Stimulating High Quality Social Media through Knowledge Barter-Auctioning

Qijin Ji
School of Computer Science and Technology
Soochow University
Suzhou, China
ji@suda.edu.cn

Haifeng Shen
School of Computer Science, Engineering and Mathematics
Flinders University
Adelaide, Australia
haifeng.shen@flinders.edu.au

Yuqing Mao
National Center for Biotechnology Information
National Library of Medicine
National Institutes of Health
Bethesda, MD, USA
yuqing.mao@nih.gov

Yanqin Zhu
School of Computer Science and Technology
Soochow University
Suzhou, China
yqzhu@suda.edu.cn

ABSTRACT

Incentives play a pivotal role in stimulating user-generated content (UGC), which is critical to the viability and success of today's social computing services. Non-financial social incentives are generally effective in boosting the quantity, but have limited effect on the quality. Conversely, financial incentives generally motivate better quality, but often complicate the efforts to attract quantity. In this paper, we propose knowledge barter-auctioning, a non-financial remunerative mechanism that is particularly effective in stimulating the quality of UGC yet without detriment to its quantity. This mechanism provides an optimal way for the knowledge vendor to choose the best barter partner in order to maximise their expected revenue, which is an extrinsic motivation for the triumph of quality as UGC of higher quality will enable the vendor to attract more bidders and consequently make a higher revenue through the barter auction. We have conducted a series of experiments using a real-world dataset to analyse the ramifications of UGC quality in knowledge bartering processes.

Categories and Subject Descriptors

H.3.5 [**Information Storage and Retrieval**]: Online Information Services—*Data sharing, Web-based services*

General Terms

Algorithms, Design

SocialCom'14, August 04 - 07 2014, Beijing, China

http://dx.doi.org/10.1145/2639968.2640086

Keywords

user-generated content, incentive, bartering, optimal auction

1. INTRODUCTION

User-generated content (UGC) is the foundation of social computing services like social media, social networking, and question-answering (Q&A). Sustained participation and UGC contributions from users are critical to the viability and success of an online social community [18]. If everyone chose to free-ride on the efforts of others, the community would eventually collapse and the social computing service would cease to exist naturally [24]. Therefore, a healthy online social ecosystem requires an effective incentive mechanism, which needs to consider both intrinsic or extrinsic motivational factors. Intrinsic motivations reflect spontaneous self-satisfaction from one's participation itself rather than its payoff, including enjoyment of altruism [17], reciprocation [1], or obligation to contribute [24]. Extrinsic motivations revolve around the payoff for one's participation rather than the participation per se, that is, the expected benefits of contributing are perceived to exceed the cost of making the contribution, including improvement of skills through receiving feedback from others [13], building up professional reputation within the community [24], or receiving rewards, which can be either financial [20] or non-financial [9].

A representative non-financial remunerative mechanism is virtual currency, which has been widely adopted in social media and online social communities for users to purchase virtual goods, virtual friends, or simply information. For example, in *Yahoo!Answers*, one is rewarded points for their answer acknowledged by the asker, which can be accumulated and redeemed to post their own questions. Virtual currency may have partially tackled the quantity issue by stimulating participants to earn more "virtual money" through making more UGC contributions, but its impact on the quality is questionable because participants can easily accumulate virtual wealth by exploiting the system rather than through the hard work of improving the quality of their contributions.

An example of non-financial remunerative mechanisms addressing the quality issue is social attention stemmed from the theory of social psychology, where a UGC contribution of higher quality is rewarded more exposure or viewer attention. Work has been done to study reasonable allocation of exposure opportunities among users based on their contributions using game-theoretic models [5, 6]. Studies [20] have further shown that social incentives (based on intrinsic and non-financial extrinsic motivational factors) are more effective in boosting the quantity than financial incentives, but the latter exert more positive influences on the quality.

In this paper, we propose knowledge barter-auctioning, a non-financial remunerative incentive mechanism that is particularly effective in stimulating the quality of UGC yet without detriment to its quantity. This mechanism provides an optimal way for the knowledge vendor to choose the best barter partner in order to maximise their expected revenue, an extrinsic motivation for the triumph of quality as UGC of higher quality will enable the vendor to attract more competitors and consequently make a higher revenue through the barter auction. We have conducted a series of experiments using a real-world dataset to analyse the ramifications of UGC quality in knowledge bartering processes.

The rest of the paper is organised as follows. We first introduce related work in the next section. We then describe the conceptual model followed by the working mechanism of knowledge barter-auctioning. After that, we present a series of experiments and discuss the experimental results. Finally, we conclude the paper with a summary of major contributions and future work.

2. RELATED WORK

From the economical point of view, knowledge has value and an online social community should be not only a platform for users to create and consume knowledge but also a market for users to trade their knowledge. Knowledge buyers are individuals who try to solve a complex issue that precludes an easy answer and knowledge sellers are those who have a reputation for their substantial knowledge about a subject or process. Knowledge trading in knowledge markets is established on the belief that both buyers and sellers can benefit from exchanging their intellectual properties [15].

