key factors driving the growth of online knowledge sharing communities.

Keywords: knowledge-based community, shared knowledge, Web 2.0, empirical study

1. INTRODUCTION

Online communities are virtual spaces on the Internet where a group of people of similar interests communicate and interact collectively or individually to achieve certain goals. Its popularity has grown tremendously in recent years that in many instances online communities have become one of the main resources of knowledge seeking. The most famous and successful example is Wiki, the largest free encyclopedia in the world, where anyone can access its web pages to contribute or modify content. However, as its name indicates, the Wiki website is only useful for acquiring information about well-established encyclopedic subjects and thus lacks the flexibility for knowledge seeking of more general and practical types.

The model of seeking general and practical knowledge on the Internet has evolved substantially over years. Previously, Internet users actively sought knowledge via search engines, such as Google and Yahoo!. However, the search efficiency highly relies on the selection of keywords. Also the information obtained tends to be fragmented, incomplete and may even be wrong sometimes. When users are unfamiliar with the subject matter, or choose inappropriate keywords, the knowledge seeking process tends to be quite inefficient.

The broad class of Web 2.0 technologies attempts to improve upon the search process by establishing a passive way of acquiring knowledge. In this model, users can propose questions in virtual communities, and expect answers provided by other users. Once they find the right place in the knowledge sharing platform to post their questions, the rest is left for others to contribute answers. The questions range from highly specialized technical questions to everyday practical questions. Interestingly, in large knowledge sharing platforms, such as Yahoo! Answers and Baidu Knows, millions of online users are active in the community, spending time to read posts of others, and answer questions if possible[1].

Launched in June of 2005, Baidu Knows is China's largest knowledge sharing platform. In Baidu Knows, the questions proposed by users are classified into over 500 categories at the time of this research, which are still increasing at a rapid pace everyday. Over 23.3 million questions and 22.8 million answers have been posted by the end of 2007. As a platform that was established only 2 years ago, Baidu Knows' phenomenal success arguably plays an important role in Baidu's competition with Google in the search engine arena in the Chinese Internet.

The success of the knowledge sharing platforms begs two important questions. First, why do people devote their time and effort to sharing their knowledge in virtual communities helping others, and who are they? Second, what is the quality of the answers provided and how useful are they? Obviously without the quantity and the quality of the answers, the usefulness of the knowledge sharing platform would dissipate, ultimately leading to reduced hit rates.

Despite the phenomenal growth of online knowledge sharing communities, there is surprisingly little empirical research about actual knowledge sharing patterns. Most prior studies use survey methods to investigate users' knowledge sharing motivation. New online knowledge sharing communities enable a new way of knowledge sharing: users freely propose their questions and exchange opinions with members. However, the technology infrastructure alone cannot guarantee meaningful and constructive knowledge sharing behavior (Alavi and Leidner 1999). Its survival totally depends upon the "kindness of strangers" as previously suggested (Constant et al. 1996). This is in sharp contrast to conventional communities, where the main factors driving knowledge sharing are identified as strong ties (Wellman and Wortley 1990), co-location (Allen 1984, Kraut et al. 1990), demographic similarities (Pelled 1996), and status similarities (Cohen and Zhou 1991). However, Wasko and Faraj (2005) argue that these factors are not applicable in virtual communities, where participants are typically strangers, and do not always have demographic or status similarities.

[1] Baidu is the largest search engine company in China.

Then why do people spend their valuable time and effort to contribute knowledge helping others? Prior studies postulated a variety of theories explaining knowledge contributions. Social capital is typically defined as "resources embedded in a social structure that are accessed and/or mobilized in purposive action" (Lin 2001, p. 29). Wasko and Faraj (2005) identified three forms of social capital related to knowledge sharing behavior in electronic networks. Chiu et al. (2006) also identified the influence of social capital on individual's willingness to share knowledge. Another theory concerns the collective action. Wasko and Faraj (2005) theorized that in online communities, individuals voluntarily contribute their time, effort, and knowledge toward the collective benefits. Intrinsic benefits such as self-worth, social norm, social affiliation, and extrinsic benefits such as economic rewards, future promotion opportunities, can drive knowledge contributions (Ma and Agarwal 2007, Bock et al. 2005, Kankanhalli et al.2005). Donath (1999) investigated Usenet newsgroup and concluded that identity plays a vital role in knowledge sharing behavior. The identity definition includes both the establishment of their own reputation and the recognition by others.

