Data Quality Guided Incentive Mechanism Design for Crowdsensing

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Abstract—In crowdsensing, appropriate rewards are always expected to compensate the participants for their consumptions of physical resources and involvements of manual efforts. While continuous low quality sensing data could do harm to the availability and preciseness of crowdsensing based services, few existing incentive mechanisms have ever addressed the issue of data quality. The design of quality based incentive mechanism is motivated by its potential to avoid inefficient sensing and unnecessary rewards. In this paper, we incorporate the consideration of data quality into the design of incentive mechanism for crowdsensing, and propose to pay the participants as how well they do, to motivate the rational participants to efficiently perform crowdsensing tasks. This mechanism estimates the quality of sensing data, and offers each participant a reward based on her effective contribution. We also implement the mechanism and evaluate its improvement in terms of quality of service and profit of service provider. The evaluation results show that our mechanism achieves superior performance when compared to general data collection model and uniform pricing scheme.

Index Terms—Crowdsensing, incentive mechanism, quality estimation, maximum likelihood estimation, information theory

1 Introduction

Crowdsensing is a new paradigm of applications that enables the ubiquitous mobile devices with enhanced sensing capabilities to collect and to share local information towards a common goal [1], [2]. In recent years, a wide variety of applications have been developed to realize the potential of crowdsensing throughout everyday life, such as environmental quality monitoring [3], [4], noise pollution assessment [5], [6], road and traffic condition monitoring [7], [8], bus arrival time prediction [9], [10], road-side parking statistics [11], [12], and indoor localization [13], [14]. However, the success of crowdsensing based services critically depends on sufficient and reliable data contributions from individual participants.

Sensing, processing, and transmitting data in crowdsensing applications requires manual efforts and physical resources. Therefore, appropriate rewards are always expected to compensate the owners of task-taking mobile devices. These owners, or say participants in the literature of crowdsensing, are commonly assumed to be rational, and will not take sensing tasks and make contributions unless there are sufficient incentives. Although researchers have proposed a number of incentive mechanisms for participation in crowdsensing [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], they have not fully exploited the connection between quality of sensing data and rewards for contributions.

Sensing data of high quality, based on which the crowdsensing service provider aggregates and extracts information for accurate decision making and attentive service providing, is fundamentally important. In crowdsensing, data quality can be affected by the difficulty of sensing tasks, the characteristics of mobile sensors, the clarity of task instructions, as well as the expertise and willingness of individual participants [30], [31]. Particularly, participants with different spatial-temporal contexts and personal effort levels are likely to submit sensing data of diverse quality. Furthermore, rational participants tend to strategically minimize their efforts, while doing the sensing tasks, and thus may degrade the quality of sensing data.

For example, careless or indifferent submissions are always found in crowdsensing based noise monitoring applications. When asked for environmental sound heard of neighborhood, a participant may perform the sensing tasks through a mobile device placed inside her pocket, rather than carefully taking out the device to sense accurately. Such a low quality submission would invalidate the estimation of noise pollution. Examples can also be found in crowdsourcing based services. A recent case study on crowdsourcing spam attacks [32] shows that the crowd services can be maliciously manipulated.

Continuous low quality sensing data undoubtedly do harm to the availability and preciseness of crowdsensing based services, and quality control should be an important concern in crowd services. However, to the best of our knowledge, few existing works have taken the observation of data quality into consideration, when designing incentive mechanisms for crowdsensing, to guarantee the quality of crowdsensing based services. It is very challenging to

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design quality based incentive mechanisms for crowdsensing. We list three major challenges:

- *Quality Estimaton*: It is technically difficult to estimate the quality of sensing data without any prior knowledge of the sensing behavior of individual participants or the ground truth of targeted contexts. Subsequent quality verification would require significant investments in deploying particular infrastructures to do on-site sensing and ground truth collecting, like Model 831-NMS permanent noise monitoring system[6]. Lacking in flexibility and scalability, the deployment of traditional static sensing infrastructures, in turn, negates the benefits of crowdsensing.
- *Incentive Design*: It is challenging to design incentive mechanisms that achieve both individual rationality and profit maximization. Here, individual rationality means that a participant should be rewarded no less than her sensing cost, and the profit of service provider is the difference between the value of crowdsensing based services and the total rewards to participants. Deliberate incentive mechanisms are required to motivate effective data contributions from rational participants, and to maintain a robust, profitable market for crowdsensing service provider.
- *Effective Feedback*: It is nontrivial to bridge the gap between quality of sensing data and rewards for contributions. Participants of crowdsensing, who perform the sensing tasks with heterogeneous physical resources and manual efforts, and therefore submit sensing data of diverse quality, may require appropriate rewards according to their contributions. While traditional uniform pricing scheme is unfair, the Pay-as-Bid pricing method used in most of the auction based incentive mechanisms is somehow troublesome for participants and indulgent of careless behavior. Feedback on data quality would be necessary to encourage long-term, effective contributions.

In this paper, we incorporate the consideration of data quality into the design of incentive mechanism, and propose to pay the rational participants as how well they do, to motivate efficient crowdsensing.

Our main contributions are listed as follows.

- We propose to design a quality based incentive mechanism that directly motivates individual participants to submit high quality sensing data for long-term, effective crowdsensing.
- Second, we extend the well-known Expectation Maximization algorithm that combines maximum likelihood estimation and Bayesian inference to estimate the quality of sensing data, and further apply the classical Information Theory to measure the effective data contribution. Based on the estimated quality and contribution, we determine fair and proper rewards to the participants. The incentive mechanism achieves individual rationality and (approximate) profit maximization.
- Finally, we implement and extensively evaluate the incentive mechanism. Our evaluation results show that it achieves superior performance in terms of quality assurance and profit management, when compared to general data collection model and uniform pricing scheme.

TABLE 1
Key Notations

Notation	Definition
$\mathbb{T}$	Set of sensing tasks
$\mathbb{A}$	Set of participants
$\mathbb{D}$	Set of discrete noise intervals
$\mathbb{A}_t$	Set of participants who complete task $t \in \mathbb{T}$
$\mathbb{T}^k$	Set of tasks that $a_k \in \mathbb{A}$ performs
S	Set of observed sensing data
P	Set of missing true noise interval indicators
E	Set of unknown effort matrices
$L(E; P, S)$	Likelihood function of E
$\mathbf{e}^k$	Effort matrix of a_k
e_{ij}^k	Probability that a_k submits data in interval d_j while the true interval is d_i
Π	Noise interval distribution
$\mathbf{p}^t$	True noise interval indicator for task t
p_i^t	Probability of task t with true noise interval being d_i
d_t^k	Noise interval that a_k's sensing data for task t falls into
$I(d_t^k = d_j)$	Indicator function for the event $d_t^k = d_j$
q_k	Quality of a_k's sensing data
$\chi_m(q_k)$	Contribution of sensing data of quality q_k
$v_m(q_k)$	Marginal contribution of sensing data of quality q_k to the cooperatively achieved service value
c_k	Reserve price/sensing cost of a_k
r_k	Reward to a_k for her contribution
r_k^m	Marginal reward to a_k for her marginal contribution
V	Value gained from qualified sensing data
$v(W)$	Overall value gained from sensing data of participants in set W
r^*	Optimal quality based reward
r_m^*	Optimal quality based marginal reward
r_u^*	Optimal uniform reward

The rest of the paper is organized as follows. We present the crowdsensing model, design objectives, and technical preliminaries in Section 2, and then describe the detailed design of our quality based incentive mechanism in Section 3. In Section 4, we extend our design to support crowdsensing systems where the service value depends on an overall quality of sensing data from all the participants. In Section 5, we evaluate our incentive mechanism and show the results. In Section 6, we briefly review related work. Finally, we discuss the limitations of our incentive mechanism in Section 7, and conclude the paper and future work in Section 8.