As a representative example of online knowledge markets, online question-answering systems can be categorised into community question-answering services (CQA) and fee-based question-answering services. Because knowledge sharing by answering questions is not subsidised in CQA, an incentive mechanism is required to encourage participants to dedicate their efforts to knowledge sharing. Altruism exists to some extent, but it is not always good enough to motivate participants to devote themselves to difficult tasks. Virtual currency is more widely adopted as a non-financial trading model for online knowledge markets, However, as it is a metaphor of real currency, it inevitably inherits most of economic problems such as inflation and deflation [8] as participants can easily accumulate virtual wealth through acts like collusions or sockpuppets.

In recent years, some research has been done to explore motivational factors from social psychology perspectives. High interaction and rating in an online social community generally make participants feel satisfied, thus encouraging them to contribute more and better. Dearman and Truong found that in CQA systems, the most significant reason for a user (not) to answer a question is not the question itself, but the perceived importance of their answer by the asker and the perceived ranking of the answer by all answerers [3]. Social psychological rewards, such as social attention, are not unlimited resources and therefore should be distributed appropriately amongst participants to incentivise desirable behaviours. Game-theoretical approach is considered a good choice for analysing the design of such allocation mechanism [22]. For example, Jain *et al.* proposed a game-theoretic model of sequential information aggregation motivated by online question-answering forums and investigated the effect of different rules for allocating points on the equilibrium behaviour [9]. A game-theoretical model was also used to analyse the impact of exposing mechanisms like elimination and ranking on the elicitation of high quality contributions as the participation or attention diverged [4].

As a pioneer of fee-based question-answering services, *Google Answers* adopted a financial trading model allowing askers to offer bounties to the experts who have provided good answers to their questions. However, financial incentives do not lead to more and sustained user participation. Shah *et al.* reported that *Google Answers* did not gain more popularity than its CQA counterpart *Yahoo! Answer* [21]. Raban analysed two expert subgroups in an online information market and showed that a pure financial incentive serves as enticement, however, social incentives induce persistent participation by experts and eventually lead to higher average economic gains [19]. Furthermore, there is no evidence that questions of higher prices would necessarily receive better answers. Chen *et al.* observed that offering a higher reward for a question often leads to a significantly longer, but unnecessarily better, answer, while answerers with a higher reputation usually provide significantly better answers [2]. Jeon *et al.* again concluded that price is a factor in determining whether a question could receive answers, however it does not have a direct effect on the quality of answers [10].

We want to investigate the quality issue from a different perspective. Increasing the price of a question may not necessarily get a better answer, but a UGC contribution of higher quality should sell for a better price through auctioning, a widely used game-theoretic model. Furthermore, to avoid the ramifications of a financial system, a non-financial payment solution based on knowledge bartering [14] is integrated into the auctioning mechanism, leading to a unique solution referred to as barter-auctioning. The auction theory has been used in many applications such as advertisement positions in web pages [23]. To the best of our knowledge, this is the first work that combines the auction theory with the bartering economic model to design an incentive mechanism for online knowledge markets.

3. A CONCEPTUAL MODEL FOR KNOWLEDGE BARTER-AUCTIONING

We proposed knowledge bartering [14] as an alternative non-financial remunerative mechanism for online social communities, which allows one to barter a knowledge item they have as an exchange for another item they wish to have. It primarily stimulates the quantity of UGC contributions because the more one can offer to others, the more one can get from others. It does have implications on the quality to some extent because the higher quality a UGC contribution has, the more likely it is accepted as barter, however it has no guarantee that a low quality UGC contribution would never be part of a successful barter transaction and consequently is unable to prevent self-interested users from exploiting the system by bartering their low quality UGC.

The online silk road solution was further proposed to automate knowledge bartering processes in order to maximise the social welfare within an online social community. It adopted a centralised strategy: first generating a complete directed graph representing participants and their supply-demand relationships, then finding potential barter transactions by discovering cycles in the graph, and finally producing all knowledge bartering online silk roads, each consisting of cycles with the maximum cardinality. The ultimate goal was to single out the maximum-weight online silk road consisting of cycles whose length is under a constraint in order to achieve social welfare maximisation, that is, the community as a whole can gain the maximum benefit.

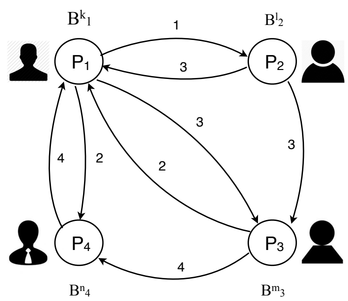

Figure 1: Supply-demand relationships

Each participant must clearly describe their supply and demand in order to establish supply-demand relationships and derive the quality of supply in relation to the demand (denoted by the weight of each edge in the graph). Figure 1 shows an example of knowledge bartering consisting of 4 participants and 8 supply-demand relationships, where the maximum-weight online silk road consists of two cycles: $\{P_1, P_2, P_3\}$ and $\{P_1, P_3, P_4\}$. A participant is allowed to barter the same UGC with multiple parties, for example, P_1 passes on her/his barter B_1^k to both P_2 and P_3 and receives B_3^m and B_4^n from P_3 and P_4 respectively as a return in the two cycles. Knowledge quality is only used in determining the maximum-weight online silk road but not directly involved in choosing the barter partners, for example, two low quality supplies $(P_1 \rightarrow P_2)$ and $(P_3 \rightarrow P_1)$ have to be included in the barter transactions.

