Auction Theory meets Collective Intelligence: Towards Designing Next-Generation Community Question Answering Systems

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ABSTRACT

Community Question Answering (CQA) systems are web-based platforms that promote collective (community) intelligence. Users (queriers) pose questions about topics they are interested in, and other users (answerers) provide answers to these questions. The queriers evaluate answers and identify the best one, and users who gave these answers are rewarded. Current systems attempt to perform this matching without consideration of the different needs of queriers, such as the necessity for receiving good answers to their questions, and as a result the allocation matching does not maximize the sum utility of queriers.

In this work, we put forward auction theory as the mathematical tool to address this challenge. Upon posing a question, a querier declares his necessity for getting an answer to it through a bid. Each answerer has a finite number of bins in his answer list, which captures time or effort limitations in answering questions. We formulate the platform utility maximization problem as one of allocating questions to the bins of answerers. The model may take into account, (i) the relevance of each question for each answerer, (ii) the usefulness of answers provided by answerers based on past experience, (iii) the impact of the position of a question in the answer list of a querier on the chances that it will be answered. We propose meaningful compensation rules for answerers, and we extend the model to cater for the question starvation phenomenon, in which some questions are displayed in the lists of several answerers, while others do not appear at all. The problem turns out to be an extension of the advertisement slot assignment problem in sponsored search auctions. This is work in progress, and as a next step, it will feature validation from publicly available real data.

Categories and Subject Descriptors

H.1 Information Systems: Models and principles; C.4 Mathematics of Computing

General Terms

Algorithms, Economics

Keywords

Collective Intelligence, Community Question Answering systems, Auction theory.

1. INTRODUCTION

Web platforms that promote collective (or community) intelligence have rapidly proliferated. Community knowledge is collectively produced by large, loosely coordinated groups of people, and this systemic intelligence in how the whole system operates would have been impossible to build otherwise. The equivalent term “social computing” is attributed precisely to the fact that the community knowledge is generated out of atomic contributions. The proliferation of these platforms is the harbinger of a new, exciting research field, namely that of building the theoretical foundations and fundamental underlying design principles of these systems.

A first instance of social computing is community or participatory sensing [1]. The goal is to represent an underlying state as accurately as possible and deliver it to interested users. Information providers submit data related to the application at hand (e.g., text, video, photos), usually through mobile devices. Information consumers place queries related to the application (e.g., about the air pollution level or free parking spots) and require to be served. The application service provider aggregates data samples of providers and forwards results to querying users for some price. The most important challenge lies in coordinating the exchange of information and the matching of information supply and demand, while meeting quality of experience constraints for provisioned data for information consumers. A fundamental issue is that the traded good is data, which is reusable, since the same data may be provided to multiple consumers at the same time. Another instance is collective consumption [2], namely a model based on sharing, swapping, bartering, trading or renting resources, which is opposed to traditional, ownership-based models. Again the goal is to match resource supply and demand as much as possible.

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A third instance is Community Question Answering (CQA) systems (Fig. 1), such as Yahoo! Answers, Baidu Zhidao, Google Answers, Facebook Questions and Reddit Ask Me Anything (AMA) [3]. There also exist other CQA platforms focused on specific subjects, which operate as forums. In a typical CQA system, a querying user places a question which falls under one of a list of predefined categories. Any user may provide an answer to the question. After an elapsed time interval, which may be set by the system or be determined by the user, the question becomes inactive, and the best answer is selected by the querying user. The user who gave this answer gets rewarded with a credit in terms of a number of points or a direct payment.

The benefits of such a system are fully harvested if the chances that querying users receive “good” answers by other users are maximized. The current practice is that users interested in answering questions need to run down long lists of loosely related questions so as to locate questions they can answer. A basic challenge lies in the fact that querying users have different valuations, which quantify how necessary or important it is for a user to receive an answer. Current systems attempt to perform the matching of questions to answerers without consideration of these different needs of queriers, and as a result the allocation matching does not maximize the sum utility to queriers. In this work, we tackle precisely this challenge.