2 Preliminaries

In this section, we present the crowdsensing model, and key techniques for quality estimation. Table 1 lists the notations and descriptions used in the paper.

2.1 Crowdsensing Model

As illustrated by Fig. 1, there are three major components in the crowdsensing system, i.e., service subscribers who request services, a service provider who conducts the crowdsensing campaign and provides services, and a crowd of participants who submit sensing data to support the services.

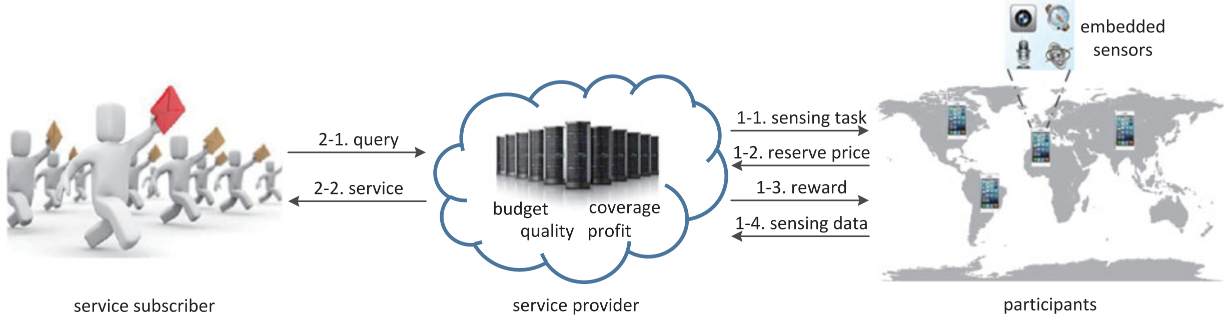


Fig. 1. A general crowdsensing model. According to participants' data quality and sensing cost, the service provider selects a subset of participants to perform sensing tasks for crowdsening based services.

The crowdsensing process (the right part) can be discribed as follows. First, the service provider releases a set $\mathbb{T}$ of sensing tasks (e.g., noise sensing on campus at 10:00 am) with an incentive announcement and a quality requirement (e.g., an error threshold). In the area of interests, there is a set $\mathbb{A} = \{a_1, a_2, \ldots, a_n\}$ of participants, with sensors embedded in their mobile devices. Each participant $a_k \in \mathbb{A}$ bears a private reserve price/sensing cost c_k (i.e., a monetary value for her consumptions of physical resources and involvements of manual efforts), and thus expects a reward for her contribution. Without sufficient rewards, the participants may not undertake the sensing tasks. The service provider estimates the quality q_k of sensing data from each participant a_k. By taking the profile of the participants' data quality and sensing costs into consideration, she selects a subset $W \subseteq \mathbb{A}$ of participants to perform each sensing task, and offers each participant $a_k \in W$ a certain amount of reward r_k according to her effective contribution. After collecting the sensing data for some tasks, the service provider updates quality estimation q_k for each participant $a_k \in W$ to guide the next round of recruitment (the right part), and extracts information to provide services (the left part).

We consider a general class of crowdsensing applications, in which the availability and preciseness of services significantly depends on the quality of sensing data, e.g., urban noise pollution monitoring, which measures ambient noise pollution based on sensing data collected from mobile devices. For each piece of sensing data with an error below the specified threshold, the service provider gains a value V (e.g., the subscription fee from service subscribers). For simplicity, we assume that V is fixed in our basic incentive mechanism, and then relax the assumption. The objective of the service provider is to maximize her own profit, by recruiting participants with proper rewards and providing services with guaranteed quality. The profit is defined as the difference between the total value gained from the sensing data and the rewards for participants, i.e.,

$$\text{Profit} \triangleq \sum_{a_k \in W} (V - r_k).$$

In this paper, we focus on the data quality that is specifically affected by participants' effort levels for sensing, and aim at designing incentive mechanisms for the service provider to stimulate high quality sensing and long-term, effective contributions.

2.2 Quality Estimation via EM

For crowdsensing, e.g., urban noise sensing, it is reasonable to calibrate the sensing data to moderate the inherent uncertainty of mobile devices. Here, we divide the reading of sensing data into discrete intervals, and suggest the service provider to deliver a certain interval to the service subscribers, rather than an accurate reading, to mitigate the impact of device variance and device error. The discrete intervals are denoted as a set $\mathbb{D} = \{d_1, d_2, \ldots, d_m\}$, where each interval spans over a range of decibels, and the granularity of interval division can be determined by the tradeoff between accuracy and complexity.

Regarding the quality of sensing data as a result of the effort levels, we estimate "effort matrix" $\mathbf{e}^k$ for each participant a_k, and map this effort matrix into a scalar quality value through function $q_k = g(\mathbf{e}^k)$. Here, the effort matrix $\mathbf{e}^k$ is an $m \times m$ matrix, with element $e^k_{ij} \in [0, 1]$, $i = 1, \ldots, m$, $j = 1, \ldots, m$, indicating the probability that participant a_k submits a piece of sensing data in interval d_j while the true reading is in interval d_i. Particularly, $\{e^k_{ii} | i = 1, \ldots, m\}$ contains the probabilities that participant a_k obediently performs outside-pocket sensing for each of the m possible cases. Furthermore, the conditional probabilities satisfy $\sum_j e^k_{ij} = 1$.

We note that, the effort matrix can be measured when we have ground truth for all spatial-temporal contexts. However, for crowdsensing, the true reading, or even the interval, cannot be ascertained in most cases, making the direct verification of data quality and the discernment of effort matrix challenging. In this paper, we resort to the well-known expectation maximization (EM) algorithm [33] to estimate each participant's effort matrix.

The EM algorithm is an iterative method for finding the Maximum Likelihood Estimation (MLE) of the parameters (e.g., the effort matrix for each participant, and the true noise interval for each task), when there is missing data (e.g., the indicators to tell right or wrong for sensing data) that precludes the straightforward estimation for the parameters. Here, MLE calculates the best estimation for parameters that maximizes the (log-)likelihood of the observations (e.g., the submitted sensing data), and converges in probability to the true value of the parameters when the number of observations is sufficiently large.

Given a set S of observed sensing data, a set P of missing true interval indicators, a set E of unknown effort matrices, and the density function f, the likelihood of unknown E is

$$L(E; P, S) = f(P, S | E).$$

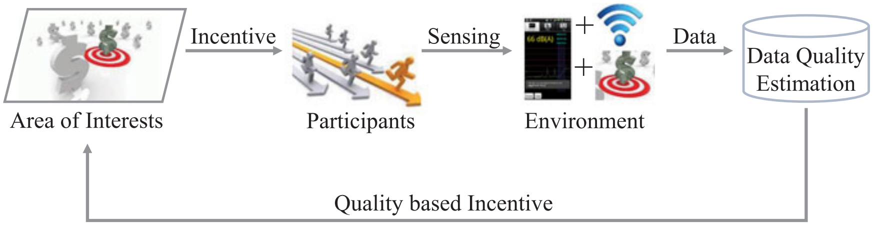


Fig. 2. Feedback of quality based incentive. The service provider estimates the data quality for participants, and offers them proper rewards based on their effective data contributions, to encourage high quality sensing data.

To find the MLE of E, the EM algorithm iteratively runs the following two steps until convergence (supposing that $\widehat{E}^t$ is the current value of E after t iterations):

E-step calculates the expected value of likelihood function, with respect to the conditional distribution of P given observation S under the estimation of E,

$$Q(E|\widehat{E}^t) = \mathbb{E}_{P|S,\widehat{E}^t}[L(E;P,S)].$$

M-step seeks the estimation $\widehat{E}$ that maximizes the expectation function,

$$\widehat{E}^{t+1} = \arg\max_{E} \ Q(E|\widehat{E}^t).$$

To estimate the interval indicators and participants' effort matrices, we extend the EM algorithm and iterate the following two steps until convergence: 1) estimate the effort matrix and noise interval distribution via maximum likelihood estimation, based on the estimated interval indicators; and 2) calculate new estimation of interval indicators, according to the estimated effort matrices and noise interval distribution.