Built upon the foundation of knowledge bartering for boosting the quantity of UGC contributions and auction as a profound theory in applied economics for selling goods to potential buyers with unknown values [11], we propose knowledge barter-auctioning to further stimulate the quality of UGC contributions through the following measures.

- It adopts a distributed strategy: no graph needs to be generated, no cycle needs to be discovered, and each barter transaction only involves two parties. The 2-party bartering solution is more efficient and robust than the multi-party one and not susceptible to a single point of failure.
- It does not ask participants to describe their demand requirements; instead each participant only needs to profile their set of interests (SOI) and label each of their UGC contributions with an appropriate SOI. In Figure 1, edges $(P_1 \rightarrow P_2)$, $(P_1 \rightarrow P_3)$, and $(P_1 \rightarrow P_4)$ indicate that P_1's B_1^k is within P_2's, P_3's, and P_4's SOIs, that is, $SOI(B_1^k) \cap SOI(P_i) \neq \varnothing$, where $1 < i \leq 4$. A SOI has a broader coverage than a specific demand, making it possible for more barter opportunities.
- It is based on the assumption that participants are self-interested. Therefore its primary objective is to maximise individuals' benefits through an optimal auctioning mechanism rather than the social welfare through discovering online silk roads.

For the example in Figure 1, for P_1 to maximise her/his benefit from bartering B_1^k, she/he would need to ensure its quality as a high-quality UGC contribution is likely to attract high-quality bids from the potential competitors P_2, P_3, and P_4 through an auctioning process. If the auction is successful, one of the competitors, for example, P_4, will win the barter and consequently P_1 will transfer her/his bartering right of B_1^k to P_4. For the same token, competitors are also motivated to ensure the quality of their UGC contributions in order to win the bid.

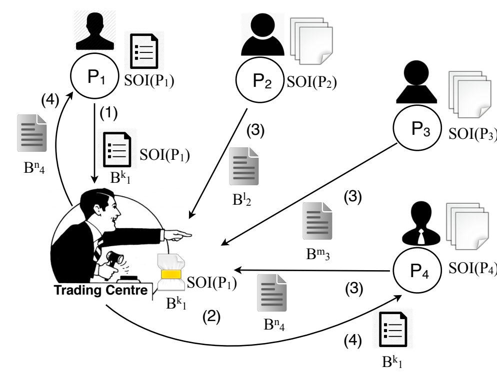

Figure 2: Knowledge barter-auctioning

Figure 2 depicts the knowledge barter-auctioning process for P_1 to auction B_1^k to the competitors P_2, P_3, and P_4 through a trading centre.

1. Vendor P_1 dispatches barter item B_1^k and $SOI(P_1)$ to the trading centre.
2. The trading centre first generates a summary of B_1^k using an extractive summarisation technique [7] and then displays the summary of B_1^k and $SOI(P_1)$ in the market. The summary serves the purpose of attracting potential buyers without revealing the full content in order to protect the vendor's intellectual property .
3. Qualified bidders $\{P_i \mid 1 < i \leq 4 \wedge SOI(B_1^k) \cap SOI(P_i) \neq \varnothing \wedge \forall i, \exists j \colon SOI(B_i^j) \cap SOI(P_1) \neq \varnothing\}$ each privately evaluate the quality of the published summary of B_1^k based on which they send a barter item of their own as a bid to the trading centre. In this example, the qualified bidders are P_2, P_3, and P_4 whose bids are B_2^l, B_3^m , and B_4^n respectively. Private quality evaluation may consider factors such as relevance, vendor's trustworthiness, and bidder's personal preferences, but it is beyond the scope of this paper.

4. The trading centre verifies the SOI and quality of each bid, determines the winner of this auction, and completes the barter-auctioning process by delivering the auctioned barter item to the winner and the winning bid to the vendor. In this example, P_1's B_1^k is successfully bartered with P_4's B_4^n.

4. AN OPTIMAL AUCTION MECHANISM FOR KNOWLEDGE BARTERING

In an open knowledge market, it is reasonable to assume all knowledge owners (vendors or buyers) are selfish, rational, and autonomous, each seeking to maximise their own expected revenue through bartering their knowledge goods. Considering each UGC contribution to be a single indivisible item, a pivotal issue is for the vendor to choose a barter partner from more than one competitor in order to maximise their expected revenue through an auction where the vendor's revenue is determined by competition among the bidders according to the rules set out by the vendor.

4.1 Auction Theory

In mechanism deign theory, an auction mechanism has three key elements: a set of bids, an allocation rule, and a payment rule. The allocation and payment rules are both functions of the bids, where the former determines the probability in which each bidder will win the competition, while the latter determines the payment the winner must make. According to the revelation principle of the mechanism design theory [16], outcomes from any equilibrium are equivalent to a truthful equilibrium of a direct mechanism, where the players report their private values truthfully. Without loss of generality, we only design a direct auction mechanism.

