# User Reputation and Fairness in Crowd-sourcing-based Peer Prediction Mechanisms

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## Abstract

Crowd-sourcing is widely proposed to solve a large variety of judgment tasks, such as classifying website content, peer grading in online courses, or collecting real-world data. As there is no available ground truth always, the data reported by workers cannot be verified. Hence, there is a tendency for the workers to report arbitrary data without actually performing the task.

This report focuses on the different papers which deal with crowd-sourcing settings with some variations where they, in general talk about, challenges in proposing the reward schemes to achieve incentive compatible mechanisms.

## Contents

# 1

# Introduction

Individuals and organizations often face the challenge of executing tasks for which they do not have enough resources or expertise. Crowdsourcing such tasks will help the organizations to complete the tasks without a need for procuring extra resources. However, with the advent of the Internet, crowdsourcing has become even more convenient. Online social platforms provided access to a huge crowd with plenty of diverse expertise. There are many crowdsourcing applications, and few of the early applications include Wikipedia, DARPA red balloon challenge. Even though this concept helps us obtain services or content from a large group of people, there are certain challenges in designing the crowdsourcing protocols that ensure trustworthiness, fairness, and incentivize contributors to report the truth.

Many incentive mechanisms were proposed in crowdsourcing. The random reporting of the crowd can be countered with a primary rule, providing rewards to a report based on its consistency with other reports is called *peer consistency*. However, the best strategy in such schemes is for all workers to report the same answer without solving the task.

## 1.1 Extension of PTS

PTSC (section 9), provides a reward scheme to achieve an incentive-compatible mechanism without assuming any prior. The most profitable strategy for workers is to put high efforts and report honestly. This mechanism is extended to elicit personalized data of agents in PPTS (section 5).

## 1.2 Fair Reward Schemes

The paper Deep Bayesian Trust (Section 7), proposes a mechanism that ensures DSIC and Fairness of rewards. FarM [9] introduces a fair reward scheme for agents in localized settings without the assumption of prior. Orthos [10] for Spatio-temporal Data, guarantees the trustworthiness and accuracy of the reported data, by implementing a game-theoretic framework via smart contract on a blockchain.

## 1.3 Quality/Reputation Scores

Section 3, 4, 6, and 10, consider a mobile crowdsensing setting, where the quality and reputation scores of the recruited crowd are considered to have a level of trust on the services/data received from them.

## 1.4 Preliminaries

**Definition 1.1** (Pure Strategy Nash Equilibrium)**.** *Given a strategic form game $\Gamma = \langle N, (S_i), (u_i)\rangle$, the strategy profile $s^* = (s_1^*, s_2^*, \ldots, s_n^*)$ is called a pure strategy nash equilibrium of $\Gamma$ if*

$$u_i(s^*, s_{-i}^*) = \max_{s_i \in S_i} u_i(s_i, s_{-i}^*) \forall i \in [n]$$

**Definition 1.2** (Common Knowledge)**.** *A fact is common knowledge among the players if every player knows it, every player knows that every player knows it, and so on.*

**Definition 1.3** (Dominant Strategy Incentive Compatible)**.** *A social choice function $f : \Theta_1 \times \ldots \times \Theta_n \to X$ is said to be dominant strategy incentive compatible if*

$$u_i(f(\theta_i, \theta_{-i}), \theta_i) \geq u_i(f(\theta_i, \theta'_{-i}), \theta_i),$$

$$\forall \theta'_i \in \Theta_i, \forall \theta_i \in \Theta_i, \forall \theta_{-i} \in \Theta_{-i}, \forall i \in N$$

**Definition 1.4** (Bayesian Incentive Compatible)**.** *A social choice function $f : \Theta_1 \times \ldots \times \Theta_n \to X$ is said to be Bayesian incentive compatible if*

$$\mathbb{E}_{\theta_{-i}}[u_i(f(\theta_i, \theta_{-i}), \theta_i)|\theta_i] \geq \mathbb{E}_{\theta_{-i}}[u_i(f(\theta_i, \theta'_{-i}), \theta_i)|\theta_i],$$

$$\forall \theta'_i \in \Theta_i, \forall \theta_i \in \Theta_i, \forall i \in N$$

**Definition 1.5** (Truthful Mechanism)**.** *Mechanism $M$ is truthful if we have,*

$$s_i = \underset{x_i}{\operatorname{argmax}}\, \mathbb{E}_{S_j}[M(x_i, S_j)|S_i = s_i], \forall i \in [n], \forall s_i \in [m]$$

*where $S_i$ is signal reported by agent $i$ and $[m]$ is a signal set possible.*

**Definition 1.6** (Minimal Mechanism)**.** *A minimal peer prediction mechanism is a function $M : [m] \times [m] \to R$, where $M(x_i, x_j)$ specifies the payment to agent $i$ when she reports signal $x_i$ and her peer agent $j$ reports signal $x_j$ without any requirement of prediction reports.*

**Definition 1.7** (Interim Individual Rationality)**.** *Individual rationality of a social choice function essentially means that each agent gains a utility that is no less than he would get without participating in a mechanism that implements the social choice function.*

$$\mathbb{E}_{\theta_{-i}}[u_i(f(\theta_i, \theta_{-i}), \theta_i)|\theta_i] \geq \overline{u_i}(\theta_i),$$

*where $\overline{u_i}(\theta_i)$ is the utility agent $i$ receives by withdrawing from the mechanism when his type $\theta_i$.*

**Definition 1.8** (Virtual Valuation)**.** *In forward auctions, the virtual valuation of bidder $i$ with valuation $v_i$ is*

$$\phi_i(v_i) = v_i - \frac{1 - F_i(v_i)}{f_i(v_i)}$$

**Definition 1.9** (Virtual Cost)**.** *In backward auctions, The virtual cost of the bidder $i$ with cost $c_i$ is*

$$\beta_i(c_i) = c_i + \frac{F_i(c_i)}{f_i(c_i)}$$

**Definition 1.10** (Peer Consistent Mechanisms)**.** *Peer consistent mechanisms evaluate the answers provided by an agent based on the correlation with answers provided by other agents.*

## 1.5 Peer Truth Serum

It is an incentive mechanism which utilizes the distribution of reported data from similar tasks as the prior probability of possible answers, and proportionally scale the reward given for agreement between agents with this distribution.