In this paper, we address knowledge sharing issues with empirical data collected from a spider engine that we developed. The data enables us to build a profile of those who post questions and those who answer questions. This allows us to address questions such as how many users are free-riders who seldom share their own knowledge while only asking questions, and who are the main contributors who are the driving force of the community? What are their main attributes, and whether knowledge sharing in different information categories exhibits different sharing patterns? With respect to the answer quality issue, we established a simple regression model to investigate the correlation between the quality of knowledge sharing and the characteristics of those who contribute knowledge. By analyzing users' true knowledge sharing behavior, this study sheds light on how to induce, promote, and manage online knowledge sharing behavior.

The rest of the paper is organized as follows. Section 2 describes the spider engine and the data collection effort, followed by a profile analysis of different classes of users. Section 3 tests several hypotheses of different behavior among user groups in motivating knowledge sharing. Section 4 looks at the free-rider phenomenon. We also established a theoretical model that investigates the correlation between answer quality and the characteristics of those who contribute answers in section 5. Section 6 contains concluding remarks.

2. USER PROFILE ANALYSIS

To collect field data, we choose from two of the largest knowledge sharing platforms in the world, Baidu Knows and Yahoo! Answers.[2] Interestingly, these two platforms adopt different mechanisms of how to reward users' sharing behavior. Yahoo! Answers makes each question have the same Reward Points as answerers. Once the question is answered, the best answerer will get the Reward Points, which are given by Yahoo! Answers. In Baidu Knows, in contrast, askers could choose how many points they want to pay, and the Reward Points are deducted from askers' cumulative points. Compared with Yahoo! Answers, Baidu Knows seems to provide more flexibility in motivating knowledge sharing. The comparison of these two mechanisms in driving their respective growth would be an interesting subject, but we will leave this issue to another research paper in the future.

We developed a spider engine to collect data in Baidu Knows as of December 2007. First we identified users who have asked or answered questions in one week from our sample in Baidu Knows' Computer and Entertainment categories. Overall, we got 2,763 questions and 7,520 answers, with each question having an average of 2.72 answers. For the Computer category, there were 1,383 questions and 3,417 answers, averaging 2.47 answers per question. For the Entertainment category, there were 1,380 questions and 4,103 answers, averaging 2.97 answers per question. Detailed descriptive statistics of questions and answers are shown in the following Table 1:

[2] This version reports data from Baidu Knows. Data from Yahoo! Answers will be incorporated in a forthcoming version.

	Computer	Entertainment	Overall
No. of Questions	1383	1380	2763
No. of Answers	3417	4103	7520
Mean of No. of Answers for Each Question	2.47	2.97	2.71
Median of No. of Answers for Each Question	2	2	2
Std. Dev of No. of Answers for Each Question	0.06	0.07	0.05
Minimum of No. of Answers for Each Question	0	0	0
Maximum of No. of Answers for Each Question	26	24	26

Table 1: Descriptive Statistics of No. of Answers for Each Question

The collected data contains past information of each user ID, which specifies three variables: No. of Answers, Reward Point and Best Answer Ratio. For privacy concerns, Baidu does not provide information about how many questions each ID has asked. We then collect all the information about these three variables for each user ID. The exact definition of these three variables are as follows:

- No. of Answers shows how many times each ID shared his or her knowledge with others.
- Reward Point tells how many points won by answering others' questions.
- Best Answer Ratio is the ratio between the answers rated as the best answers by askers and the total number of questions one member answered.

Each user ID's past history of asking and answering questions allows us to enlarge the sample size to include 2,114,930 questions. Based on the profile of questions posted and answered, we classify all members into several categories: top contributors, casual contributors and non-registered free riders.