Let V be the vendor of a barter item and $C = \{C_i \mid i = 1, 2, \cdots, N\}$ be the set of N competitors. Competitors individually assess the private quality values of V's barter, which are independently distributed. Assume competitor C_i's private quality value X_i is distributed over the interval $\chi_i = [0, \varpi]$ according to the distribution F_i with associated density function f_i. We allow for asymmetries among the competitors: the distributions of the estimated quality values might be different among competitors. Let $\chi = \prod_{j=1}^{N} \chi_j$ denote the product of the sets of estimated quality values and for $\forall i, \chi_{\neg i} = \prod_{j \neq i} \chi_j$. Define $f(x)$ to be the joint density of $X = (x_1, x_2, \cdots, x_N)$. Since estimated quality values are independently distributed, $f(X) = \prod_{j=1}^{N} f_j(x_j)$ and similarly we define $f_{\neg i}(X_{\neg i}) = \prod_{j \neq i} f_j(x_j)$ to be the joint density of $X_{\neg i} = (x_1, \cdots, x_{i-1}, x_{i+1}, \cdots, x_N)$.

Consider a direct mechanism (Q, M) for knowledge barter-auctioning, which consists of a pair of functions: $Q\colon \chi \rightarrow \Delta$ and $M\colon \chi \rightarrow R^N$, where $Q_i(x)$ is the probability in which competitor C_i will win the competition and $M_i(x)$ is the expected payment made by C_i. With the distributions of knowledge quality values from the competitors, given a direct mechanism, denote

$$q_i(z_i) = \int_{\chi_{\neg i}} Q_i(z_i, x_{\neg i}) f_{\neg i}(x_{\neg i}) dx_{\neg i} \tag{1}$$

the probability in which C_i will win the competition when their reported value is z_i and all other competitors report their private values truthfully. Similarly, denote

$$m_i(z_i) = \int_{\chi_{\neg i}} M_i(z_i, x_{\neg i}) f_{\neg i}(x_{\neg i}) dx_{\neg i} \tag{2}$$

the expected payment from C_i when their reported value is z_i and all other competitors tell the truth.

Then $U_i(x_i)$, the expected payoff (or utility) for competitor C_i, is the revenue minus the corresponding cost. When C_i's true value is x_i, but the reported value is z_i, again assuming that all other competitors tell the truth, C_i's utility is expressed as

$$U_i(z_i) = q_i(z_i)x_i - m_i(z_i). \tag{3}$$

Apart from the goal of maximising the vendor's revenue, *Incentive Compatibility (IC)* and *Individual Rationality (IR)* are two other desired properties.

Definition 1. *Incentive Compatibility (IC)*

The direct mechanism (Q, M) is said to be incentive compatible, if for $\forall i, U_i(x_i) \equiv q_i(x_i)x_i - m_i(x_i) \geq q_i(z_i)x_i - m_i(z_i)$, where C_i's true and reported values are x_i and z_i respectively.

We refer to $U_i(x_i)$ as the equilibrium payoff function, which can also be expressed as

$$U_i(x_i) = \max_{z_i \in \chi_i} \{q_i(z_i)x_i - m_i(z_i)\}. \tag{4}$$

The IC property is to ensure that rational competitors will prefer telling the truth about their private quality values because it would help increase their expected payoff as compared to not doing so. A competitor's expected payoff in an incentive compatible direct mechanism (Q, M) depends only on the allocation rule, up to an additive constant.

Definition 2. *Individual Rationality (IR)*

Assume that by no participation a competitor's payoff is zero. A direct mechanism (Q, M) is said to be individual rational, if for $\forall i, U_i(x_i) \geq 0$, where competitor C_i's true value is x_i.

If the payment required by an auction mechanism is too high, potential competitors may choose not to participate. The IR property is to ensure rational competitors that they would never be worse off by participating in the auction.

4.2 Optimal Auction for Quality-aware Knowledge Bartering

From the game-theoretic point of view, knowledge bartering can be considered a game among the competitors whose bidding strategies are functions of their private value distributions. The game will reach the equilibrium if the players all want to maximise their expected payoff.

In an auction, the vendor's revenue, denoted by R, comes from the payment of all competitors. It is generally the sum of all competitors' payment. Because a UGC contribution is indivisible in knowledge bartering, only one competitor will win it. In a direct mechanism, the expected revenue of the vendor is defined as

$$E[R] = \sum_{i \in N} E[m_i(X_i)].$$

An optimal auction mechanism is defined as follows for each vendor to maximise their expected revenue by bartering their UGC contribution with the auction winner.

Definition 3. *Optimal Auction Mechanism*

A direct mechanism is an optimal auction if the outcome resulted from the mechanism's allocation and payment rules maximises the expected revenue of the vendor under the constraints of incentive compatibility and individual rationality.

Specifically, an optimal auction mechanism needs to define the allocation and payment rules in order to solve the following problem:

$$\begin{aligned} &\max(E[R]), \text{subject to} \\ &(1)\ U_i(x_i) = \max_{z_i \in \mathcal{X}_i} \{q_i(z_i)x_i - m_i(z_i)\} \text{ and} \\ &(2)\ U_i(0) \geq 0. \end{aligned}$$

In a direct mechanism (Q, M), the *ex ante* expected payment of competitor C_i is

$$\begin{aligned} E[m_i(X_i)] &= \int_0^{\omega_i} m_i(x_i) f_i(x_i) dx_i \\ &= m_i(0) + \int_0^{\omega_i} x_i q_i(x_i) f_i(x_i) dx_i \\ &\quad - \int_0^{\omega_i} (1 - F_i(x_i)) q_i(x_i) dx_i. \end{aligned} \tag{5}$$

This optimisation problem can be further clarified by defining virtual valuation of private value.