### 1.5.1 Bayesian truth Serum

It is a mechanism that takes both information and prediction reports, and rewards responses that are surprisingly common without assuming any prior.
Formally defining, If there are $r$ indexed respondents, with $m$ responses and let $x^r = (x_1^r, .., x_m^r)$ be reported answers and $y^r = (y_1^r, .., y_m^r)$ be predictions.

$$\overline{x_k} = \lim_{n\to\infty} \frac{1}{n} \sum_{r=1}^{n} x_k^r$$

$$\overline{y_k} = \lim_{n\to\infty} \frac{1}{n} \sum_{r=1}^{n} y_k^r$$

The scoring rule is defined as sum of information score and prediction score:

$$u^r = \sum_k x_k^r log \frac{\overline{x_k}}{\overline{y_k}} + \alpha. \sum_k \overline{x_k} log \frac{y_k^r}{\overline{x_k}}$$

### 1.5.2 Robust Bayesian Peer Truth Serum

This mechanism asks for agents to submit both information report $x_i$ and prediction report $y_i$. For each agent $i$ a reference agent is selected $j \equiv i + 1 (\text{mod } n)$ and a peer agent $k \equiv i + 2 (\text{mod } n)$.
Calculate

$$y'_i = \begin{cases} y_j + \delta, & \text{if } x_i = 1 \\ y_j - \delta, & \text{if } x_i = 0 \end{cases}$$

where $\delta = min(y_j, 1 - y_j)$. Agent $i$'s reward is

$$u_i = R_q(y'_i, x_k) + R_q(y_i, x_k)$$

$R_q$ is strictly proper scoring rule.

### 1.5.3 Logarithmic Peer Truth Serum

Consider a sensor $s$ whose report is equal to $Y_s$. Let $P$, denote sensor $s$'s peers, i.e, sensors that are in vicinity of sensor $s$.
The reward for the reports are calculated as follows:
Frequency of reports equal to $x$ among sensor s's peers:

$$x_{local}(x) = \frac{1}{|P|} \sum_{p\in P} 1_{Y_p = x}$$

Frequency of reports equal to $x$ among reference sensors $\sigma(|\sigma| >> 1)$ that are not each other's peers nor peers of sensor $s$:

$$x_{global}(x) = \frac{1}{|\sigma|} \sum_{s'\in\sigma} 1_{Y_{s'} = x}$$

Reward for sensor

$$s := a. \log \frac{x_{local}(Y_s)}{x_{global}(Y_s)} + b$$

where $a > 0$ and $b$ are constants.

# 2

## Overview

| Paper | Appeared in | Problem Statement | Solution Proposed |
|---|---|---|---|
| ***Reward Scheme using Quality and Reputation Scores*** | | | |
| Are You Contributing Trustworthy Data? The Case for a Reputation System in Participatory Sensing | MSWIM 2010 | Data Elicitation using Reputation Score | This paper proposes a novel reputation system that employs the Gompertz function for computing device reputation score |
| Quality-Aware and Fine-Grained Incentive Mechanisms for Mobile Crowdsensing | IEEE 2016 | Estimation of the quality of services/data provided by each individual mobile user | Presents novel auction for quality-aware and fine-grained MCS, which minimizes expected expenditure for different models characterizing the quality of crowd |
| Quantifying User Reputation Scores, Data Trustworthiness, and User Incentives in Mobile Crowd-Sensing | IEEE Access 2017 | To ensure trustworthiness of the acquired data by improving utility of the MCS platform | Introduces a three metrics, *platform metric, user utility, false payments* improving platform utility and minimizing false payments |
| Truthful Data Quality Elicitation for Quality-Aware Data Crowdsourcing [1] | IEEE 2020 | To estimate the accuracy of the data provided by the workers | Incentivizes workers to truthfully reveal their worker quality and data, and make truthful effort as desired by the crowdsourcing requester |
| Reputation-based Worker Filtering in Crowdsourcing | NIPS 2014 | Aggregating noisy labels to infer the underlying true labels of binary tasks is studied | Proposed an algorithm that uses a combination of disagreement-based penalties and optimal semi-matching's to identify adversarial workers |
| An Incentive Mechanism in Mobile Crowdsourcing Based on Multi-Attribute Reverse Auctions [1] | Sensor 2018 | To improve utility of crowdsourcing platform | Proposed an incentive based mechanism based on reverse auctions and multi attribute auction in MCS |
| ***Fairness in Reward Schemes*** | | | |
| Deep Bayesian Trust : A Dominant and Fair Incentive Mechanism for Crowd | AAAI 2019 | Data elicitation from crowd | Proposes a mechanism that assigns gold tasks to only a few workers and exploits transitivity to derive accuracy of the rest of the workers from their peers' accuracy |
| A Budget-Limited Mechanism for Category-Aware Crowdsourcing Systems | AAMAS 2020 | Wise allocation of budget spent among tasks and workers such that the overall outcome is good | This paper introduces a incentive mechanism, INCARE that achieves high quality outcomes given a budget |
| ***Improvisation of PTS for Different Settings*** | | | |
| Incentives for effort in crowdsourcing using the peer truth serum | ACM 2016 | To Incentivize workers to put in efforts in a crowdsourcing setting | This paper extends PTS and incentivizes all workers to exert high effort and report truthfully |
| Personalized Peer Truth Serum for Eliciting Multi-Attribute Personal Data | UAI 2019 | Introduces a problem of eliciting personal attributes of the agents | Extends Logarithmic Peer Truth Serum (LPTS) to elicit multi-attribute personal data from a crowd |

Table 1: **Research Papers Summarised**

# 3

## Are You Contributing Trustworthy Data? The Case for a Reputation System in Participatory Sensing

[Read3]
**Author:** Kuan Lun Huang, Salil S. Kanhere, Wen Hu

### 3.1 Problem Addressed

Participatory sensing is a revolutionary new paradigm in which volunteers collect and share information from their local environment using mobile phones. The inherent openness of this platform makes it easy to contribute corrupted data. This paper proposes a novel reputation system that employs the Gompertz function for computing device reputation score as a reflection of the trustworthiness of the contributed data

### 3.2 Previous Work

- Ganeriwal et. al. [5] proposed a reputation framework referred to as RFSN, to counter faulty and misbehaving nodes in traditional embedded wireless sensor networks.
- Beta distribution has been employed in [13], where the authors address the problem of selecting suitable participants for participatory sensing applications.
- The problem of verifying data received from user devices in participatory sensing was also studied and their solutions rely on auxiliary trusted platform module (TPM).