The converged estimation of participant's effort matrix indicates the quality of sensing data, while the noise interval distribution is suggestive of the noise pollution level.

3 Quality Based Incentive

In this section, we detail the design of our quality based incentive mechanism for crowdsensing. To pay each individual participant a_k as how well she does in sensing, we estimate her effort matrix $\mathbf{e}^k$, calculate her quality q_k of sensing data, quantify her effective contribution $\chi_m(q_k)$, and offer her a proper reward r_k.

The feedback of quality based incentive is illustrated by Fig. 2. Rewards are determined for each participant according to the quality of historical sensing data, and in turn, the participants adjust their personal effort levels for completing the succeeding sensing tasks. We assume that participants do not dramatically change their effort levels over a short time, and estimate the quality of their sensing data periodically. Taking the quality of sensing data into consideration, our incentive mechanism can encourage long-term, effective contribution for crowdsensing based services.

3.1 A Simple Case

We first regard all of the submitted sensing data as qualified, and present a simple pricing scheme. We assume that the participants' sensing costs follow a probability distribution, with a probability distribution function $f(c_k)$, and a cumulative distribution function $F(c_k)$.

A rational participant a_k will not do a given sensing task unless she gets a reward $r \geq c_k$. Therefore, the service provider's profit by providing services and recruiting participant a_k, which is defined as the difference between value V gained from the sensing data, and the reward r to participant a_k, where $V \geq r$, is formulated as

$$\text{Profit}(c_k, r) = \begin{cases} 0, & r < c_k, \\ V - r, & r \geq c_k. \end{cases}$$

While the distribution of c_k is independent of value V and reward r, the expected profit is calculated as

$$\begin{aligned} \text{Profit}(r) &= \int_0^{\infty} \text{Profit}(c_k, r) f(c_k) dc_k \\ &= \int_0^{r} (V - r) f(c_k) dc_k = F(r)(V - r). \end{aligned}$$

Therefore, the service provider can maximize her profit by taking the first derivative of the function $\text{Profit}(r)$, solving the following equation, and getting the optimal reward, i.e.,

$$r^* = V - \frac{F(r^*)}{f(r^*)}.$$

3.2 Quality Estimation

In practice, due to their various effort levels, different participants may submit sensing data of diverse quality. In this section, we extend the Estimation Maximization algorithm to estimate the effort matrix $\mathbf{e}^k$ for each participant a_k, and then estimate the quality of her sensing data as $q_k = g(\mathbf{e}^k)$.

Specifically, we denote the set of participants that submit sensing data to task t as $\mathbb{A}_t \subseteq \mathbb{A}$, and the set of tasks that participant a_k performs as $\mathbb{T}^k \subseteq \mathbb{T}$. For task $t \in \mathbb{T}^k$, the true noise interval is denoted as d_t^0, while the interval into which participant a_k's sensing data falls is denoted as d_t^k. An indicator function $I(d_t^k = d_j)$ (i.e., $I(d_t^k = d_j) = 1$ when event $d_t^k = d_j$ is true; otherwise, $I(d_t^k = d_j) = 0$) is applied to describe the submission of sensing data.

We assume that the effort levels of participants are independent, and do not change for a period of time. So that we can periodically learn the effort matrix $\mathbf{e}^k$ for each participant a_k, and put this knowledge into practice. Without the true interval indicator, i.e., $\mathbf{p}^t = \{p_i^t | i = 1, \ldots, m\}$ for each task t ($p_i^t = 1$ if $d_t^0 = d_i$ for sure) is unavailable, we resort to the EM algorithm that combines Maximum likelihood estimation and Bayesian inference to iteratively estimate the unknown effort matrix $\mathbf{e}^k$ and noise interval distribution $\Pi = \{\pi_i | i = 1, \ldots, m\}$. The pseudo-code is shown in Algorithm 1, which runs as follows.

(1) Initialization: For each task t, the probability distribution of true noise interval indicator $\mathbf{p}^t$ is initialized as

$$p_i^t = p(d_t^0 = d_i) = \frac{\sum_{a_k \in \mathbb{A}_t} I(d_t^k = d_i)}{|\mathbb{A}_t|}.$$

(2) Estimation of effort matrix and noise interval distribution: Given the likelihood function

$$L(E; P, S) = f(P, S|E),$$

and

$$L(E; S) = f(S|E) = \sum_P f(P, S|E),$$

where $E = \{\mathbf{e}^k | a_k \in \mathbb{A}\}$, $P = \{\mathbf{p}^t | t \in \mathbb{T}\}$, and $S = \{d_t^k | t \in \mathbb{T}, a_k \in \mathbb{A}_t\}$, the maximum likelihood estimate of E makes the observation S most likely to happen.

We note that the effort matrix $\mathbf{e}^k$ for each participant a_k follows the Multinomial Distribution. When participant a_k performs n_i^k independent tasks with true interval d_i, her sensing data for these tasks falls into interval d_j with probability e_{ij}^k, where $e_{ij}^k \geq 0$ and $\sum_j e_{ij}^k = 1$, $j = 1, \ldots, m$. Let $n_{i1}^k, \ldots, n_{im}^k$ be the number of submissions corresponding to interval $d_1, \ldots, d_m$, respectively. Then we have $\sum_j n_{ij}^k = n_i^k$, and the likelihood function of $\mathbf{e}_i^k$,

$$f(n_{i1}^k, \ldots, n_{im}^k | e_{i1}^k, \ldots, e_{im}^k) = \frac{n_i^k!}{\prod n_{ij}^k!} \prod (e_{ij}^k)^{n_{ij}^k}.$$

Taking the log-likelihood, Lagrange multipliers, and derivatives, we get the most natural estimates [34],

$$e_{ij}^k = \frac{n_{ij}^k}{n_i^k} = \frac{\sum_{t \in \mathbb{T}^k} p_i^t I(d_t^k = d_j)}{\sum_{t \in \mathbb{T}^k} p_i^t}, \quad j = 1, \ldots, m.$$

The noise interval distribution is estimated as

$$\pi_i = \frac{\sum_{t \in \mathbb{T}} p_i^t}{|\mathbb{T}|}, \quad i = 1, \ldots, m.$$

(3) Estimation of true noise interval indicator: Given the observed sensing data S, the effort matrices E, and the noise interval distribution Π, we apply the Bayesian inference to estimate the true noise interval indicators P. Considering the n independent sets $\{S^1, \ldots, S^n\}$ of observations from individual participants, where $S^k = \{d_t^k | t \in \mathbb{T}\}, k = 1, \ldots, n$, we have

$$p(P|S) = \frac{p(P)p(S|P)}{p(S)} = \frac{p(P)p(S^1|P)\ldots p(S^n|P)}{p(S)}.$$

When all terms not involving the true noise interval indicator are absorbed into the proportionality sign, we calculate the distribution of true noise interval indicator for each task as

$$p_i^t = \frac{\pi_i \prod_{a_k \in \mathbb{A}_t} \prod_j (e_{ij}^k)^{I(d_t^k = d_j)}}{\sum_q \pi_q \prod_{a_k \in \mathbb{A}_t} \prod_j (e_{qj}^k)^{I(d_t^k = d_j)}}, \quad i = 1, \ldots, m.$$

(4) Convergence: We iterate step $2 - 3$ until the two estimates converge, i.e., $|\widehat{E}^{t+1} - \widehat{E}^t| \leq \varepsilon, |\widehat{P}^{t+1} - \widehat{P}^t| \leq \eta$. For each iteration (the while loop), the computation complexity is polynomial as $O(|\mathbb{A}||\mathbb{T}||\mathbb{D}|) = O(n)$, since the number of tasks and the number of intervals are constant and decided by the service provider before the algorithm works.