1.1 Related work

1.1.1 CQA Platforms

There exists a significant body of work on existing CQA systems and on methods for improving them. The main shortcoming is that the potential of harvesting community intelligence by having users answering questions well, is not fully exploited. For example, it is estimated that approximately 15% of submitted questions in the Yahoo! Answers system remain unanswered [4]. Similar conclusions were reached for a Java online forum [5]. Hence, a fundamental challenge is how to incentivize user participation so as to increase the number and quality of provided answers. A method to achieve this is to route questions to potential answerers. In [6], this matching problem is addressed through multi-channel recommendation systems. The relevance of each question to each user is quantified with multiple criteria based on content (e.g., categories of interest to each user) and social signals (e.g., the querying / answering activity of users, voting, etc.). In [7] the authors studied methods for characterizing the expertise of a user based on her answering history. The question-answerer matching problem is also challenging in social search engines [8]. In [9] the authors proposed a reputation-based incentive protocol so as to improve the quality of the answers. This is also studied in [10]. In [11] the authors consider a general model of crowd-sourcing systems and study how incentives affect user participation.

A method to decrease the number of unsatisfied requests and improve performance of CQA platforms is to use previously given answers for recurring questions [4], [12]. In [13], the authors showed that incentives increase quality and quantity of provided answers. Using real data, they demonstrated that users asking factual and difficult questions are more willing to pay for answers. From a different perspective, the authors in [14] considered methods for predicting the quality of a question in CQA systems. These findings provide support to our argument that, appropriately designed incentive mechanisms will improve the performance of CQA platforms.

1.1.2 Auction Mechanisms

Auction mechanisms [15] are most suitable for resource allocation in systems where the demand has unknown parameters such as the form of utility functions of users that request resources. Auctions manage the competition for the limited resources and ensure efficient allocation, in the sense of maximizing social welfare, despite the unknown parameters of the demand. The last few years, auctions have attracted increasing interest and have been applied to a variety of problems, ranging from spectrum allocation in wireless networks to sponsored search auctions (SSAs) for allocating advertisement slots.

SSA auctions [16] are used in internet search engines like Google and Yahoo! for selling advertisement slots in web pages that display web search results of internet users. A SSA mechanism determines whether an advertisement will appear in the user page with the search results, out of the multiple competing ones of different advertisers, and if so, in which slot (position) of the page. Advertisements that are displayed higher in the page are expected to attract more users through clicks. Unlike other auctions, the bids of competing advertisers are weighted by a factor which determines their importance and relevance through click probabilities. SSA auctions are of particular interest to our work and, in fact, they are a special case of the class of mechanisms that are discussed here as we will see in the sequel.
time or effort for answering questions. Hence, a sophisticated allocation is needed, which guarantees that appropriate questions are assigned to each answerer. Ideally, each answerer would like to have in his list questions that he feels an expert in answering, so that the possibility that her answer is best is increased, and his credit is also increased. Second, different querying users have different necessity for obtaining an answer. The mechanism should guarantee that the allocation is performed in a way that distinguishes these necessities. Third, these necessities are not known to the system. In fact, these parameters are private information to each user and to the platform. In addition, appropriate incentives for high-quality answers should be given to answerers. The system should apply a question allocation rule to answerers and a payment rule that encourages participation and high-quality answers, while adhering to the assumption that querying user valuations are unknown. The problem turns out to be an extension of the advertisement slot assignment problem in SSAs.

This work attempts to address the problem of efficient allocation of questions to answerers, while taking into account the aforementioned challenges. The proposed model is simple to implement and is amenable to a real-data-driven approach. This allows for fine-tuning of system parameters and for the validation of the solution method through data traces from actual CQA systems that are available in online repositories such as [17]. Our future agenda includes this validation. The contribution of our work to the literature is as follows:

- We provide a model for an enhanced CQA platform that takes into account the time or effort availability constraints of each answerer. These constraints give rise to a competition of questions for the limited time resources of answerers that has not been explicitly discussed in the prior literature.
- We formulate the problem of maximizing the efficiency of the platform as one of placing questions to answering bins of answerers, by taking into account the different necessity of queriers.
- We propose an auction-based mechanism that consists of a question allocation rule and a payment rule, and we extend the model to cater for the question starvation phenomenon, in which some questions are displayed in the lists of several answerers, while others do not appear at all.

2. SYSTEM MODEL

2.1 Description of a typical CQA platform

In a typical CQA platform, each user may ask a question and provide answers to questions submitted by other users. Users may also provide feedback by rating the received answers with positive or negative signals, but this option is not considered in our model. Each question is assigned to a predefined category and remains active for a certain time period. If the querier is satisfied with a given answer, he closes the question and flags it as answered. The question remains active until a satisfactory answer is given.