### 3.3 System Overview

The architecture of the system primarily consists of: *watchdog module* and *reputation module*, both are implemented at the application server. The system can readily work with any typical participatory sensing applications.

Let us assume $n$ devices contributing data within a particular grid. The watchdog module processes sensor values from these $n$ devices in epochs of duration $T$. For every epoch $k$, the sensor values from device $i$ is denoted by a vector $X_{i,k} = [x_{i,t}, \ldots, x_{i,t+T-1}]$ $\forall i$ with $t = (k-1) \times T + 1$. The watchdog module executes an outlier detection algorithm on the vector $X_{i,k}$ and produce a set of cooperative ratings, $p_{i,k}$ for each device $i$ in epoch $k$. For each epoch $k$, the reputation module incorporates past cooperative ratings and computes reputation scores, $R_{i,k}$, for each device $i$.

The instantaneous average values for epoch $k$ are computed as :

$$r_t = \sum_{i=1}^{n} p_{i,k}.x_{i,t}, \quad (k-1) \times T < t \leq k \times T \tag{1}$$

It is shown that Eq.1 becomes robust average if $p_{i,k}$ is computed as follows:

$$p_{i,k} = \frac{\frac{1}{\frac{\sum_{t=1}^{T}(x_{i,t}-r_t)^2}{\sum_{i=1}^{n}\sum_{t=1}^{T}(x_{i,t}-r_t)^2}+\epsilon}}{\frac{\sum_{j=1}^{n}\frac{1}{\sum_{t=1}^{T}(x_{i,t}-r_t)^2}}{\sum_{i=1}^{n}\sum_{t=1}^{T}(x_{i,t}-r_t)^2}} + \epsilon \tag{2}$$

**Algorithm 1 Iterated Outlier Detection**

Let $p^l_{i,k}$ and $r^l_t$ be the values of $p_{i,k}$ and $r_t$ at the $l^{th}$ iteration, respectively

1. Initialize $l = 0$ and $p^l_{i,k} = \frac{1}{n}$
2. Compute $r^{l+1}_t$ from $p^l_{i,k}$ using Eq.1
3. Compute $p^l_{i,k}$ from $r^l_t$ using Eq.2
4. $l \leftarrow l + 1$
5. Start from Step 2 if no convergence.

### 3.4 Reputation Module

This module uses the above epoch-based ratings to build a long term view of the trustworthiness of each device. This gradually builds up trust in a person after several instances of trustworthy behavior and rapidly tear down the reputation for this individual if there is any dishonest behavior.

Gompertz function for computing reputation scores:

$$R_{i,k}(p^{'}_{i,k}) = ae^{be^{cp^{'}_{i,k}}} \tag{3}$$

The aggregating process must account for the fact that the most recent information is more relevant than the past. Hence, $p_{i,k}$ needs to be mapped to the interval [-1,1]

$$p^{norm}_{i,k} = \frac{2(p_{i,k} - \min\{p_{i,k}\}^n_{i=1})}{\max\{p_{i,k}\}^n_{i=1} - \min\{p_{i,k}\}^n_{i=1}} - 1$$

Thus, $p^{'}_{i,k} = \sum_{k'=1}^{k} \lambda^{(k=k^{'})} p^{norm}_{i,k}$ is the input of the Gompertz function Eq. 3 which computes the device reputations.

## 3.5 Conclusion

This paper proposes an architecture consists of a watchdog module that produces cooperative ratings for each device using the 'Outlier detection algorithm' and reputation module that uses Gompertz function for computing reputation scores taking the output of the watchdog module as input. The reputation score associated with each device reflects the level of trust perceived.

## 3.6 Novelty

- The system proposed is well-suited to quickly adapt to the transitions in user behavior.
- The reputation scheme is implemented in real world participatory sensing application for monitoring noise pollution in urban environment and achieved three-fold improvement in comparison with the state-of-the-art Beta reputation scheme.

# 4

# Quality-Aware and Fine-Grained Incentive Mechanisms for Mobile Crowdsensing

[Read7]
**Author:** Jing Wang, Jian Tang, Dejun Yang, Erica Wang, Guoliang Xue

## 4.1 Problem Addressed

This paper introduces optimal expected expenditure by characterizing the quality of recruited crowd and improves flexibility and effectiveness by presenting a reserve auction based incentive mechanism for quality-aware and fine-grained mobile crowd sensing (MCS).

## 4.2 MCS System

A service user can make a sensing service request via a web portal. The request is then analyzed by the cloud operator, that uses an incentive mechanism to recruit a sensing crowd (a set of mobile users) and distribute the request to them. Their smartphones perform the corresponding sensing activities and report sensor data to the cloud operator. The cloud operator aggregates and analyzes sensor data, and sends results back to the service user through the web portal.

To incentivize the mobile user, a reverse auction based incentive mechanism is used which enables fair pricing between cloud operator and mobile users in MCS.
A fine-grained MCS is considered, in which each sensing task consists of multiple subtasks and a mobile user may make contributions to multiple subtasks.

## 4.3 Auction Formulation

1. The cloud operator (the buyer) announces a sensing task to mobile users (bidders and sellers).
2. Each mobile user $i$ submits a bid $b_i = (w_i, Z_i)$, where $w_i$, $Z_i$ are mobile user $i$'s declared cost and quality vector.
3. The cloud operator uses an incentive mechanism to select the winners and determine payments.
4. Winners carry out the sensing task and submit results to the cloud operator.
5. The cloud operator checks the results and makes payments to winners.