Algorithm 1. Effort Matrix Estimation

Input: A set $S = \{d_t^k | t \in \mathbb{T}, a_k \in \mathbb{A}_t\}$ of observations.
Output: Estimation of effort matrix E, marginal distribution of noise interval Π, and posterior estimation of true noise interval indicators P.

`// Initialization of Noise Interval Indicator`
foreach $t \in \mathbb{T}$ **do**
  $\mathbf{cnt}_{[m]} \leftarrow \mathbf{0}$;
  foreach $a_k \in \mathbb{A}_t$ **do**
    $i \leftarrow d_t^k$; $cnt_i \leftarrow cnt_i + 1$;
  $num \leftarrow cnt_1 + \cdots + cnt_m$;
  foreach $i \in \mathbb{D}$ **do**
    $p_i^t \leftarrow cnt_i / num$;
while not converged **do**
  `// Estimation of Effort Matrix`
  foreach $a_k \in \mathbb{A}$ **do**
    $\mathbf{c}nt_{[m]} \leftarrow \mathbf{0}$; $\mathbf{e}^k_{[m \times m]} \leftarrow \mathbf{0}$;
    foreach $t \in \mathbb{T}^k$ **do**
      $j \leftarrow d_t^k$;
      foreach $i \in \mathbb{D}$ **do**
        $e_{ij}^k \leftarrow e_{ij}^k + p_i^t$; $cnt_i \leftarrow cnt_i + p_i^t$;
    foreach $i, j \in \mathbb{D}$ **do**
      $e_{ij}^k \leftarrow e_{ij}^k / cnt_i$;
  `// Estimation of Noise Interval`
  foreach $i \in \mathbb{D}$ **do**
    $\pi_i \leftarrow 0$;
    foreach $t \in \mathbb{T}$ **do**
      $\pi_i \leftarrow \pi_i + p_i^t$;
    $\pi_i \leftarrow \pi_i / |\mathbb{T}|$;
  `// Estimation of Noise Interval Indicator`
  foreach $t \in \mathbb{T}$ **do**
    $\mathbf{p}^t_{[m]} \leftarrow \mathbf{1}$;
    foreach $i \in \mathbb{D}$ **do**
      foreach $a_k \in \mathbb{A}_t$ **do**
        $j \leftarrow d_t^k$; $p_i^t \leftarrow p_i^t e_{ij}^k$;
      $smp \leftarrow \pi_1 p_1^t + \cdots + \pi_m p_m^t$;
    foreach $i \in \mathbb{D}$ **do**
      $p_i^t \leftarrow \pi_i p_i^t / smp$;
Return $E = \{\mathbf{e}^k | a_k \in \mathbb{A}\}$, $\Pi = \{\pi_i | i \in \mathbb{D}\}$, $P = \{\mathbf{p}^t | t \in \mathbb{T}\}$;

We claim that the EM algorithm increases the likelihood function in each iteration, and finally converges to a stable estimation [35]. To circumvent the problem of getting trapped in a local optimum, we try several executions of the algorithm with different initializations on subsets of submissions. Although it is hard to provide theoretical guarantee for its performance, the EM algorithm has been widely used, and a provably optimal convergence rate up to a logarithmic factor has been shown in [36].

With the estimation for effort matrix $\mathbf{e}^k$, we can get the quality of a_k's sensing data through the mapping function. For simplicity, we focus on pure obedience, and set $q_k = g(\mathbf{e}^k) = \sum_i e_{ii}^k / m$. With the estimation for distribution of true noise interval indicator $\mathbf{p}^t = \{p_1^t, p_2^t, \ldots, p_m^t\}$ for task t, the interval d_i^* to be delivered is the one with maximum possibility, i.e., $d_i^* = \arg\max_i \; p_i^t$.

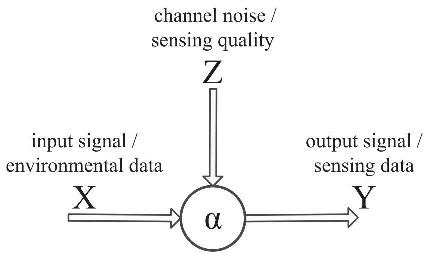


Fig. 3. A discrete channel (α, Z), where $Y = \alpha(X, Z)$.

3.3 Contribution Quantification

Various analyses and experiments have confirmed that expert work can be accomplished by the local crowd, even if they are lack of expert knowledge. However, the contribution of each individual participant remains unknown. Here, inspired by ideas in Information Theory and Shannon's Channel Coding Theorem [37], [38], we quantify the participants' contributions through information uncertainty reduction.

We regard the right part of crowdsensing system (Fig. 1) as a signal transmission system (Fig. 3). The input signal X is the environmental data that the crowdsensing system targets to collect, and the output signal Y is the sensing data that service provider actually receives from the participants. Transmitted through the channel, an input signal may be distorted in a random way depending on the channel condition (i.e., the noise variable Z, which is independent of X, on the transmission channel), and thus the output signal may be different from the input signal. Similarly, in crowdsensing system, the quality of sensing data would be effected by participant's sensing quality $q_k \in [0, 1]$. We use $p(z = 0) = q_k$ to indicate that the output signal is equal to the input signal with probability q_k, and $p(z = 1) = 1 - q_k$ to indicate that an error occurs with probability $1 - q_k$.

Similar to the capacity of a noisy channel [37], the contribution of the sensing data can be expressed as mutual information,

$$\begin{aligned} I(X;Y) &= H(X) - H(X|Y) \\ &= H(X) - \sum_y p(y) H(X|Y = y) \\ &= H(X) - \sum_y p(y) h_b(q_k) \\ &= H(X) - h_b(q_k), \end{aligned}$$

where $H(X)$ is entropy of X, $H(X|Y)$ is the conditional entropy of X given Y, and $h_b(q_k)$ is a binary entropy for the binary random noise Z with distribution $\{q_k, 1 - q_k\}$, i.e.,

$$h_b(q_k) = -q_k \log(q_k) - (1 - q_k) \log(1 - q_k).$$

This mutual information $I(X;Y)$ measures how much information the presence of Y contributes to making the correct inference for X.

In our crowdsensing system, when no sensing data is submitted, the service provider gets little information about the environment, and thus all the m optional intervals of environmental data are equally likely to be observed with probability $1/m$, making the uncertainty maximal at

$$H(X) = -\sum_m \frac{1}{m} \log\left(\frac{1}{m}\right) = \log(m).$$

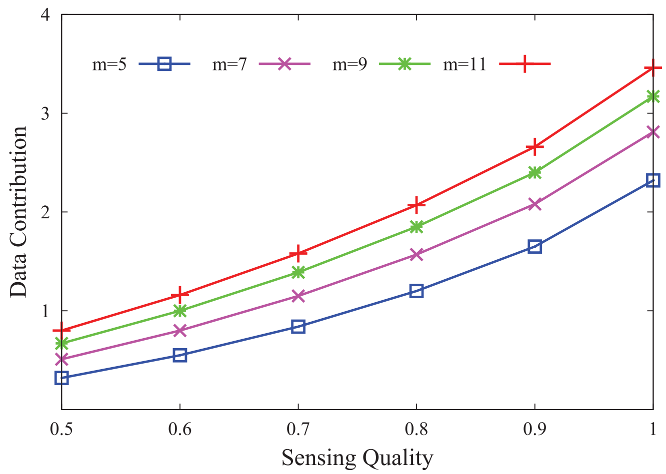


Fig. 4. Data contribution changes with sensing quality.