Users may answer any of the currently active questions. The latter are usually organized (tagged) in categories in order to facilitate search. Each user may browse questions by category (e.g., Environment) and subcategory (e.g., Global Warming, Renewable Energy Sources). Users can see which questions are currently active and which have been answered. Finally, questions can be sorted based on popularity, the number of answers received, and the time they have been submitted. In some cases (e.g., in Reddit AMA) the questions and the answers can be evaluated by all users through voting.

In order to encourage participation and incentivize users toward high quality answers, some CQA platforms have adopted a credit (point) system. For example, in Yahoo! Answers, each new user is initially awarded 100 points. Each submitted question consumes 5 points, while for every answer the user provides, he receives 2 points. Finally, when an answer provided by the user is selected (or, voted) as the best answer, the user earns 10 points. Note that these point rewards and penalties are the same for all users and questions.

2.2 Queriers and Answerers

We assume that the system operates in fixed-duration time intervals, the epochs. Each epoch may be of the order of some minutes. At the beginning of an epoch, there exist $M$ questions that need to be answered. Without loss of generality, we assume that each question is placed by a distinct user, whom we refer to as the querier. The set of $M$ queriers is denoted by $Q$. We use the same index to refer to the queriers and the questions.

Each question (querier) $j \in Q$ is associated with a certain value $u_j \geq 0$ units. This captures the utility (or benefit) that the querier will perceive if his question is answered. Equivalently, it quantifies the importance or necessity for the querier to have the question answered. Different questions have different importance for queriers who submit them, and hence different values of $u_j$. These values are private information for each querier.

There also exist $N$ users that could potentially answer this question. We refer to these users as answerers and denote the answerer group by $A$. We assume that each answerer has $T$ available bins, and each bin denotes a position for a question. By introducing the constraint of $T$ bins, we explicitly model the limited available time or limited attention budget that each answerer has for answering questions. In order to simplify the model, we take this time constraint to be the same across all answerers. We also implicitly assume that the time needed to provide an answer to a question is the same and equal to one time unit. The system is depicted in Fig. 2.

For each potential answerer $i$ and question $j$ we define a coefficient $a_{ij}$ that quantifies the relevance (or appropriateness) of answerer $i$ for question $j$. This coefficient could be computed from historical data as follows. A correlation metric may be defined among each pair of questions. Questions that answerer $i$ has answered in the past may be correlated with question $j$, and we can also include a metric denoting the quality of answers provided, based on feedback from queriers. Hence, coefficient $a_{ij}$ may be derived as

$$a_{ij} = \sum_{k \in Q_i} \rho_{kj} p_{ik},$$

where $Q_i$ is the set of already answered questions by $i$, $\rho_{kj} \in [0, 1]$ is a correlation metric between questions $k$ and $j$, and $p_{ik}$ is the quality of answer by answerer $i$ to question $k$. Coefficient $a_{ij}$ may be normalized in the interval $[0, 1]$. 

3. THE MECHANISM

An auction-based mechanism consists of an allocation and a payment rule. The objective of the CQA platform is to increase the benefit for queriers through appropriate assignments of questions to answerers bins.

Upon placing a query, a querier $j$ provides a bid $b_j$ in an effort to implicitly declare to the system the private valuation $u_j$ for the answer, or in other words the necessity to obtain an answer to the question. Namely, the bid denotes the amount of money (or, points) the user is willing to give so as to have his question answered. For each querier $j$, we define $b_{-j}$ as the vector of bids of queriers other than $j$, $b_{-j} = (b_1, \ldots, b_{i-1}, b_{i+1}, \ldots, b_T)$.

The mechanism performs the allocation of questions to bins of answerers and imposes a payment $h(j)$ per answer, for each querier $j$. We define the net utility $\omega_j$ of querier $j$ as the difference between the derived utility and the total payment,

$$\omega_j = u_j - x_j h(b_j, b_{-j})$$

where $x_j$ is the number of answers to question $j$ received by different answerers. Without loss of generality, this is taken to be continuous-valued. The payment $h(b_j, b_{-j})$ depends on the entire bid vector $b = (b_j, b_{-j})$.

3.1 Allocation Rule

At the beginning of each epoch, the platform collects submitted bids. Accordingly, for each question $j \in Q$, it determines whether it will appear at the bin of an answerer. Clearly, some questions will not appear at all in the answerers, while others may appear at the answering bin of more than one answerer. Let the control variable $x_{ij}(s) \in \{0,1\}$ indicate whether question $j$ will appear or not at the $s$-th bin of answerer $i$. Define vectors $x_{ij} = (x_{ij}(s) : s = 1, \ldots, T)$ and $x = (x_{ij} : i \in A, j \in Q)$.