Definition 4. *Virtual valuation*

The virtual valuation of competitor C_i is $\psi_i(.) \equiv x_i - \dfrac{1 - F_i(.)}{f_i(.)}$.

The auction problem is said to be *regular* if for $\forall i, \psi_i(.)$ is an increasing function of the true value x_i. In the remainder of the paper, we assume the auction problem is regular. Then Equation 5 can be reformulated as

$$E[m_i(X_i)] = m_i(0) + \int_{\mathcal{X}} \psi_i(x_i) Q_i(x) f(x) dx$$

by using the definition of $q_i(x_i)$ from Equation 1 and $\psi_i(.)$ from Definition 4.

So the vendor's objective is to design a direct mechanism so as to maximise

$$\sum_{i \in N} m_i(0) + \int_{\mathcal{X}} (\sum_{i \in N} \psi_i(x_i) Q_i(x)) f(x) dx. \tag{6}$$

while satisfying the constraints of incentive compatibility and individual rationality. As $m_i(0)$ is a constant, maximising $\sum_{i \in N} \psi_i(x_i) Q_i(x)$ will maximise Equation 6.

Vickrey - Clarke - Groves (VCG) [11] is an efficient auction mechanism that can maximise social surplus of the bidders' set, that is $\sum_{i \in N} x_i Q_i(x)$. Considering $\sum_{i \in N} \psi_i(x_i) Q_i(x)$ to be the virtual social surplus, that is the social surplus comprised of virtual private quality values, we design the *Knowledge Optimal Barter-Auction (KOBA)* algorithm based on VCG in order to achieve maximisation of virtual social surplus, which is illustrated by Algorithm 1.

ALGORITHM 1: Knowledge Optimal Barter-Auction (KOBA)

a. Estimate each C_i's virtual private quality value distribution $\psi_i(x_i)$ towards the vendor's barter.

b. Run the VCG mechanism over a set of virtual quality private value distributions (PQVDS) from all competitors $PQVDS = \{\psi_i(x_i) \mid i = 1, 2, \cdots, N\}$: $(Q', M') \leftarrow VCG(PQVDS)$.

c. Derive the allocation and payment rules: $Q_i(x_i) = Q'_i(x_i)$ and $M_i(x_i) = \max(M'_i(x_i), \psi_i^{-1}(0))$

Because there is only one indivisible barter item for auction in every knowledge trading process using KOBA, the mechanism can actually be reduced to a second price auction. Let $y_i(x_{\neg i}) = \inf\{z_i : \psi_i(z_i) \geq 0 \wedge \forall j \neq i, \psi_i(z_i) \geq \psi_j(x_j)\}$, which is the minimum private quality value corresponding to the non-negative virtual value that can win the auction. The allocation and payment rules in Algorithm 1 can be reformulated as

$$Q_i(z_i, x_{\neg i}) = \begin{cases} 1 & \text{if} \quad z_i \geq y_i(x_{\neg i}) \\ 0 & \text{if} \quad z_i < y_i(x_{\neg i}), \end{cases}$$

$$M_i(x) = \begin{cases} y_i(x_{\neg i}) & \text{if} \quad Q_i(x) = 1 \\ 0 & \text{if} \quad Q_i(x) = 0. \end{cases}$$

5. EXPERIMENTS AND RESULTS

The goal of conducting experiments is to test the feasibility and also measure the performance of the knowledge barter-auctioning solution using a real-world dataset. Because there is no system that adopts knowledge barter auctioning, we collected real data from a question-answering system *Yahoo!Answers* to simulate a knowledge market underpinned by the barter-auctioning mechanism. We are conscious that the system actually adopts a remunerative incentive mechanism based on virtual currency. We only used their answers and the associated questions as UGC contributions to simulate knowledge barter-auctioning, that is, participants barter auction knowledge items that each comprises an answer and the corresponding question.

5.1 Data Collection and Experimental Design

To best simulate the environment where participants interact in a knowledge market, our experimental dataset was collected from *Yahoo!Answers New Zealand* using open APIs to retrieve the questions and answers in different categories. We collected $92,112$ questions each with at least one answer in the period from April 2008 to March 2011.

There are 26 top-level categories and each category was treated as an interest in our experiments. Two participants have overlapping sets of interests if they have knowledge items falling into each other's SOI. By applying this rule, we obtained hundreds of potential trading groups, each consisting of one vendor and tens of competitors, as illustrated by Figure 2. The number of trading groups and the size of each trading group can be scaled up/down by adjusting the each participant's SOI. Furthermore, we need to measure the knowledge quality as it is the pivot of the allocation and payment rules in the knowledge barter-auctioning solution. As a proof of concept, we measured the quality of a knowledge item based on the relevance of the answer to the question using Kullback-Leibler divergence [12] in our experiments.

Experiments were designed to compare the vendor's expected revenue between the quality-aware knowledge barter-auctioning mechanism and a quality-unaware knowledge bartering mechanism. Additional experiments were also designed to compare the performance of the two mechanisms, including how the quality of bids affects the competitors' winning probability and how the number of competitors affects the vendor's expected revenue.