## 4.4 Quality Aware Incentive Mechanism

This consists of two sub problems: *Winner Selection* and *Payment Determination*
Consider $M$ mobile users, and $x$ be the winner selection vector. $q_i$ quantifies the quality of services/data the sensing crowd is potentially capable of providing for a subtask $j$. $\beta_i$ denotes virtual cost of user $i$
**Winner Selection:** Formulated as IP problem

$$\min_{i=1}^{M} \beta_i(w_i)x_i$$

Subjected to

$$q_j = g_j(\mathbf{Z}, \mathbf{X}) \geq r_j \forall j \in \{1, \ldots, N\}$$

$$x_i \in \{0, 1\}$$

**Payment Determination** Let $\Omega(\mathbf{B})$ denote optimal value of IP-Winner and $\Omega(\mathbf{B}_i)$ denote optimal value of IP-Winner with bid $b_i$ removed.

$$p_i = \begin{cases} \beta_i^{-1}(\Omega(\mathbf{B}_{-i}) - (\Omega(\mathbf{B}) - \beta_i(w_i))), & \text{if } x_i = 1 \\ 0, & \text{otherwise} \end{cases}$$

## 4.5 Conclusion

The authors provide a truthful, individually rational, and computationally efficient algorithm for Winner Selection from the bids submimtted in the reverse auction and Payment Determination to determine the payment for winning mobile user in of Quality-aware Incentive Mechanism (QIM). Extensive simulation conducted using mobility dataset of San Francisco taxies results have shown that the proposed incentive mechanism achieves noticeable expenditure savings compared to two well-designed baseline methods.

## 4.6 Novelty

- Unlike many other papers, This paper considers fine-grained MCS, in which a sensing task consists of multiple subtasks.
- This paper considers different mathematical models for quality and present auction formulation based on these models.
- The auction formulation with objective of minimizing expected expenditure subjected to required quality is considered.

# 5

## Personalized Peer Truth Serum for Eliciting Multi-Attribute Personal Data

[Read2]
**Author:** Naman Goel, Boi Faltings

## 5.1 Problem Addressed

Considering the problem of eliciting the personal attributes of the agents where the tasks cannot be shared between two agents and designing a Personalized Peer Truth Serum (PPTS) which incentivize the peer consistency.

## 5.2 Previous Work

- The Deep Bayesian Trust mechanism [Read1] ensures dominant strategy incentive compatibility and also computes fair rewards in large scale crowdsourcing by using both peer answers and some gold standard answers.
- Miller [7] proposed original peer prediction mechanism for information elicitation without verification.
- Radanovic and Faltings introduced a mechanism, *Logarithmic Peer Truth Serum* (LPTS) [11].
- Peer Truth Serum (PTSC) mechanism for incetivizing efforts for crowdsourcing was proposed [Read6].

## 5.3 Contribution

- **Step1:** Define which agents can act as peers for one another in settings when agents can't share tasks.
- **Step2:** Show that even if such peers are estimated from the reports submitted by the agents, the incentive compatibility is not affected.
- **Step3:** Extend the mechanism to handle continuous data values instead of only discrete answers.

## 5.4 Model

- In this model the data is collected from large no.of agents $W(|W| = n \to \infty)$.
- The elicited data consists of set of attributes $A(|A| = d \geq 2)$.
- Let $P(X_{ij})$ be agent $i$'s prior belief about measurement of attribute $j$.
- Random variable $G_j$ models the global factors that affect the attribute $j$ of any random agent. $P(G_i)$ is prior belief and $P(G_i|X_{ij})$ is posterior belief agent's have about global factors.
- For every agent $i$, set of other agents $N_i \in W$ called cluster of agent $i$ which share only some personal factors.
- Let $L_{ij}$ denote random variable for personal factors where $k$ being the cluster to which agent $i$ belongs. $P(L_{ij})$ is prior belief and $P(L_{ij}|X_{ij})$ is posterior belief agent's have about personal factors.
- The global distribution $P(X_{ij}|G_j)$ is modeled as $P(X_{ij}|G_j) = \sum_{k=1}^{K} \alpha.P(X_{ij}|L_{kj})$ where $K(<< N)$ is the number of clusters and $\alpha_k$ is the mixing probability of $k$th cluster.

## 5.5 Mechanism

- The center collects reports from all agents for all their attributes. Then each agent is assigned to a cluster corresponding to agent $i$'s belief.
- $j$th attribute score of agent $i$ for reporting $X_{ij} = y$ is $r_{ij} = \log \frac{f(y|\widehat{\mu}_{L_{ij}}, \widehat{\sigma}^2_{L_{ij}})}{\sum_{k=1}^{K} \widehat{\alpha}_k . f(y|\widehat{\mu}_{L_{kj}}, \widehat{\sigma}^2_{L_{kj}})}$ where $f$ is a Gaussian function given by $f(x|\mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ where $\widehat{\mu}_{L_{kj}}$, $\widehat{\sigma}^2_{L_{kj}}$ are mean and variance of values of reported for attribute $j$ by agents in the cluster $N_i$. $\widehat{\alpha}_k$ is the empirical relative mixing frequency of cluster $k$.
- Agent $i$ finally gets a cumulative reward (CR) equal to the average of attribute score $r_{ij}$ for all attributes $j \in \{1, 2.., d\}$. More formally, $CR(i) = \frac{\sum_{j=1}^{d} r_{ij}}{d}$

## 5.6 Analysis

- PPTS mechanism rewards 'surprisingly common' reports. The PPTS mechanism is Bayes-Nash incentive compatible, with strictly positive expected payoffs in the truthful reporting equilibrium.
- Heuristic reporting equilibria result in zero expected payoff in the mechanism.

- In the PPTS mechanism, an equilibrium strategy profile defined by a function $g(x) = ax + b$ is not in expectation more profitable than the truthful strategy.