Generally, if Z is not a binary random variable, but distributed with q_k in the correct interval and equal probability $(1 - q_k)/(m - 1)$ for each of the $m - 1$ rest intervals, then the information uncertainty will be

$$\begin{aligned} h_m(q_k) &= -q_k \log(q_k) - \sum_{m-1} \frac{1 - q_k}{m - 1} \log\left(\frac{1 - q_k}{m - 1}\right) \\ &= -q_k \log(q_k) - (1 - q_k) \log\left(\frac{1 - q_k}{m - 1}\right). \end{aligned}$$

Therefore, the effective contribution of sensing data of quality q_k, can be formulated as

$$\chi_m(q_k) = \log(m) + q_k \log(q_k) + (1 - q_k) \log\left(\frac{1 - q_k}{m - 1}\right).$$

With the convention $0 \log 0 = 0$, sensing data of quality $q_k = 1$ will result in minimal uncertainty, $h_m(1) = 0$, and maximal contribution, $\chi_m(1) = \log(m)$. Though a binary channel which never makes errors and one always makes errors are equally good for communication, we only consider and reward sensing data of quality within a range of $[0.5, 1]$. As Fig. 4 shows, the effective contribution of sensing data increases with sensing quality.

Practically, with the same volume, sensing data of high quality carries larger amount of constructive information than that of low quality. Specifically, the high quality data contains intrinsic efficiency, while the low quality data needs extra information, functioning like error-correcting code (ECC), to detect and/or correct errors without resubmission. In crowdsensing, such kind of error correction, is more often conducted in the form of verification by recruiting another group of participants or sensing another kind of data (i.e., light signal to determine if the device is out of pocket). Here, we elide the specific ECC and focus on its cost (i.e., accounting for a part of the data volume), and quantify the effective contribution of sensing data as the information uncertainty reduction.

3.4 Reward Distribution

In this section, we take a step further and reward each selected participant proportionally to her qualified contribution, i.e., $r_k = r\chi_m(q_k) = r\chi_m(g(\mathbf{e}^k))$, where r is a benchmark reward.

We adjust parameters of the simple case. From participant a_k with an effort matrix $\mathbf{e}^k$, the profit that the service provider gains from her sensing data is

$$\mathrm{Profit}(c_k, \mathbf{e}^k, r) = \begin{cases} 0, & r\chi_m(g(\mathbf{e}^k)) < c_k, \\ V - r\chi_m(g(\mathbf{e}^k)), & r\chi_m(g(\mathbf{e}^k)) \geq c_k. \end{cases}$$

Given the joint distribution[1] $f(c_k, \mathbf{e}^k)$ of sensing cost and effort matrix, we can calculate the expected profit of the service provider, by integrating the function over all possible sensing cost and effort matrix, i.e.,

$$\mathrm{Profit}(r) = \int_{\mathbf{e}^k} \int_0^\infty \mathrm{Profit}(c_k, \mathbf{e}^k, r) f(c_k, \mathbf{e}^k) dc_k d\mathbf{e}^k.$$

Then, the optimal benchmark reward is determined by the solution to the maximization problem

$$r^* = \arg\max_r \ \mathrm{Profit}(r).$$

Each selected participant a_k will get her quality based reward $r_k = r^* \chi_m(g(\mathbf{e}^k))$.

We note that, for simple joint distribution $f(c_k, \mathbf{e}^k)$, the optimal benchmark reward r^* can be calculated by solving the integral equation and taking the derivation of r. However, for complex cases, greedy algorithms can find the proper reward with approximate profit more efficiently.

4 Quality Aware Service Value

In previous section, we assume that the service provider gains a fixed value V for sensing data with an error below threshold, and reward each participant independently and solely upon her quality of sensing data. While in practical scenarios, the value of crowdsensing based service is achieved as a cooperative work from participants, or we say, each participant contributes marginal value to the service. In this section, we relax the assumption on fixed value, and reward participants according to their marginal contribution to the service value.

4.1 Marginal Contribution Quantification

The service value gained from the overall selected participants is denoted by $v(W)$, where W is the finite set of participants, and $v : 2^W \mapsto \Re$ associates with each subset $S \subseteq W$ a real-valued value $v(S)$ to which each selected participant makes a contribution. In General, $v(S)$ is dependent on the overall value V (e.g., subscription fee from service subscribers) and the sensing quality and effective contribution of this subset of participants. We have $v(\emptyset) = 0$ by default.

To motivate participants in a fair manner, we calculate the marginal contribution $v_m(q_k)$ for each participant. Here, fairness means that, if participant a_i and participant a_j always behave the same in each cooperation with the other participants, i.e., for all S that contains neither a_i nor a_j, $v(S \cup \{a_i\}) = v(S \cup \{a_j\})$, then they should make the same contributions. Their behavior is characterized by the estimated quality of sensing data. Also, to encourage high quality sensing, the marginal contribution, as well as the marginal reward, should monotonically increase with the quality of sensing data.

With an elegant axiomatic characterization, the Shapley value [39] is well-studied in the field of cooperative game theory. Shapley value meets a collection of desirable properties, i.e., efficiency, symmetry, dummy, and additivity, which provides excellent fairness for our marginal contribution analysis.

In our design, the Shapley value of participant a_k is calculated by

$$v_m(q_k) = \sum_{S \subseteq W \setminus \{a_k\}} \frac{|S|!(|W|-|S|-1)!}{|W|!} (v(S \cup \{a_k\}) - v(S)),$$

where $|S|$ and $|W|$ are cardinalities of sets S and W respectively. It captures the average marginal contribution of participant a_k, averaging over all possible selection orderings according to which the cooperation could be built up from the original empty set.

The above Shapley value would calculate all the $|W|!$ permutations of W. To mitigate the complexity, we randomly select a const number K of permutations out of the $|W|!$ ones with equal possibility, calculate the marginal contribution for each participant, and take the average value over these permutations, i.e.,

$$v_m(q_k) = \sum_{S_i \subseteq W \setminus \{a_k\}, i=1,\ldots,K} \frac{v(S_i \cup \{a_k\}) - v(S_i)}{K}.$$

The approximate Shapley value may not strictly hold the properties like symmetry and additivity, but we can guarantee efficiency by normalization and dummy by nature. Compared to a one-step (e.g., greedy) marginal contribution calculation, this approximate value can mitigate the differences of marginal contributions which result from orderings, and thus can improve the fairness among the participants.

4.2 Marginal Reward Distribution

Based on the approximate Shapley value, we determine the marginal reward for each participant. Similar to the independent reward scenario, the marginal rewards for participants are proportional to their marginal contributions, i.e., $r_k^m = r_m v_m(q_k)$, where r_m is a reward ratio between (0,1].

Thus, the profit for service provider is $(1 - r_m)v(W)$, and the optimal ratio maximizes the profit with individual rationality.

5 Evaluation Results

In this section, we conduct simulations to evaluate performance of our quality based incentive mechanism. We first analyze the improvement in quality assurance. Then, we compare our quality based reward mechanism to the uniform pricing scheme, and illustrate the superior performance in profit management.

5.1 Quality Assurance

We install NoiseTube mobile app [40] on Google Nexus 7, and use the embedded acoustic sensor to measure noise in a meeting room. We recruit 10 participants to take part in the

1. Although this joint distribution can be learnt from historical data or general survey, it is not our main contribution. Here, we assume that the distribution is common knowledge, and consider two kinds of joint distributions, where there is no correlation or a strong positive correlation between sensing cost and effort matrix.