Figure 1 illustrates the distribution of all registered members. Data along the x axis in Figure 1 is rank-ordered by the No. of Answers in the past, and the y axis is the No. of Answers provided by each corresponding registered member. These is clearly a concentration of users who often answered questions. Therefore we classify the top 10% of registered members as top contributors, who answered 1,618,161 questions in total, accounting for 76.6% of the total questions. Casual contributors are those registered members who answer questions occasionally. They account for 90% of the registered members. There are clearly also non-registered members of online knowledge sharing communities outside our sample. We define them as non-registered members who only come to the website to view questions and answers without contributing anything.

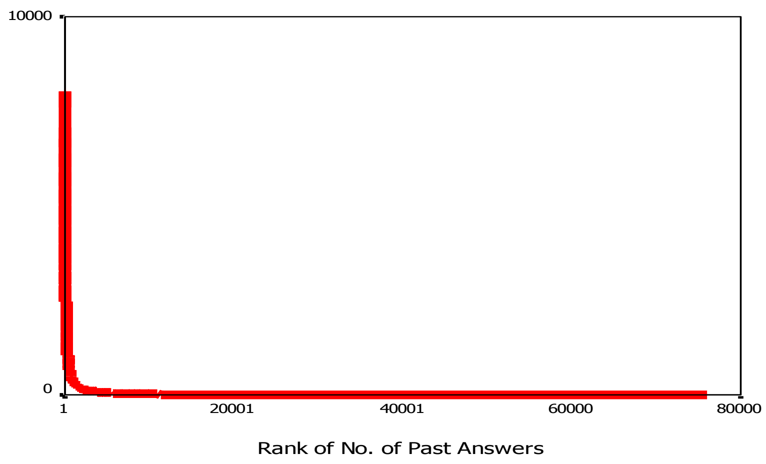

Figure 1: Users' Knowledge Sharing Pattern

Past literature reports that knowledge contribution in Linux working groups follows a power distribution. Figure 1 seems to indicate the same pattern, as 10% of the members account for about three quaters of all answers. We test the power distribution for this dataset as well in SPSS. The power test is significant at 99% level.