**Theorem 5.1.** *The ex-ante expected score of a truthful agent is equal to the conditional mutual information (CMI) of the attribute measurements and the personal factors given the global factors.*

**Definition 5.1** ($\epsilon$- Correct Clustering Algorithm)**.** *A clustering algorithm is called $\epsilon$ - correct, if given true reports, it assigns a true report to a wrong cluster with probability at most $\epsilon$ and $\epsilon$ is such that as $|N_k| \to \infty$, the MLE estimates $\{\widehat{\mu}_{L_{kj}}, \widehat{\sigma}^2_{L_{kj}}\}$ converge to $\{\mu_{L_{kj}}, \sigma^2_{L_{kj}}\}$ and $\widehat{\alpha}_k$ converge to $\alpha_k$, $\forall k$.*

**Theorem 5.2.** *Given an $\epsilon$ - correct clustering algorithm, the PPTS is Bayes-Nash incentive compatible even if the clusters are approximated from the reports.*

## 5.7 Conclusion

A novel incentive mechanism to elicit continuous valued, multi-attribute and personal data from crowd was proposed and presents that the mechanism ensures truthful equilibrium is profitable compared to any other undesired equilibria.

# 6

# Quantifying User Reputation Scores, Data Trustworthiness, and User Incentives in Mobile Crowd-Sensing

[Read5]
**Author:** Maryam Pouryazdan, Burak Kantarci, Tolga Soyata, Luca Foschini, Houbing Song

## 6.1 Problem Statement

In mobile crowdsensing correctness and truthfulness of the acquired data must be verified, because the users might provide incorrect or inaccurate data, whether due to malicious intent or malfunctioning devices. So, the authors introduced a new metric, 'Collaborative reputation scores' and can provide an effective alternative to the previously proposed metrics.

## 6.2 Previous MCS Application

- Benazzouz et al. [1] introduced the term IoT-centric social networks, defining a set of connected smart mobile devices that form a social network community by sharing resources and information.
- Bulut et al. [2] present a crowdsourced wait-time estimation system called 'LineKing' for monitoring and estimating the waiting time to enter a coffee shop.
- Zhang et al. [16] presented a self-contained indoor navigation system (GROPING) by using MCS to generate floor maps.
- Zhang et al. [17] formulated the life cycle of MCS applications as a four-stage series events with the following stages: 1) task creation, 2) task assignment, 3) individual task execution, and 4) crowd-data integration.

## 6.3 Theme

There are three component of mobile crowd-sourcing:

1. User Recruitment
2. Platform Utility and User Utility
3. True Payments and False Payments

The goal of any successful MCS system is to maximize platform utility by compensating the users sufficiently, which will keep the user utility at an acceptable minimum. The third metric false payments, must be minimized to avoid paying for bad information.
Two primary factors that contribute to user reputation are:

1. The sensory accuracy or the possibility of device malfunction, i.e. Hard reputation.
2. The average probability of inaccurate or outright wrong readings that stem from malicious intelligence (either malicious users manipulating readings or a virus causing incorrect reporting),i.e. Soft Reputation.

Thus, data trustworthiness of a user $i$ ($\mathfrak{T}_i$) is function of hard and soft reputation. It is defined as follows:

$$\mathfrak{T}_i = \begin{cases} f(R_i^{hard}, R_i^{soft}), & \text{if } Q_i < Q^{TH} \\ R_i^{soft} = R_i, & \text{if } Q_i \geq Q^{TH} \end{cases}$$

where $Q_i$ is the accuracy of hardware sensors of user $i$ and $Q^{TH}$ is accuracy threshold.

Three Reputation score based MCS are discussed in the paper:

- Statistical Reputation
- Voted Reputation
- Anchor-Assisted Decentralized Reputation

## 6.4 Conclusion

Using collaborative reputation scores in user recruitment improves platform utility and data trustworthiness by reducing false payments. When collaborative methods are employed, using statistical reputation in the assessment of the value of a recruited crowd can reduce the user bias in the decentralized vote-based component of the reputation score.

# 7

## Deep Bayesian Trust : A Dominant and Fair Incentive Mechanism for Crowd

[Read1]
**Author:** Naman Goel, Boi Faltings

## 7.1 Problem Addressed

This paper study challenges in peer-based mechanisms and other classical mechanisms which use gold tasks and pay workers accordingly.

## 7.2 Previous Work

- Many early mechanisms in this category were either not detail-free (required knowledge about the beliefs of the workers) [8] or not minimal.
- The Peer Truth Serum for crowdsourcing [Read6] does not require even this assumption for the theoretical guarantees and works with a bounded number of tasks overall.
- The Correlated Agreement mechanism [14] generalizes the mechanism of Dasgupta and Ghosh 2013 [4] to non-binary answer spaces with moderate assumptions on correlation structure of worker's observations.
- Output-agreement mechanism [15] works only under strong assumption on the correlation structure of workers' observations.

## 7.3 Model

In a large scale crowdsourcing, tasks given to workers have discrete answer space $\{0, \dots, K-1\}$ of size $K$ denoted by $[K]$. let $g$ be ground truth for the task, $x_i$ be the signal obtained by worker $i$ and $y_i$ be the reported answer. $g, x_i, y_i \in [K] \forall i$. Here, The effort strategy of the worker is considered binary that is, $e_i$ is either 0 or 1.

**Reporting Strategy:** When $e_i = 1$, reporting strategy $S_i$ of worker $i$ is a $K \times K$ matrix, where $S_i[x, y]$ is a probability of her reported answer on a task being $y$ given that the observed answer is $x$.
When $e_i = 0$, the reporting strategy $S_i$ is $K$ dimensional probabilistic vector where $S_i[x]$ is the probability of her reported answer on a task being $x$.

**Proficiency Matrix:** A $K \times K$ matrix $(A_i)$ where $A_i[g, x]$ is probability that the obtained answers on a task is $x$ given that the ground truth is $g$.

**Trustworthiness Matrix:** A $K \times K$ matrix $(T_i)$ where $T_i[g, y]$ is probability that the reported answers on a task is $y$ given that the ground truth is $g$.