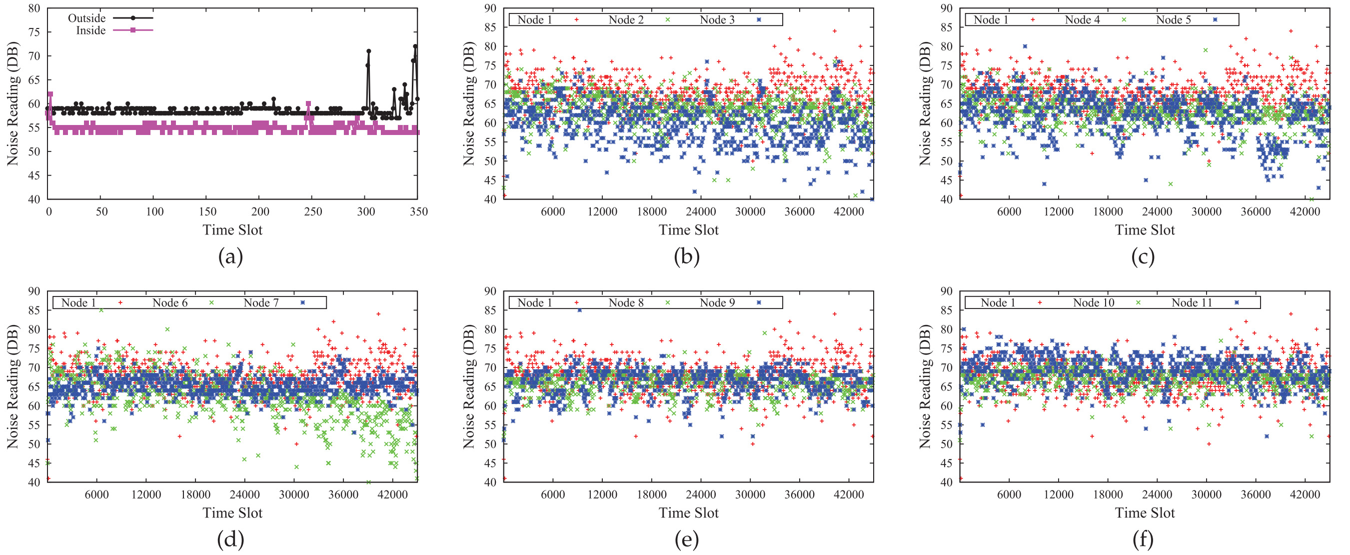


Fig. 5. Accuracy of noise pollution monitoring with different effort levels of participants. (a) General noise reading differences between outside pocket sensing and inside pocket sensing. (b)-(f) Noise readings of ground truth (Node 1) and from the 10 participants (Node 2-11).

experiment, each of which carries a nexus and randomly puts it into his/her pocket or on the table. The participants are well told that accurate monitoring occurs when they put out the nexuses and keep them undisturbed.

The basic experiment is to test whether the participants' effort levels will effect the noise readings. As Fig. 5a shows, the noise reading from a muffled microphone inside pocket is at least 5dBs lower than that of outside pocket sensing. The sensing data submitted by participants, as shown in Figs. 5b, c, d, e, f, also presents such reading differences, based on which we can roughly tell the effort levels of participants, i.e., node 10 is sensing with the highest effort level and submits almost perfect readings; node 7, node 8, node 9 and node 11 are 85 percent accurate with high effort levels at most of the time; node 2 and node 4 are helpful with 70 percent accuracy; node 6 is careless with high accuracy at first and then gradually slacks off; node 5 is indifferent with half accuracy and the other half deviation intermittently; and node 3 is sensing with the lowest effort level with all readings lower than ground truth.

Given the reading differences, we compare the quality assurance, i.e., the overall monitoring accuracy, as a collective work from the crowd, in our quality measured model (QM), traditional majority voting model (MV), and all and average model (AA). The difference is: QM excludes sensing data with low quality (i.e., with accuracy less than 50 percent) and assigns quality-estimated data with different weights; MV selects the most frequent noise interval at first, and then calculates the noise reading averagely; and AA takes in all submissions and reports the average reading.

Results, as shown in Fig. 6, indicate that QM outperforms the other two models, in monitoring the noise pollution more accurately (i.e., the readings keep closely to the ground truth), and more robustly to the efforts fluctuation of participants, especially when careless and indifferent participants take up more than half of the whole population. Furthermore, the MV model may direct the monitoring into a fierce fluctuation when the noise interval is highly precise, which is 5dBs per interval in our setting. Despite a similar trend with QM, the AA model is more vulnerable to large amount of low quality submissions.

5.2 Profit Management

To test the performance of our quality based incentive mechanism in terms of profit management, we first generate the sensing costs and effort matrices for participants, and then compare the profit of our mechanism to that of the uniform pricing scheme.

We draw v_c and v_e from a bivariate normal distribution, $(c, e) \sim \mathcal{N}(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho)$, where $\mu_1 = 2.0$, $\mu_2 = 0.75$, $\sigma_1 = 1.0$, $\sigma_2 = 0.125$, and $\rho = 0.0$ is set to indicate that there is no correlation between sensing cost and effort matrix (Fig. 7a), or $\rho = 0.8$ for a strong positive correlation (Fig. 7b). According to the $68-95-99.7$ rule/3σ rule [41], the 95.45 percent

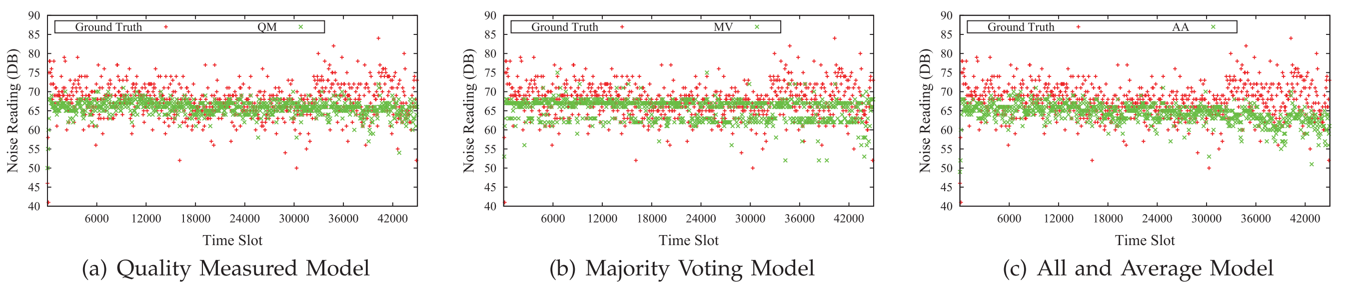
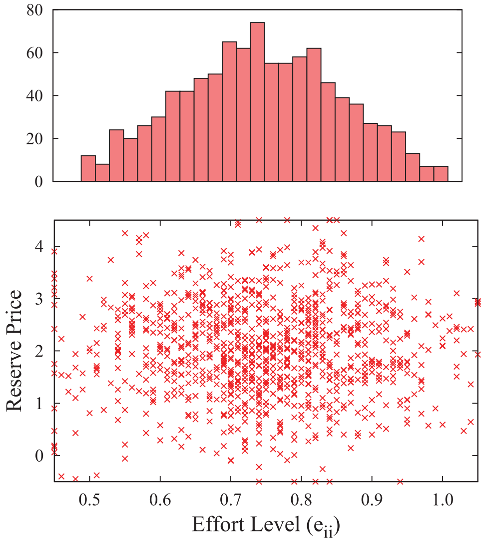
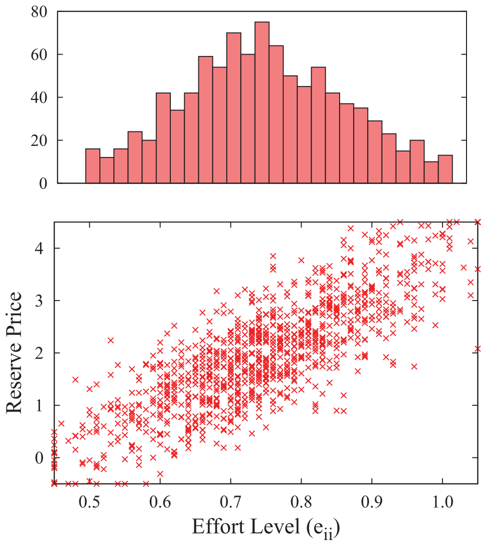


Fig. 6. Comparison of monitoring accuracy of different models. Our quality based incentive mechanism outperforms the majority moving model and the all and average model, in monitoring accuracy and robustness to quality fluctuation.