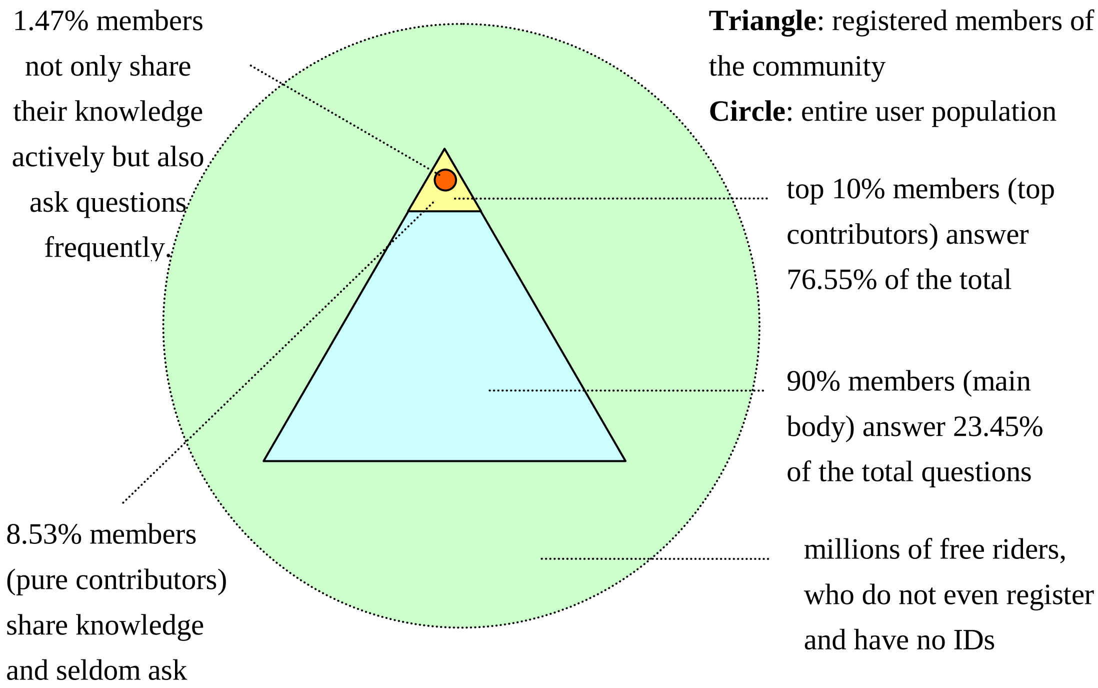

Figure 2: Knowledge Sharing Pattern

Figure 2 above illustrates the distribution of member segments as defined previously. One interesting fact about top contributors is that not only the quantity but also the quality of their answers is higher than others. The quality of shared knowledge is measured by Best Answer Ratio. For each question proposed in Baidu Knows, askers are required to select and mark one best answer, if possible, from all the answers proposed by other members. The profile of each member contains the Best Answer Ratio, which shows the percentage of answers that are rated as the best among all answers provided by each member. The average Best Answer Ratio of top contributors is 20.9%, which is much higher than the 12.5% average for the rest.[3] This indicates that top contributors appear to be the driving force of the knowledge sharing communities. They answer about three quarters of the total questions, and one fifth of their answers have been selected as the best answer by askers. On average, each of them has answered 2,021 questions, which is quite astonishing considering the two year time span of our sample data.

Interestingly, the data shows that top contributors can be further classified into two different subgroups by using the 1,000 Reward Points as the demarcation point. 85.3% of the top contributors' Reward Points are less than 1,000, indicating that they asked less than 223 questions in the past. This is in sharp contrast to the 2,021 questions they answered. As a result, we call these members pure contributors, as they seem to be inclined to passing knowledge to others without expecting anything in return.

The second group of top contributors not only answers many questions but is also active knowledge seekers by asking many questions. 14.7% of the top contributors' Reward Points are higher than 1000, with the average at 2,619, which means that they asked 589 questions on average in the past. We call these members active contributors and knowledge seekers. On one hand, they are keen on sharing knowledge with others. On the other hand, they are also active knowledge seekers, who frequently propose questions and give high rewards to answerers.

[3] When we calculate the average Best Answer Ratio, we delete those members whose No. of Answer is less than 10.

Casual contributors are 90% of all registered members in the community. They answered 496,769 questions, accounting for 23.5% of the total questions. Both the quantity and the quality of their shared knowledge are inferior to that from the top contributors.

3. KNOWLEDGE SHARING MOTIVATIONS

Social exchange theory states that members engage in social interaction based on the expectation that it will lead in some way to social rewards, such as approval, status, and respect (Blau 1964). Ma and Agarwal (2007) theorized that participants share knowledge in online communities for both extrinsic benefits and intrinsic benefits. Donath (1999) proposed that in Usenet newsgroups, identity, both the establishment of their own reputation and the recognition of others, plays a vital role.

In knowledge sharing platforms, Reward Points could serve both as extrinsic award and intrinsic award. First, Reward Points act as the electronic money in the community. When members propose their questions, they need to pass some of their Reward Points to answerers. Second, Reward Points indicate the status of the member. In Baidu Knows, members are classified into 18 levels. Once members have accumulated certain Reward Points, they could be promoted to a higher level, indicating that they are more knowledgeable and have higher willingness to help others. As a result, high Reward Points can help members move up to higher levels and receive more esteem from others. This is hypothesis 1:

H1: Members share knowledge because of extrinsic and intrinsic motivations. The higher the Reward Points are associated with a question, the more answers it will get from others.

To check whether the Reward Points assigned to a question are related to Number of Answers it is likely to solicit, we use nonparametric test: Pearson's r, Spearman's rho, and Kendall's tau_b. The results are reported in Table 2:

	Computer	Entertainment	Both Categories
Pearson's r	0.516***	0.249***	0.372***
Spearman's rho	0.254***	0.105***	0.167***
Kendall's tau_b	0.208***	0.084***	0.136***

*** Significant at the 0.01 level (2-tailed)

Table 2. Nonparametric correlation between Reward Points and No. of Answers

Our results show that in both the Computer category and the Entertainment category, Reward Points are significantly correlated with No. of Answers. The strength of correlation is higher in the Computer category than that in the Entertainment category. Therefore, H1 is accepted.