**Lemma 7.1.** *As $|Q_i \cap Q_j| \to \infty$, the following holds with high probability*

$$\omega(Y_i = y_i | Y_j = y_j) = \sum_{g \in [K]} T_i[g, y_i]. \left( \frac{T_j[g, y_j].P(g)}{\omega(Y_j = y_j)} \right)$$

*, where $Q_i$ is the set of tasks assigned to worker $i$ and $\omega$ is the empirical distribution of answers reported.*

## 7.4 Deep Bayesian Trust Mechanism

1. Assign task set to oracle $o$ and obtains its answers.
2. Initialize an *Informative answer pool* (IAP) with the answers given by the oracle.
3. Select some tasks from IAP.
4. Prepare a set of batches of tasks such that each contains tasks selected in previous step and some fresh tasks.
5. Publish the batches on the platform and let workers select a batch they solve.
6. For any worker $i$ who submits her batch, find $T_i$ according to lemma 7.1. Reward worker $i$ with an amount equal to $\beta. \left( \sum_{g \in [K]} T_i[g, g] \right) - 1$, where $\beta$ is a scaling constant.
7. If the answers of the worker $i$ satisfy informative criteria, add the answers to IAP and assign trustworthiness $T_i$ as obtained in Step 6.
8. Asynchronously repeat steps 3, 4, 5, 6, 7 until desired numbers of answers are collected for all tasks.

## 7.5 Informativeness Criterion

If $\omega(Y_j = y_j) \neq 0$ and coefficient matrix $\frac{T_j[g,y_j].P(g)}{\omega(Y_j=y_j)}$ is full rank, the informative criterion is said to be satisfied. $C^E$ denote the the cost of effort required to solve batch of tasks.

**Theorem 7.2.** *If* $\beta > \frac{C^E}{(\sum_{g\in[K]} A_i[g,g])-1}$ *and* $A_i[g,g] > A_i[g',g], \forall g' = g$, *then the Deep Bayesian Trust Mechanism*

1. *is dominant uniform strategy incentive compatible (DUSIC) for every worker i*
2. *ensures strictly positive expected reward in the truthful strategy.*

**Theorem 7.3.** *In the Deep Bayesian Trust Mechanism, a heuristic strategy gives zero expected reward.*

## 7.6 Conclusion

This paper proposes a dominant uniform strategy incentive compatible (DUSIC) mechanism, called the Deep Bayesian Trust Mechanism, which rewards a constant number of workers with gold tasks and the rest using peer answers. This mechanism is guaranteed to be game theoretically robust to any strategic manipulation and also ensures fair rewards to workers, thus contributing towards the bigger movement of making algorithmic decisions fair.

# 8

# A Budget-Limited Mechanism for Category-Aware Crowdsourcing Systems

**Author:** Yuan Luo,Nicholas R. Jennings

## 8.1 Problem Addressed

When the budget is tight compared to size of task pool, major challenge for an initiator is to design an effective allocation scheme. Wise decision on how many answers to be collected for each task and how to assign tasks to appropriate workers is required.

## 8.2 Previous Work

- Chen et al. [3] proposed an algorithm, called Opt-KG, to address the budget allocation problem with imperfect workers by assuming that the costs of workers are the same.
- Zhang et al. [18] proposed DI-Greedy-MUL, which solves the problem of eliciting truthful costs in the budget allocation problem.
- Zheng et al. [19] do exploit workers' diverse qualities in different categories by designing an algorithm called DOCS.

## 8.3 Contribution

- Proposes a first budget limited mechanism for category aware crowdsourcing applications, INCARE.
- INCARE payment scheme is incentive compatible, individual rational and guarantees budget feasibility.

## 8.4 INCARE Mechanism

Initiator publicizes a task set $N$ and each worker $k \in K$ reply with a bid set $\Phi_k = \{\phi_k^1, \phi_k^2, \ldots, \phi_k^{m_k}\}$. Each submitted bid is task-price pair $\phi_k^m = (n_k^m, b_k^m)$, where $n_k^m$ is the task selected by worker $k$ in $m$-th bid and $b_k^m$ is price claimed.
Initiator sequentially determines the winning bid set which reveals a task-worker pair $\omega^t(\phi_k^m) = \{n^t, k^t\}$.
**Information Update Process**:
For task $j \in N$ and $j$ , $n^t$ , its difficulty level in State Space $S^t$ is

$$\eta_{n,l}^t = \eta_{n,l}^{t-1}, \theta_j^t = \theta_j^{t-1}$$

$\eta_{n,l}^t$ is the value of task $n$ difficulty for the l-th category in round $t$, $\theta_j^t$ denotes the difficulty level of task $n$ in round $t$. For task $n^t$ , its difficulty level in State Space $S^t$ is

$$\eta_{n,l}^t | y_{n^t,k^t} = \begin{cases} \frac{\eta_{n,l}^{t-1}.\delta_{k,l}^{t-1}}{\eta_{n,l}^{t-1}.\delta_{k,l}^{t-1}+(1-\eta_{n,l}^{t-1}).(1-\delta_{k,l}^{t-1})}, & \text{if } y_{n^t,k^t} = 1 \\ \frac{\eta_{n,l}^{t-1}.(1-\delta_{k,l}^{t-1})}{\eta_{n,l}^{t-1}.(1-\delta_{k,l}^{t-1})+(1-\eta_{n,l}^{t-1}).\delta_{k,l}^{t-1}}, & \text{if } y_{n^t,k^t} = 0 \end{cases}$$

where $\delta_{k,l}^{t-1}$ is quality of worker $k$ for $d_l$ category in round $t$

$$\theta_n^t | y_{n^t,k^t} = \sum_{l=1}^{L} r_{n,l}.(\eta_{n,l}^t | y_{n^t,k^t})$$

Selected worker's quality is updated as follows:

$$\delta_{k,l}^t | y_{n^t,k^t} = \begin{cases} \frac{\delta_{k,l}^{t-1}.v_{k,l}^{t-1}+\theta_n^t.r_{n,l}}{v_{k,l}^{t-1}+r_{n,l}}, & \text{if } y_{n^t,k^t} = 1 \\ \frac{\delta_{k,l}^{t-1}.v_{k,l}^{t-1}+(1-\theta_n^t).r_{n,l}}{v_{k,l}^{t-1}+r_{n,l}}, & \text{if } y_{n^t,k^t} = 0 \end{cases}$$

After updating the information, then the new winning bid id selected and initiator pays each winning bid $\phi_k^m$ an amount of money $p(\phi_k^m)$

## 8.5 Conclusion

By incentivizing workers to report their costs truthfully and considering workers' diverse abilities across different task categories, INCARE produces significant savings for the initiator.