5.2 Estimation of Private Quality Value Distributions

In a quality-unaware knowledge bartering process [14], quality is only factored in the derivation of the edge weight representing a supply-demand relationship but not in the selection of barter partners. A low quality supply would still be bartered if it were an indispensable constituent of the maximum-weight online silk road that achieves social welfare maximisation. Therefore, the probability of a UGC contribution being successfully bartered is essentially independent of its quality. Therefore, for the sake of simplicity yet without losing generality, random selection of a barter partner is used in a quality-unaware knowledge bartering process in our experiments and such mechanism is referred to as Quality-Unaware Random Bartering (QURB).

Conversely, in a quality-aware knowledge barter-auctioning process consisting of vendor V who wants to barter auction their knowledge B^V and N competitors $\{C_i \mid i = 1, 2, \cdots, N\}$ who can offer an exchange in V's set of interests. Let q_i^V denote competitor C_i's private quality value estimate towards B^V and $BS_i = \{B_i^j \mid i = 1, 2, \cdots, N \wedge j = 1, 2, \cdots, M \wedge SOI(B_i^j) \cap SOI(V) \neq \varnothing\}$ denote the set of C_i's barter items that are within V's set of interests. If $Q_i = \{q_i^j \mid j = 1, 2, \cdots, M\}$ denotes the set of quality values of C_i's M barter options, then C_i's quality of bid is set to the quality closest to but no more than the private quality value estimate, that is, $q_i^b = \min(q_i^V, q_i^k)$, where $k = \arg\min_{j=1}^{M}(\mid q_i^j - q_i^V \mid)$. So the bidding quality set is comprised of the private quality values of all competitors' bids, that is, $Q^b = \{q_i^b \mid i = 1, 2, \cdots, N\}$.

In a Bayesian optimal auction, probability distributions of private values are assumed common knowledge for both the vendor and the competitors and the probability density functions should be monotonically increasing to satisfy the regularity requirement. Many functions, such as uniform distributions, exponential distributions and normal distributions, satisfy this requirement. For the sake of simplicity yet without losing generality, we use an exponential distribution $f(x) = x^\theta$ as the probability density function for all competitors in our experiments. It is clear that $f(x)$ is regular when $\theta > 1$ and partially regular when $0 < \theta < 1$. As such we generate different sets of private quality value distributions by random selection of θ.

5.2.1 *Vendor's expected revenue in relation to the private quality value distributions of the bids*

This experiment tests how the private quality value distributions of the bids affect the vendor's expected revenue using QURB and KOBA respectively.

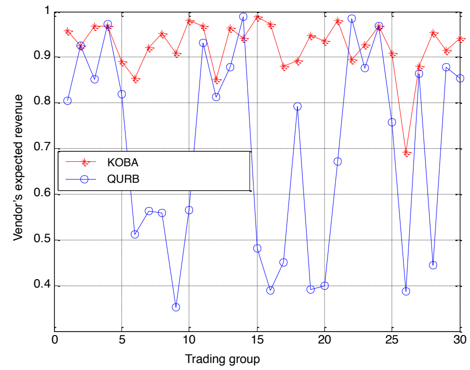

Figure 3: Vendor's expected revenue in relation to the quality of bids (using PQVDS-1)

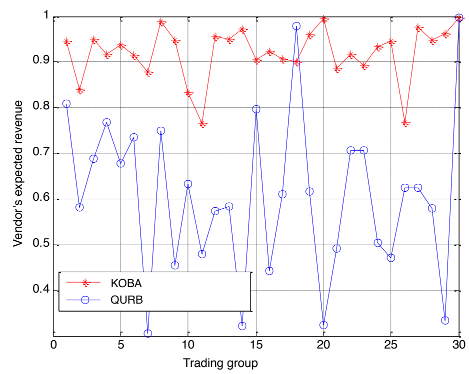

Figure 4: Vendor's expected revenue in relation to the quality of bids (using PQVDS-2)

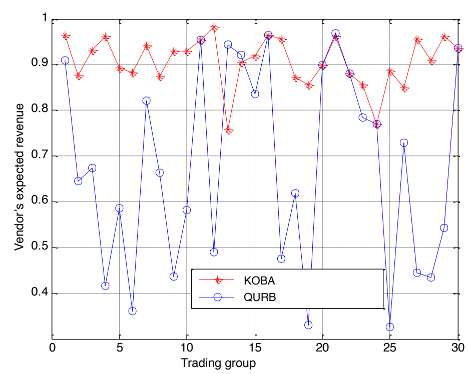

Figure 5: Vendor's expected revenue in relation to the quality of bids (using PQVDS-3)

We randomly selected 30 trading groups from the collected dataset, each consisting of a vendor and up to 15 competitors who were randomly chosen from all qualified bidders and assigned different private quality value distributions for their bids. For each trading group, we recorded the vendor's expected revenue, which is the quality value of the winning barter, using 3 different sets of private quality value distributions, referred to as *PQVDS-1*, *PQVDS-2*, and *PQVDS-3* respectively, as shown in Figure 3, 4, and 5 respectively.