People are not only pragmatic but also expressive of feelings, values, and self-identities (Baudura 1986, Schlenker 1985, Shamir 1991). In knowledge sharing communities, members could increase self-worth, personal identification with the organization, self-respect, respect from others, and feelings of commitment by helping others. Bandura (1986) posited that self-evaluation based on competence and social acceptance is an important source of intrinsic motivation that drives engagement in activities for the sake of the activity itself, rather than for external rewards. Wasko and Faraj (2000) also demonstrated that members may contribute knowledge within the collective because solving problems is challenging or fun, and because helping others is enjoyable. Therefore, we may expect that enjoyment of helping is one of the main motivations for members' contribution to the collective.

In knowledge sharing platforms, some questions do not provide Reward Points to answerers. If such questions are still answered by other members, we may expect that the answerers reply such questions not for Reward Points, but for the joy they achieved during the helping process. Therefore, we propose the hypothesis 2:

H2: Some member share their knowledge because of the enjoyment of helping others.

Overall, the Reward Points given out are very low. 47.86% of questions do not have any Reward Points. 92.8% of questions have Reward Points less than 30. Only 3.3% of the questions have Reward Points higher than 100, the highest being 200. Those questions having zero Reward Points have on average 1.91 answers, and only 17.8% of them are not answered. These results seem to indicate that some members are not motivated by extrinsic awards, but possibly by the enjoyment of helping others, thus confirming H2.

Although exchanges in electronic social networks occur through weak ties between strangers, there is evidence of reciprocal supportiveness (Wellman and Gulia 1999). In online communities, members tend to show generalized reciprocity. Scholars believe that in online communities with strong sharing social norms, members may offer their help either because that they may have been helped by others in the past or they may expect that some one in the community would help them if they have a question in the future. If reciprocal supportiveness is one motivation for members' knowledge sharing behavior, a member's helping tendency should be valued by others in the community. In other words, a member who used to help others should be more likely to get help from others compared with free riders. Therefore, we propose the following hypothesis

H3: Members who shared their knowledge more frequently in the past will get more responses when they post their questions.

We use the following regression function to check the correlation between members' past answering behavior and the No. of answers they received when they propose their own questions. The result are reported in Table 3

No. of Answers= Reward Points + Askers' No. of Answers in History

	Constant	Reward Points	No. of Answers in History
Whole Sample	2.289(0.048) t =47.417***	0.035(0.002) t =21.076***	0.00001(0.000) t =0.206
	R Square=0.139 F=222.152***		
Computer Category	1.884(0.059) t =31.735***	0.04(0.002) t = 22.390***	0.00001(0.000) t = -0.802
	R Square=0.267 F=250.793***		
Entertainment	2.674(0.075) t = 35.865***	0.028(0.003) t = 9.555***	0.0001(0.000) t = 1.031
	R Square=0.063 F=46.152***		

Table 3. Regression Results for No. of Answers against Asker's No., of Answers in History

This regression results show that No. of Answers is correlated with Reward Point, which of course confirms H1. However, Askers' No. of Answers in History is not significantly correlated with No. of Answers a qustion gets. The result is quite important: members' helping behavior does not pay off in terms of getting more answers when they need help in the future. No. of Answers in History indicates how many times a user helped others and contributed his/her knowledge. When this user calls for help and posts questions, others do not seem to value the asker's past behavior. That means, the conclusion that people help others due to reciprocal supportiveness motivation cannot be drawn in the Baidu Knows sample data, thus rejecting H3.

When members ask for help in online communities, they usually send out their Reward Points to attract others to answer their questions. However, around half of the questions do not send out Reward Points and the askers can be viewed as free riders. Such phenomenon begs the question who tends to value more others' knowledge sharing behavior?