The objective is to come up with the allocation that maximizes a metric that shows the efficiency of the question-to-answerer assignment. A possibility may be that the allocation is performed so that priority is given to questions with higher declared valuation, and that these questions are assigned to the bin with the highest probability of being answered. Consider the following optimization problem:

$$\max \sum_{j=1}^{M} \sum_{i=1}^{N} \sum_{s=1}^{T} b_j p_j(s) x_{ij}(s)$$

subject to:

$$\sum_{j=1}^{T} x_{ij}(s) \leq 1, \forall i \in A, j \in Q$$

$$\sum_{j=1}^{M} x_{ij}(s) \leq 1, \forall i \in A, s = 1, \ldots, T.$$
impact \( p_{ijk}(\cdot) \) more and hence affect the question assignment (and thus, the solution of the above problem). On the contrary, for CQA platforms with small \( T \) (e.g., \( T = 2 \)), the impact of placing a question in different position is very small. For these cases, the problem above is further simplified by omitting the summation over \( s \) in (3) and modifying accordingly the constraint set.

### 3.2 Allocation Rule for Mitigating the Starvation Phenomenon

In the previous allocation rule, we did not impose a limitation on the number of answerer lists on which each question can appear. However, this may result in an assignment where questions with high bids are favored more and are assigned to several bins (of different answerers), while questions with low bids do not appear in any answerer list. In order to ensure that queriers with lower bids will not starve, we propose an alternative allocation rule.

The main idea is to gradually discount the bid of each question as the number of the slots that the question is assigned to increases. First, we define the expander set of questions \( Q' \) which stems from \( Q \) by creating \( K \) replicas of each question \( j \in Q \). Each one of the different instances of question \( j \in Q' \) can be assigned at most to one slot of any answerer. In other words, \( K \) is the maximum number of total slots across all answerers that each question \( j \) can be assigned to. This is set by the CQA platform.

For each replica \( k = 1, 2, \ldots, K \) of question \( j \), we define the bid \( b^k_{ij} \) which comes out the initial bid \( b_j \), submitted by querier \( j \), but it is discounted by a certain parameter \( \theta \),

\[
b^k_{ij} = b_j \cdot (k\theta)^{-1},
\]

where \( \theta > 1 \) is a discount parameter which is tuned by the CQA platform. Clearly, it is \(|Q'| = MK \). We also define variable \( x_{ijk}(s) \in \{0, 1\} \) indicating whether the \( k\)-th replica of question \( j \) will appear in the \( s\)-th position of answerer \( i \) or not. As extension of parameter \( p_{ijk}(s) \) above, we have parameter \( p_{ijk}(s) \).

The new allocation rule is derived from the solution of optimization problem:

\[
\max_{x} \sum_{j=1}^{M} \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{s=1}^{T} b^k_{ij} p_{ijk}(s)x_{ijk}(s),
\]

subject to:

\[
\sum_{s=1}^{T} x_{ijk}(s) \leq 1, \forall i \in \mathcal{A}, j = 1, \ldots, M, k = 1, \ldots, K,
\]

\[
\sum_{k=1}^{K} \sum_{j=1}^{M} \sum_{i=1}^{N} x_{ijk}(s) \leq 1, \forall i \in \mathcal{A}, s = 1, \ldots, T,
\]

\[
\sum_{i=1}^{N} \sum_{s=1}^{T} x_{ijk}(s) \leq 1, j = 1, \ldots, M, k = 1, \ldots, K,
\]

where the additional constraint (10) dictates that each expanded question must be assigned at most one slot. It is easy to see that with this modified allocation rule, the bid of each question \( j \) is artificially discounted as the question is assigned to more answerer bins. This increases the chances that the bids of other question will exceed the bid of question \( j \), and will therefore gain priority in being assigned to answerer bins.