# 9

## Incentives for effort in crowdsourcing using the peer truth serum

[Read6]
**Author:** Goran Radanovic, Boi Faltings, Radu Jurca

### 9.1 Problem Addressed

Crowdsourcing is a widely used method for eliciting information for a variety of tasks. The selection of workers and getting them to invest efforts for obtaining accurate answers are the major challenges. Most of the previous works have been devoted to the issue of how to select the workers for the tasks. The second major issue is to get the workers to invest sufficient effort.

A novel mechanism Peer Truth Serum for Crowdsourcing (PTSC) [Read6], which combines the ideas from Dasgupta and Ghosh [4] with Peer truth serum (PTS) was proposed. The idea behind the mechanism is to use the distribution of reported answers from similar tasks as the prior probability of possible answers, and scale the reward given for agreement between workers with this distribution. The payments in this mechanism depend on the accuracy of the answers, so only those workers who work are rewarded. PTSC mechanism rewards based on *surprisingly common* policy.

### 9.2 Assumptions

1. The worker should believe that the answer of her peer will be positively correlated with her own. More precisely, the worker should believe that her posterior $P_{p|w}$ differs from her prior $P_p$ by giving the highest increase to her own answer $x$:

   $$\frac{P_{p|w}(x|x)}{P_p(x)} > \frac{P_{p|w}(y|x)}{P_p(y)}, \forall y \neq x$$

   This is *Self Prediction condition.*

2. We assume that a worker $w$ solves only one task $t_w$ in a family of tasks $T$. If the assumptions does not hold within set $T$, we can simply partition $T$ into subsets that satisfy the assumption.

3. A worker in $W$ is assumed to be a risk neutral rational agent who aims to maximize her expected profit.

4. We assume workers' beliefs to be fully mixed, i.e. for any two workers $w$ and $p$ we have that $\forall x, y \in X$ : $P_p(x) > 0, P_{p|w}(x|y) > 0$.

### 9.3 Algorithm

The Algorithm 9.3 is a robust version of PTSC algorithm that can operate with smaller number of statistically independent tasks.

**Algorithm 2** RPTSC

Reward a worker $w$ for solving task $t_w$ as follows:

1. Randomly sample $n$ samples from $n$ different tasks, including the task $t_w$, but not the worker $w$'s report.

2. Calculate the frequency $R(w)$ of reported values within this sapmle, $R(w) = \frac{num(x)}{\sum_{y \in \chi} num(y)}$.

3. Select a peer worker $p$ who was given task $t_w$ to solve.

4. Worker $w$ is rewarded for reporting $Y_w = x_w$ with the score:

   $$\tau(x_w, x_p) = \begin{cases} \alpha.\left(\frac{\mathbb{I}_{x_w = x_p}}{R_w(x_w)} - 1\right), & \text{if } R_w(x_w) \neq 0 \\ 0, & \text{if } R_w(x_w) = 0 \end{cases}$$

   where $\mathbb{I}_{x_w = x_p}$ is indicator variable (equal to 1 if $x_w = x_p$ and 0 otherwise), $\alpha$ is a constant strictly greater than 0.

As a rational agent, worker $w$ will choose the action that maximizes her expected reward. PTSC mechanism works for all kinds of strategies workers can choose. In all three cases of heuristic, honest and strategic PTSC incentivizes workers to invest effort and report truthful answers. For settings like crowdsensing and peer grading, PTSC mechanisms can perform empirically better than other peer grading mechanisms.

### 9.4 Properties

#### 9.4.1 Incentive Compatibility:

**Theorem 9.1.** *Suppose that for all workers $w$ and answers $x \in \chi$, parameter $\alpha$ and the number of tasks $n$ satisfy:*

$$\overline{\tau}_w(\alpha) \geq c_w(e_1) - c_w(e_0)$$
$$\frac{1 - (1 - P_q(x))^{n-1}}{1 - P_q(x)^{n-1}} \geq \Delta_w$$

*where $\Delta_w$ is the self predictor of worker $w$. Then the RPTSC mechanism admits the honest reporting strategy profile as a strict equilibrium.*

#### 9.4.2 Low-effort aversion

**Definition 9.1.** *Consider a parameter $\beta \in (0, 1]$ and a strategy profile that is a mixture of the honest and heuris-*

*tic strategies, where the honest strategy is adopted with probability $\gamma$. A mechanism is $\beta$ - low effort averse if it does not admit the mixed strategy as an equilibrium for any $\gamma$ such that $\beta \le \gamma \le 1$.*

**Theorem 9.2.** *Suppose that scaling parameter $\alpha$ is such that:*

$$\alpha > \frac{c_w(e_1) - c_w(e_0)}{\beta.\mathbb{E}_{X_w=x}[P_{p|w}(x|x) - P_p(x)]}$$

*for all workers $w$, where $\mathbb{E}_{X_w=x}$ is the expectation over possible evaluations of a worker $w$. Then RPTSC is $\beta$ - low effort averse.*

#### 9.4.3 Optimality

**Theorem 9.3.** *Suppose that for all workers $w$ and answers $x \in \chi$, parameter $\alpha$ and number of tasks $n$ satisfy:*

$$\overline{\tau}_w(\alpha) > c_w(e_1) - c_w(e_1)$$

$$\left(1 - (n-1).P_p(x).\frac{(1-P_p(x))^{n-2}}{1-(1-P_p(x))^{n-1}}\right) \ge \Delta_w$$

# 10

## Reputation-based Worker Filtering in Crowdsourcing

[Read4]
**Author:** Srikanth Jagabathula, Lakshminarayanan Subramanian, Ashwin Venkataraman

### 10.1 Problem Addressed

The problem of aggregating noisy labels from crowdsourcing reports is not very trivial. To infer true labels of binary tasks, a computationally efficient reputation algorithm to identify and filter out adversarial workers in crowdsourcing systems is proposed.