Individual centrality concept defines that individuals who are centrally embedded in a collective have a high probability of direct ties with other members. They have a richer social capital. Such members can exert more influence than others. They are more likely to cooperate with others and comply with group norms and expectations (Rogers and Kincaid 1981).

Members who frequently shared their knowledge and have high Best Answer Ratio are core members of the community. Members with high Best Answer Ratio are more connected to other members and have developed the habit of cooperation. They understand the efforts of sharing knowledge through their past experience. When they call for help from others, they tend to follow the sharing group norm and value the efforts of others. Therefore, we propose the following hypotheses:

H4: Members who shared their knowledge more frequently before will set high Reward Points when they post their own questions.
H5: Members who have high Best Answer Ratio will set high Reward Points when they post their own questions.

To check H4 and H5, we use nonparametric tests to check the correlation between Reward Points and No. of Answers in History, and Best Answer Ratio. The results are reported in Table 4 and Table 5 respectively.

	Computer	Entertainment	Both Categories
Pearson's r	0.013	0.021*	0.006
Spearman's rho	0.064**	0.047*	0.000
Kendall's tau_b	0.051**	0.003	0.001

Table 4. Correlation between Reward Points and No. of Answers in History

	Computer	Entertainment	Both Categories
Pearson's r	0.119***	0.059*	0.089***
Spearman's rho	0.073***	0.023	0.026
Kendall's tau_b	0.059***	0.19*	0.020

Table 5. Correlation between Reward Points and Best Answer Ratio

The results show that Reward Points of questions in the Computer category are correlated with askers' past behavior. In that category, members who answer more questions, or Members whose answers are frequently adopted by others as the best answer tend to set high Reward Points for their question. Therefore, H4 and H5 are accepted in the Computer category, while the same can not be said about the Entertainment category.

4. FREE RIDER BEHAVIOR

To investigate free rider behavior, we classify members into askers and answerers. Askers are defined as those members in the sample who have asked at least one question. Answerers are defined as those members who have answered at least one question. Table 6 shows the cumulative percentage of members' past No. of Answers in the Computers category. According to their past behavior, 38.4% of askers never answered questions. 63.1% of askers answered less than 10 questions before. In contrast, only 1.3% of answerers never answered question before and answered their first question in our sample. Also, only 9.3% of answerers answered less than 10 questions before. Further more, 87.4% askers answered less than 100 questions, while only 43.6% answerers answered less than 100 questions.

Past No. of Answers in Computer Category	Askers' Cumulative Percentage	Answerers' Cumulative Percentage

0 (free riders)	38.4%	1.3%
Less than 10	63.1%	9.3%
Less than 100	87.4%	43.6%
Less than 1000	99.2%	87.1%

Table 6. The Cumulative Distribution of Past No. of Answers in Computers Category

In the Entertainment category, the results are quite similar. As shown in Table 7, 33.8% of the askers are free riders, while only 1.6% of the answerers are free riders.

Past No. of Answers in Entertainment Category	Askers' Cumulative Percent	Answerers' Cumulative Percent
0	33.8%	1.6%
Less than 10	59.3%	13.1%
Less than 100	87.4%	54.8%
Less than 1000	98.8%	87.5%

Table 7. The Cumulative Distribution of Past No. of Answers in Entertainment category

Such results clearly illustrate that askers show less willingness to help others compared with answerers. In both categories, askers show much less willingness to help than answerers. Around 35% to 40% askers in both categories are free-riders, as they never answered questions before. Around 60% askers in both categories answered less than 10 questions before. Although such members show more selfishness in contributing knowledge than others, it appears that they are actually the key factor to sustain the online community. They are active knowledge seekers and propose around 60% of questions. They value the answers from others and actively rate which one is the best. Because of the existence of such members, online community is able to sustain and prosper.

The free rider phenomenon may also be viewed from a box-plot of user behavior. We collect past behavior of askers and answerers and examine how many times each member have shared their knowledge before. The box-plot of the Computer category [Figure 3] and the Entertainment category [Figure 4] clearly show that answerers usually shared knowledge more frequently than askers. Moreover, answerers have much more outliers compared with askers, indicating that more answerers are extremely generous with respect to sharing their knowledge.