It is clear that the vendor's expected revenue fluctuates with the quality of bids using both QURB and KOBA, however KOBA is less sensitive to the changes of quality of bids. More importantly, the average revenue using KOBA is significantly higher than that using QURB. This result is independent of the private quality value distribution sets.

5.2.2 Vendor's expected revenue in relation to the number of competitors

This experiment tests how the number of competitors in a trading group affects the vendor's expected revenue using QURB and KOBA respectively. We randomly selected 30 trading groups from the collected dataset, each consisting of a vendor and a varying number of competitors who were randomly chosen from all qualified bidders and assigned different private quality value distributions for their bids. The number of competitors in each group was set to 5, 10, 15, 20, 25, and 30 in 6 tests. We recorded the vendor's expected revenue in each trading group for each of the 6 tests and then computed the average expected revenue.

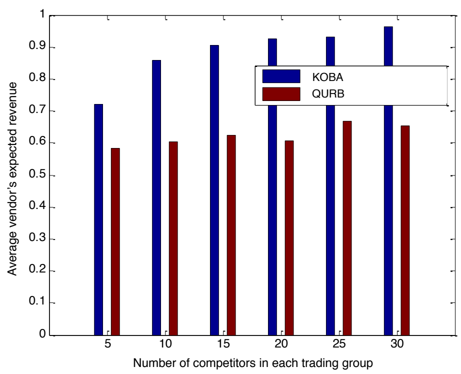

Figure 6: Expected revenue in relation to the number of competitors

It is clear from Figure 6 that with the increase of the number of competitors, the expected revenue obtained by KOBA is approaching the optimum of 1.0, which confirms the theoretical result of auction theory. In contrast, the expected revenue obtained by QURB is independent of the number of competitors. Figure 6 again confirms the result in the first experiment that the average expected revenue obtained by KOBA is much higher than that by QURB.

5.2.3 Competitors' winning probability in relation to bids' private quality value distributions

This experiment tests how the private quality value distributions of the bids affect competitors's winning probability using QURB and KOBA respectively. We randomly selected 100 trading groups from the collected dataset, each consisting of a vendor and up to 15 competitors who were randomly chosen from all qualified bidders and assigned different private quality value distributions for their bids. For each trading group, we recorded the quality of bids from all competitors and computed the percentage of winning in different quality intervals accordingly using 3 different sets of private quality value distributions of *PQVDS-1*, *PQVDS-2*, and *PQVDS-3*, as shown in Figure 7, 8, and 9 respectively.

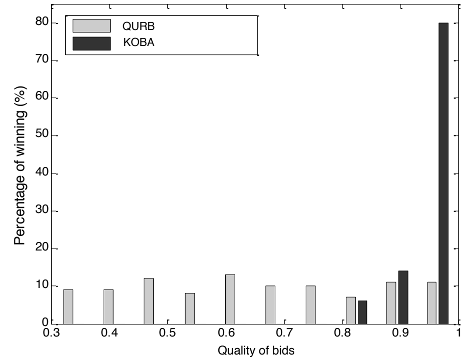

Figure 7: Winning probability in relation to the quality of bids (using PQVDS-1)

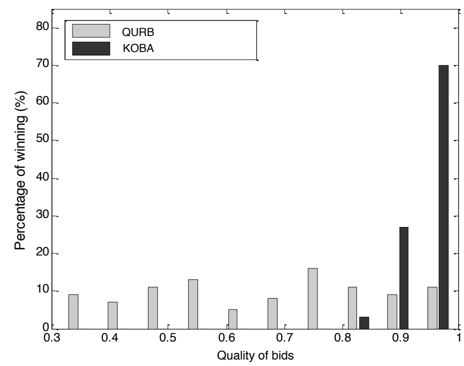

Figure 8: Winning probability in relation to the quality of bids (using PQVDS-2)

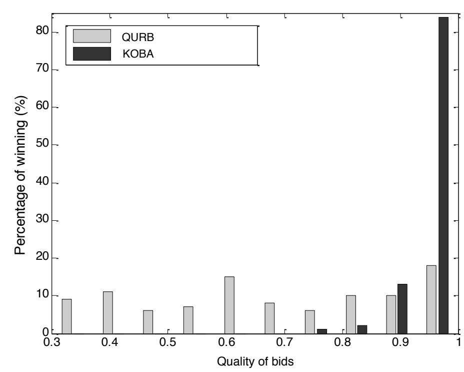

Figure 9: Winning probability in relation to the quality of bids (using PQVDS-3)

It is clear that the quality of bids has no direct impact on the competitors' winning probability using QURB, which is constantly low. In contrast, the quality of bids plays a pivotal role in winning the auction using KOBA, where bids of higher quality obviously have a higher winning probability and a mild improvement of quality can dramatically increase the winning probability. This result is independent of the private quality value distribution sets.

6. CONCLUSIONS AND FUTURE WORK

In this paper, we presented knowledge barter-auctioning as an alternative non-financial incentive mechanism, in which bartering is used to motivate quantity and auctioning is used to stimulate quality. It provides an optimal way for the vendor to choose the best barter partner in order to maximise their expected revenue. A UGC contribution of higher quality will enable the vendor to attract more competitors and consequently make a higher revenue through auctioning. Competitors are equally motivated to offer their own high-quality UGC contributions to barter with the vendor because the higher quality of the bid a competitor offers, the more likely they will win the auction. Experimental results have confirmed the ramifications of UGC quality in knowledge bartering processes.