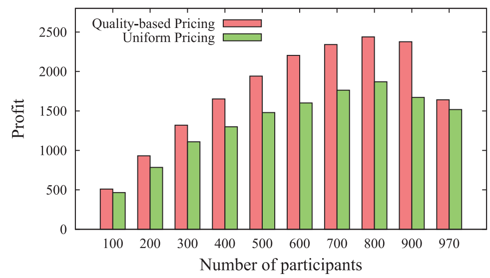


(a) No correlation, $\rho = 0.0$

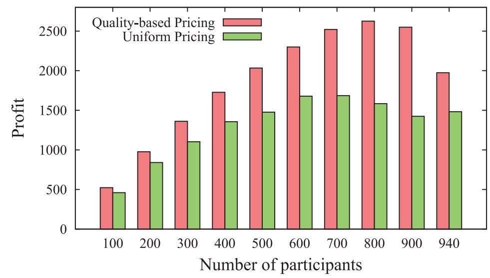


(b) Positive correlation, $\rho = 0.8$

Fig. 7. Joint distribution of sensing cost and effort matrix.



(a) No correlation, $\rho = 0.0$



(b) Positive correlation, $\rho = 0.8$

Fig. 8. Comparison on profit of different pricing schemes. Our quality based incentive mechanism overwhelmingly outperforms the uniform pricing scheme, in both of the two distributions.

confidence interval is $\mu \pm 2\sigma$, which empirically states that about 95.45 percent data drawn from the normal distribution lies within $[0.0, 4.0] \times [0.5, 1.0]$ in our setting. Then, we transform v_c and v_e to c_k and $\mathbf{e}^k$ correspondingly by setting $c_k = \max(-0.5, \min(v_c, 4.5))$ and $e^k_{ii} = \max(0.45, \min(v_e, 1.05))$, $i = 1, \ldots, m$. Therefore, the extreme data is excluded and the rest majority approximately follows the same normal distribution. Notably, other forms of distribution are also experimentally possible, and the exact joint distribution needs to be carefully estimated in practical crowdsensing markets [42].

After getting the joint distribution, we compare the profit of our quality based incentive mechanism and that of the uniform pricing scheme. We note that, the quality based incentive mechanism gains a full value V from sensing data by providing an error-bounded service, and offers each participant a proper reward based on her effective contribution. In the uniform pricing scheme, the sensing data is regarded equally with the same quality, and the participants are offered the same reward,

$$r^*_u = \max_{a_k \in \mathbb{A}_t} c_k.$$

However, the gained value is restricted by the actual quality q_k of sensing data, i.e., $v_k = y(V, q_k)$, which monotonously increases with quality q_k.

For simplicity, we consider that there are $|\mathbb{D}| = 2$ noise intervals, and omit the subscript of $\mathbf{e}$. Then, the effective contribution is calculated as

$$\chi_m(g(\mathbf{e})) = c_2(e) = 1 + e\log e + (1-e)\log(1-e).$$

Value function is set to be $v_k = V\sin(\chi_m(g(\mathbf{e})) \times \pi/2)$, which is concave with feasible $\chi_m \in [0, 1]$.

We select participants from sufficient crowd, in an increasing order of cost/contribution ratio, and calculate the optimal reward for the top proportion of them, ranging from 10 to 100 percent. The optimal reward, in our quality based incentive mechanism, is determined by

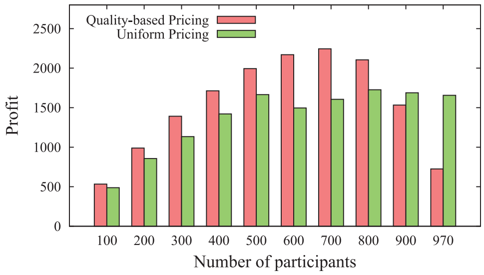
$$r^* = \arg\min_r \; r\chi_m(g(\mathbf{e}^k)) - c_k \geq 0, \forall a_k \in \mathbb{A}_t.$$

Each participant a_k will get a proper reward,

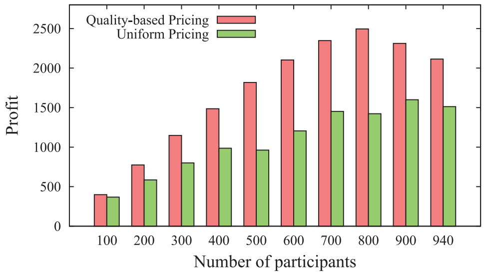
$$r_k = r^* \chi_m(g(\mathbf{e}^k)).$$

Results, as shown in Fig. 8, indicate that our quality based incentive mechanism overwhelmingly outperforms the uniform pricing scheme, in both of the two distributions. Our mechanism complies with the cost/contribution ratio to set the optimal reward in every stage, and thus can fully leverage the power of participants to complete the sensing tasks at a low cost, when compared to the uniform pricing scheme. Moreover, with the guaranteed value of service, the quality based incentive mechanism, with higher accuracy and less fluctuation in noise monitoring, is more appealing to the service provider.

The results also suggest the proper fraction of participants that the service provider should try to recruit, which is 80



(a) No correlation, $\rho = 0.0$



(b) Positive correlation, $\rho = 0.8$

Fig. 9. Comparison on profit of different marginal pricing schemes. Our quality based incentive extension achieves better performance than that of the uniform pricing scheme before over-recruitment, in both of the two distributions.

percent for both schemes when sensing cost and effort matrix has no correlation, and 80 and 70 percent, for our quality based incentive mechanism and the uniform pricing scheme, respectively, when the factors are positively correlated. It is reasonable to see such a turning point in profit, from a smooth rise to a fall, since there are always some participants with sensing costs higher than what they deserve to be rewarded according to the their effective contributions, i.e., with unreasonably high sensing costs for subpar contributions. The x-axis ends with 970 (Fig. 8a) and 940 (Fig. 8b), respectively, since we have excluded extreme data from the distribution.

These results also help to demonstrate the significant importance of quality estimation and contribution quantification to guarantee both quality and profit of crowdsensing based services. Through reward control, the participants who submit low quality sensing data will be paid less or even nothing, and will try to increase their sensing effort to get proper rewards again. On the other hand, being well paid, those participants who submit high quality sensing data will keep doing sensing tasks. Through this dynamic interaction, our mechanism can help the service provider to distinguish the valuable participants from the rest, and to maintain long-term, efficient crowdsensing.

5.3 Marginal Profit Management

We also compare the marginal profit of our extended quality based incentive mechanism and uniform pricing scheme. Different from the experiments in previous section, here, the value of service is achieved by the cooperative work of participants.

We use a submodular function on the mean quality to describe the marginal contribution, i.e.,

$$v(W) = V \times \frac{h(|W|)\sum_{a_k \in W} g(\mathbf{e}^k)}{|W|},$$

where $h(n) = n/(n + 1000)$ models the relationship between the number of participants and the credibility of the data. The function $v(W)$ takes into consideration both the number and the sensing quality of selected participants.