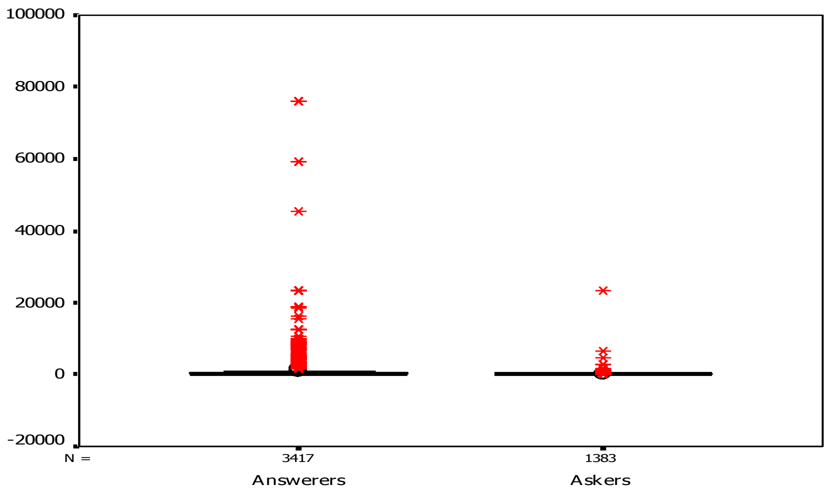

Figure 3. The Boxplot of the Computer Category

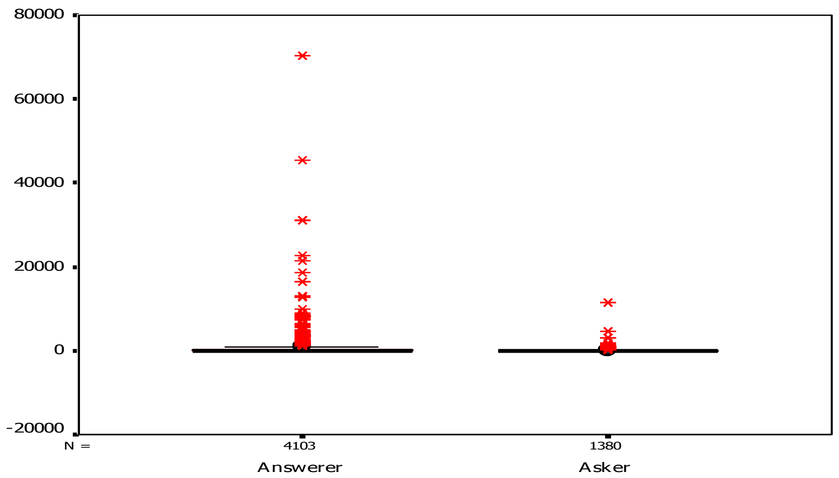

Figure 4. The Boxplot of the Entertainment Category

Besides the free rider behavior associated with askers and answerers, many other non-registered free riders are not included in our sample. Baidu Knows is an open community, that attracts users who did not register at Baidu Knows, but still browse the questions and answers in seeking knowledge. Baidu Knows also gets routed traffic from the regular Baidu search engine. Since this type of free rider behavior does not leave any trace in the community, it is difficult to investigate their behavior and assess their population size. We did surveys in two undergraduate and three postgraduate classes in a well-established university in China. All the students in these classes had visited Baidu Knows and browsed questions and answers. However, only one tenth of them were registered members in Baidu Knows. Such simple survey results indicate that the proportion of free riders in the knowledge sharing communities is much larger than that reflected in our sample.

5. QUALITY OF KNOWLEDGE SHARING

Quality of shared knowledge is one of the key factors determining whether the community will be sustainable over the long run. Those members who share high quality knowledge are the most valuable resources of the community. Who will share high quality knowledge? What are the characteristics of the members who share high quality knowledge? These are the questions we address in this section.