### Numerical Example

We give a simple example to demonstrate the difference between the allocation rules above. Consider a toy system with 2 answerers (\( \mathcal{A} = \{1, 2\} \)), and \( T = 2 \) bind for each. Assume that there are 3 queriers with valuations \( u_1 = 10, u_2 = 6 \) and \( u_3 = 4 \) units respectively. For simplicity, we consider that parameters \( p_{ijk}(s) \) are identical for all queriers, answerer lists and slots. It is easy to see that the first allocation rule assigns the two slots of each answerer to queriers \( i = 1 \) and \( i = 2 \). Hence, querier \( i = 3 \) would not appear in any slot of any answerer. Consider now the second allocation rule with parameters \( K = 2 \) and \( \theta = 2 \). According to (6), the discounted bids for querier \( i = 1 \) are \( b^1_1 = 5 \) and \( b^2_1 = 2.5 \), for querier \( i = 2 \), \( b^1_2 = 3 \) and \( b^2_2 = 1.5 \), and for querier \( i = 3 \), \( b^1_3 = 2 \) and \( b^2_3 = 1 \). With these new bids, the slot allocation changes and querier 3 receives one slot.

### 3.3 Payment Rule

The payment rule determines the price \( h(b_j, b_{-j}) \) that each user \( j \in \mathcal{Q} \) will be charged by the mechanism. This may involve actual monetary, virtual currency or point transfer. There exist various options that yield different prices for queriers and hence have different revenue for the platform. Furthermore, while some payment schemes are simple to implement, others come with high computational complexity, such as the Vickrey Clarke Grooves (VCG) auction [19], [20].

One payment scheme that has been employed in SSAs is that of generalized second price (GSP) auctions [21]. In a very simple version, this rule can be stated as follows. Each querier \( j \) pays a total price for all answering bids in which his question appears. That is, for each bin in an answerer, the querier pays a price which is equal to the bid of the querier who is assigned the immediate next slot. If querier \( j \) is in the last answering bin of an answerer, he pays the highest bid among queriers that did not appear in this answerer’s list [16, Ch.3]. Other versions of GSP payments can also be defined. It has been shown that GSP mechanisms fail to induce bidders to reveal their actual valuations[21]. Actually, the only auction that achieves truthfulness is the VCG mechanism.

Alternatively, a first-price payment rule can be used, where each querier is charged a price equal to his bid. In this case, the price charged to each bidder \( j \) depends only on his bid \( b_j \) and not on the bids submitted by others. Nevertheless, since the allocation is determined by considering the entire bid vector \( b \), the payment, which is charged only to questions that receive answering bids, is indirectly determined by all participants in the auction.

### 4. DISCUSSION AND FUTURE WORK

#### 4.1 Real Data and Implementation Issues

The proposed scheme can be put in practice and can be incorporated with minor modifications in various existing CQA platforms. The payment rule has been explicitly selected so as to be simple to implement and easy to understand by queriers. In addition, the payments can be mapped to actual or virtual currency transfers ones. Our model emerged after an elaborate studying how different CQA platforms operate. We believe that these parameters can be calculated either directly on the platforms, or by using available online data repositories such as [17].
Besides, previous works have focused exactly on estimating these parameters and using them to identify optimal matchings among questions and answerers [6], [7], [8]. These results are complementary to our work and can be incorporated in the proposed formulations. Unlike the vast majority of the related papers in this area, our focus was to set the stage for the optimal question assignment by taking into account the time and effort limitations of answerers and the different needs of queriers.

4.2 Future Work

The study presented in this paper is a first step towards igniting further studies for designing next-generation CQA platforms. We focused on the proposition of some rules for question allocation and payment. Our model is a non-trivial extension of the one of SSA [16, Ch.3] that are used to allocate advertisements of competing advertisers on different ad slots in the end-user web page. In fact, for the simple case of one answerer, namely if $N = 1$, our model coincides with that of advertisement placement in SSAs. However, for multiple answerers, i.e. $N > 1$, the problem becomes different. The multiple answerers correspond to a hypothetical situation where there are multiple competing web search engines in whose result pages the advertisements must be placed.

Besides elaborating more on the model specifics, in the future, we aim at focusing towards rules that ensure incentive compatibility, namely they discourage the misreporting of utility by queriers. Such a property would be prerequisite for sustainable system operation. Additionally, we will investigate methods which provide certain (probability) guarantees that users’ questions will receive satisfactory answers. Notice that the presented algorithms maximize the expected utility of the queriers but do not give lower bounds. This is a challenging direction for future work.

Also, our model focused more on the arising competition among queriers for time (bin) resources. It encapsulated only charging rules for queriers and did not include rewards to answerers. Following the current practice, we assumed that rewards to answerers are not part of the model. However, there also exists a tussle among answerers as well—in the sense that they compete for the answers to question. Therefore, answerers should also be awarded for their effort in a dynamic fashion, possibly through a reverse auction. We intend to address this issue and the arising two-sided competition in the future.

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6. REFERENCES