While this work has shown promising results, we are conscious that it is non-trivial to choose an appropriate private quality value distribution in practice. Therefore, an imminent task is to devise an optimal auction algorithm that does not require prior knowledge of private quality value distributions. We will work on a quality evaluation strategy that takes into account more factors than only the relevance. We will need to design and conduct experiments to compare knowledge barter-auctioning with other non-financial incentive mechanisms such as the virtual currency.

7. ACKNOWLEDGMENTS

The work was partially supported by an NSF China Grant (61373164) and a Flinders University Research Grant (37011). Dr Ji's contribution to this paper was mainly made during his visit at Flinders University between 2012 and 2013.

8. REFERENCES

[1] S. L. Bryant, A. Forte, and A. Bruckman. Becoming wikipedian: transformation of participation in a collaborative online encyclopedia. In *ACM Conference on Supporting Group Work*, pages 1–10, 2005.

[2] Y. Chen, T.-H. Ho, and Y.-M. Kim. Knowledge market design: A field experiment at google answers. *Journal of Public Economic Theory*, 12(4):641–664, 2010.

[3] D. Dearman and K. Truong. Why users of yahoo! answers do not answer questions. In *ACM Conferece on Human Factors in Computing Systems*, pages 329–332, 2010.

[4] A. Ghosh and P. Hummel. A game-theoretic analysis of rank-order mechanisms for user-generated content. In *ACM Conference on Electronic Commerce*, pages 189–198, 2012.

[5] A. Ghosh and P. McAfee. Incentivizing high-quality user-generated content. In *ACM Conference on World Wide Web*, pages 137–146, 2011.

[6] A. Goel and F. Ronaghi. A game-theoretic model of attention in social networks. In *The International Conference on Algorithms and Models for the Web Graph*, pages 78–92, 2012.

[7] J. Goldstein, M. Kantrowitz, V. Mittal, and J. Carbonell. Summarizing text documents: sentence selection and evaluation metrics. In *ACM SIGIR conference on Research and development in information retrieval*, pages 121–128, 1999.

[8] D. Irwin, J. Chase, L. Grit, and A. Yumerefendi. Self-recharging virtual currency. In *ACM SIGCOMM Workshop on Economics of Peer-to-peer Systems*, pages 93–98, 2005.

[9] S. Jain, Y. Chen, and D. C. Parkes. Designing incentives for online question and answer forums. In *ACM Conference on Electronic Commerce*, pages 129–138, 2009.

[10] G. Y. Jeon, Y.-M. Kim, and Y. Chen. Re-examining price as a predictor of answer quality in an online Q&A site. In *ACM Conferece on Human Factors in Computing Systems*, pages 325–328, 2010.

[11] V. Krishna. *Auction theory*. Academic Press, 2009.

[12] J. D. Lafferty and C. Zhai. Document language models, query models, and risk minimization for information retrieval. In *ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 111–119, 2001.

[13] K. R. Lakhani and E. von Hippel. How open source software works: "free" user-to-user assistance. *Research Policy*, 32(6):923–943, 2003.

[14] Y. Mao, H. Shen, and C. Sun. Online silk road: Nurturing social search through knowledge bartering. In *ACM Conference on Computer Supported Cooperative Work*, pages 1193–1201, 2013.

[15] M. Merx-Chermin and W. J. Nijhof. Factors influencing knowledge creation and innovation in an organisation. *Journal of European Industrial Training*, 29(2):135–147, 2005.

[16] R. B. Myerson. Optimal auction design. *Mathematics of Operation Research*, 6(1):58–73, 1981.

[17] K. K. Nam, M. S. Ackerman, and L. A. Adamic. Questions in, knowledge in?: a study of naver's question answering community. In *ACM Conferece on Human Factors in Computing Systems*, pages 779–788, 2009.

[18] O. Nov, M. Naaman, and C. Ye. Analysis of participation in an online photo-sharing community: A multidimensional perspective. *Journal of the American Society for Information Science and Technology*, 61(3):555–566, 2009.

[19] D. R. Raban. The incentive structure in an online information market. *Journal of the American Society for Information Science and Technology*, 59(14):2284–2295, 2008.

[20] S. Rafaeli, D. R. Raban, and G. Ravid. How social motivation enhances economic activity and incentives in the google answers knowledge sharing market. *International Journal of Knowledge and Learning*, 3(1):1–11, 2007.

[21] C. Shah, J. S. Oh, and S. Oh. Exploring characteristics and effects of user participation in online social Q&A sites. *First Monday*, 13(9), 2008.

[22] V. K. Singh, R. Jain, and M. Kankanhalli. *Mechanism Design for Incentivizing Social Media Contributions*, chapter Chapter of S.C.H. Hoi et al. (eds.), Social Media Modeling and Computing. Springer-Verlag London Limited, 2011.

[23] H. R. Varian. Position auctions. *International Journal of Industrial Organization*, 25(2007):1163–1178, 2006.

[24] M. M. Wasko and S. Faraj. Why should I share? examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly*, 29(1):35–57, 2005.