The self-verification concept, rooted in cognitive dissonance theory, suggests that people are more satisfied and likely to participate in a relationship when their salient identities are confirmed by others in a group (Swann 1983, Swann et al. 1987). Members who shared high quality knowledge obviously have higher Best Answer Ratio. Their sharing behavior is acknowledged by others. They will have a relatively high self verification than others and have higher motivation to help others in the future. Therefore, we suggest the following hypotheses:

H6: Members whose ratios of best answer are high will share knowledge more in the community.

H7: Members whose ratios of best answer are high will set high Reward Points for others.

H8: Answerers have higher ratios of best answer compared with askers.

To investigate who are sharing high quality knowledge in the community, we use the following regression function to examine the relationship between quality of shared knowledge and members' characteristics.

Y=Best answer ratio	Computer Category	Entertainment	Whole Sample
	R2=0.098 F=173.50***	R2=0.098 F=197.38***	R2=0.086 F=242.9***
No. of Answers	0.001(0.000) t =7.922***	0.001(0.000) t =15.163***	0.001(0.000) t =14.857***
Reward Points sent out by certain ID	0.001(0.000) t =3.484***	0.005(0.001) t =8.255***	0.002(0.000) t =6.726***
Asker/Answerer (Asker=0; Answerer=1)	8.666(0.436) t =19.869***	7.110(0.470) t =15.144***	7.877(0.323) t =24.357***

Table 8: The correlation between Best Answer Ratio and Reward Points

The regression results show some interesting findings: first, members answered more questions shared high quality knowledge as well. Second, members who shared high quality knowledge sent out more Reward Points, which means that they value others' sharing behavior more. Third, compared with askers, answerers' shared knowledge has high quality compared with askers'.

Such results indicate that those answerers who frequently answer questions are the most valuable resources in the community. They not only answered most questions but answered with higher quality. Also, we may envision a positive circulation formed in the community. Answerers who share high quality knowledge will be acknowledged by others and have high Best Answer Ratio. In return, those members are motivated due to the acknowledgment by other members, and thus will answer more questions. Further more, since they understand the efforts involved in sharing knowledge, they will send out high Reward Points to others when they propose their questions.

6. CONCLUDING REMARKS

This paper uses empirical data that we collected from a spider engine to investgate user profile, knowledge sharing motivations and quality of sharing knowledge in online communities. We found two groups of people are extremely important in driving the growth of these communities. First, the top contributors unselfishly answer other questions, contributing their own knowledge. Among these people, there are approximatley 85% are pure contributors, seldom asking any questions. The second group of users are those who seldom answer questions, but always ask questions. Although their behavior seems selfish at the surface, they are actually the key factors driving the growth of online knowledge sharing communities. It is precisely because of these users' questions that the online communities see reasons of existence.

Majority of free riders appear to be those non-registered members outside our sample. In order to spur further growth, organizors of online knowledge sharing communities may think of ways to have these free riders join the community.

We also investigated motivations of contributing knowledge. Although Reward Points and reciprocal-supportiveness are clear factors explaining knowlege sharing behavior, there are also many members who do not care about rewards. Our conjecture is that these members derive satisfaction from helping others as a motivation of contributing knowledge.

Unlike previous results, we found that members' past behavior does not seem to be acknowledged by others. That is to say, those who have a history of helping others, do not seem to get above-average help from others when they need help. This may be because knowledge sharing communities are simply too large with too many members, and the bonding relationship seems to exist between members and the community itself, as opposed to between members. When users decide whether to answer a question, he may be more concerned about his relationship with the community, instead of the ID identity of the author of the question.

We also found that the value of shared knowledge sees a positive correlation with past behavior. Those members who historically contributed a lot tend to award members higher who answer their questions. These people are also the core members driving the growth of online communities.

Our study confirms the intrinsic and extrinsic motivations of knowledge contribution based on real member usage data, supplementing the survey methods that have been traditionally used in this type of studies. In future research, we plan to incorporate data from the Yahoo! Answers, to investigate different user behavior under the different reward mechanisms. We conjecture that there might be also different cultural factors in driving knowledge sharing behavior.

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