The optimal marginal reward is determined by

$$r^*_m = \arg\min_r \; r v_m(g(\mathbf{e}^k)) - c_k \geq 0, \forall a_k \in W.$$

Each participant a_k will get a proper reward,

$$r^m_k = r^*_m v_m(g(\mathbf{e}^k)).$$

Results, as shown in Figs. 9a and b, state that our quality based extension achieves better performance than that of the uniform pricing scheme, in both of the two distributions for cooperative crowdsensing. We select participants according to their ratio of cost over marginal contribution in a non-decreasing order, which leads to high quality of service with a moderate cost. The results also suggest similar recruitment proportion. While there is an obvious oscillation of profit from uniform pricing scheme, our quality based incentive mechanism guarantees an increasing profit, before an over-recruitment, i.e., a high benchmark reward is set to take in participants who require much high reward but contribute little to the service value. The service provider could detect and avoid this side effect, by considering both the marginal contribution and sensing cost of participants, and recruiting a proper number of participants.

6 Related Work

In this section, we briefly review related work on incentive mechanism design and data quality estimation in crowdsourcing and crowdsensing.

6.1 Incentive Mechanisms for Crowd

There are extensive researches targeting the incentive mechanism design for crowdsourcing and crowdsensing. We classify these designs as quantity-oriented or quality-oriented.

6.1.1 *Quantity-Oriented Incentive Mechanisms*

These incentive mechanisms are designed to increase the quantity of data, or we say, to motivate participation of crowd. Lee and Hoh [15] proposed a reverse auction based dynamic pricing scheme to motivate participants to sell their sensing data with claimed bids. Yang et al. [16] considered a platform-centric incentive model, where the reward is proportionally shared by participants in a Stackelberg game, and a user-centric incentive model, where participants in the auction bid for tasks and get paid no lower than the submitted bids. Zhao et al. [18] and Gao et al. [19] suggested online incentive mechanisms to flexibly recruit participants who appear opportunistically in the phenomena of interests. Chandr et al. [20] considered participant reliability, i.e., the ratio of responses submitted timely to tasks accepted by the participant, in their online, time sensitive crowdsourcing platform. Wei et al. [21] considered the dynamic nature of both participants and service providers. Luo et al. [22] studied an all-pay auction with realistic constraints such as information asymmetry, population uncertainty, and risk aversion. More related work and open research challenges have been discussed in the survey [29].

In general, these reverse auction based incentive mechanisms have not considered the quality of sensing data, and thus will face limitations on the guarantee and improvement of quality of service. To free participants from extra sensing-unrelated efforts, we don't require the participants to rigorously calculate their reserve prices, nor to reveal this private information and bid for sensing tasks, which is different from those auction based incentive mechanisms.

6.1.2 Quality-Oriented Incentive Mechanisms

There are also systems considering reputation of participants and impact of incentive on personal effort. Reddy et al. [23] built a performance based reputation system to identify and select well-suited participants for crowdsensing. They had an expert, peer comparison, and progress review for quality estimation. Cheung et al. [24] considered heterogeneous initial locations, movement costs, movement speeds, and participant reputation levels, to help participants determine task selections and mobility plans. The reputation level, as a prior knowledge, is described as the eligibility for sensing tasks. Pan et al. [43] recorded performance for reputation and studied how to assemble teams of participants through intelligent task allocation for efficient quality-time-cost trade-offs. On the other hand, although various empirical experiments [30], [44] demonstrate that financial and social incentives do have an impact on the performance of participants, such as engagement, compliance and quality, they fail to generalize an incentive model to adaptively guide the participants' behavior.

Koutsopoulos [25] considered participation level (sample frequency) in the incentive mechanism design. However, this work separately addresses the quality issue and incentive distribution, and does not tell how to improve the sensing quality of participants. While Kawajiri et al. [26] steered participants to cover sufficient locations to improve the quality of service, they based their quality of service on the number of data submissions from different locations in their wireless indoor localization system. In contrast, we systemically consider and measure the effort levels of participants, and bridge the gap between data quality and reward distribution.

Multi-attributive auction [45] allows us to use a powerful additive utility function to combine sensing cost, participant credibility, sensing quality, and privacy concern, to enable dynamic negotiation between participants and the service provider. While it shows how to bridge the gap between quality, privacy, and incentive through a utility function for the service provider from each single participant, our mechanism considers both independent and marginal data contributions from participants.

6.2 Quality Estimation of Sensing Data

While majority voting and all-and-average can be used to aggregate sensing data, these methods treat each participant as equal in expertise and willingness, and take their sensing data as equal in quality and contribution, which may discourage diligent participants and indulge careless sensing behavior.

The expectation maximization (EM) algorithm we adopt is originally introduced by Dawid and Skene [33], where it is used to obtain maximum likelihood estimates of observers' error rates and to infer the true response of patients. The convergence properties is discussed in [35]. Wang and Ipeirotis [46] applied EM algorithm to estimate the quality of crowdsourced labeling workers. Zhang et al. [36] proposed to combine spectral methods and EM algorithm to address the problem of crowdsourced multi-class labeling with an optimal convergence rate up to a logarithmic factor.

Other quality estimation methods include [47] which learns a prediction model in the absence of gold labels with uncertainty-aware learning and soft-label updating to analyze participant performance, [48] which applies reinforcement learning to dynamically decide when and how many gold questions to insert to estimate participant reliability, and [49] which evaluates different strategies, e.g., beta reputation, Gompertz function, robust averaging, maximum likelihood estimation, and a Bayesian model, to predict participant trustworthiness.

7 Discussion and Limitations

In this section, we discuss the limitations and possible improvement of our quality based incentive mechanism for crowdsensing.

Generally, an issue that lacks discussion and verification in the literature of crowdsensing is the detailed definition and determination of quality of data in various crowdsensing based applications.

We have considered analyzing the data reading to estimate the quality of data. In such environmental monitoring scenarios, the spatial and temporal contexts, e.g., location accuracy and sampling frequency, also matter a lot to the quality of data. For other applications where there is no clearly calculable metric like dB level for quality analysis, we should take other metrics (e.g., accessibility, value-added, and ease of understanding) into consideration. Quantifying data quality is not uniquely difficult in crowdsensing. Machine learning techniques and manual judgment may be required to address it.

As to the incentive part, we have evaluated our quality based incentive mechanism and compared it to the uniform pricing scheme. Another promising branch of pricing mechanisms is based on reverse auction, where participants bid to sell their sensing data to the service provider. While desirable properties like truthfulness are achieved, the assumption of perfect rationality and the concern of privacy revelation of participants is needed to understand.

We should further search for and go beyond the current reputation systems and quality aware incentive mechanisms to address these issues, and conduct more practical experiments to improve and validate our mechanism for real-world applications.

8 Conclusion and Future Work

In this paper, we have incorporated the consideration of data quality into the design of incentive mechanism for crowdsensing. By applying the expectation maximization algorithm and information theory, we have bridged the gap between quality of sensing data and proper reward for contribution, and proposed the quality based incentive mechanism, which achieves both individual rationality and (approximate) profit maximization. Our incentive mechanism estimates the effort matrix for each participant, calculates the quality of sensing data, and offers a reward in accordance with each effective contribution, aiming to motivate individual participants with different sensing costs to place sufficient manual efforts and submit high quality sensing data in crowdsensing. We have also implemented part of the mechanism with extensive experiments and simulations. Compared to the existing data collection model and uniform pricing scheme, our mechanism achieves superior performance in quality assurance and profit management.

As for future work, we are interested in designing incentive mechanisms that can analyze the quality of sensing data in a more comprehensive way and steer the participants to improve their sensing quality over time in large-scale deployments.

Acknowledgments

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