### 10.2 Related Work

- [6] aggregated penalties in a "load-balanced" manner using the concept of optimal semi-matching.
- [12] Proposed an empirical Bayesian algorithm to eliminate workers who label randomly without looking at the particular task.

### 10.3 Model

Consider set of binary tasks $\mathcal{T}$ having true labels in $\{-1, +1\}$ and worker set $W$. $w_i(t_j)$ denote label provided by worker to task $t_j$, $\mathcal{L} = w_i(t_j)$ where $\mathcal{L} \in \{-1, 0, +1\}$. $\mathcal{T}_{cs}$ is conflict set which has both '+1' and '-1' labels. $d_j^+$ and $d_j^-$ denote the number of workers labeling task $t_j$ as 1 and -1 respectively.

In order to overcome over-penalizing honest workers, Two techniques of penalty are considered. (1)Soft Penalty, (2)Hard Penalty.

**Algorithm 3** **Soft Penalty**

1. Input: $W, \mathcal{T}, \mathcal{L}$
2. For every task $t_j \in \mathcal{T}_{cs}$, assign penalty $s_{ij}$ to each worker $w_i \in W_j$ as follows:

$$s_{ij} = \frac{1}{d_j^+} \quad \text{if } \mathcal{L}_{ij} = 1$$

$$s_{ij} = \frac{1}{d_j^-} \quad \text{if } \mathcal{L}_{ij} = -1$$

3. Output: Penalty of worker $w_i$

$$pen(w_i) = \frac{\sum_{t_j \in \mathcal{T}_i \cap \mathcal{T}_{cs}} s_{ij}}{|\mathcal{T}_i \cap \mathcal{T}_{cs}|}$$

**Hard Penalty.** It addresses the case sophisticated adversaries, the key idea is not to distribute the penalty evenly across all the workers. This uses the concept of semi-optimal matchings on a bipartite graph. In a bipartite graph $B = (U, V, E)$, a semi-matching in $B$ is a set of edges $M \in E$ such that each vertex in $V$ is incident to exactly one edge in $M$. $deg_M(u)$ denote the number of $u$ is incident on in $M$ and cost is defined as

$$cost_M(u) = \sum_{i=1}^{deg_M(u)} i = \frac{deg_M(u)(deg_M(u)+1)}{2}$$

. The optimal semi-matching minimizes:

$$\sum_{u \in U} cost_M(u)$$

**Algorithm 4 Hard Penalty**

1. Input: $W, \mathcal{T}, \mathcal{L}$
2. Create a bipartite graph $B^{cs}$ as follows:

   i. Each worker $w_i \in W$ is represented by a node on the left

   ii. Each task $t_j \in \mathcal{T}_{cs}$ is represented by two nodes on the right $t_j^+$ and $t_j^-$

   iii. Add the edge $(w_i, t_j^+)$ if $\mathcal{L}_{ij} = 1$ or edge $(w_i, t_j^-)$ if $\mathcal{L}_{ij} = -1$

3. Compute an optimal semi-matching OSM on $B^{cs}$ and let $d_i$ be the degree of $w_i$ in OSM
4. Output: Penalty of worker $w_i$

$$pen(w_i) = d_i$$

## 10.4 Conclusion

The reputation based worker filtering that uses disagreement-based penalties and optimal semi-matchings to identify adversarial workers is proposed. Shows that our reputation scores are consistent and algorithm can be applied to real crowd-sourced datasets.

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## List of Papers Summarized

[Read1] Naman Goel and Boi Faltings. Deep bayesian trust : A dominant and fair incentive mechanism for crowd, 2018.

[Read2] Naman Goel and Boi Faltings. Personalized peer truth serum for eliciting multi-attribute personal data. In *UAI*, 2019.

[Read3] Kuan Lun Huang, Salil S. Kanhere, and Wen Hu. Are you contributing trustworthy data? the case for a reputation system in participatory sensing. In *Proceedings of the 13th ACM International Conference on Modeling, Analysis, and Simulation of Wireless and Mobile Systems*, MSWIM '10, page 14–22, New York, NY, USA, 2010. Association for Computing Machinery.

[Read4] Srikanth Jagabathula, Lakshminarayanan Subramanian, and Ashwin Venkataraman. Reputation-based worker filtering in crowdsourcing. In *Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2*, NIPS'14, page 2492–2500, Cambridge, MA, USA, 2014. MIT Press.

[Read5] M. Pouryazdan, B. Kantarci, T. Soyata, L. Foschini, and H. Song. Quantifying user reputation scores, data trustworthiness, and user incentives in mobile crowd-sensing. *IEEE Access*, 5:1382–1397, 2017.

[Read6] Goran Radanovic, Boi Faltings, and Radu Jurca. Incentives for effort in crowdsourcing using the peer truth serum. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 7(4):1–28, 2016.

[Read7] J. Wang, J. Tang, D. Yang, E. Wang, and G. Xue. Quality-aware and fine-grained incentive mechanisms for mobile crowdsensing. In *2016 IEEE 36th International Conference on Distributed Computing Systems (ICDCS)*, pages 354–363, 2016.

## References

[1] Y. Benazzouz, C. Munilla, O. Günalp, M. Gallissot, and L. Gürgen. Sharing user iot devices in the cloud. In *2014 IEEE World Forum on Internet of Things (WF-IoT)*, pages 373–374, 2014.

[2] M. F. Bulut, M. Demirbas, and H. Ferhatosmanoglu. Lineking: Coffee shop wait-time monitoring using smartphones. *IEEE Transactions on Mobile Computing*, 14(10):2045–2058, 2015.

[3] Xi Chen, Qihang Lin, and Dengyong Zhou. Statistical decision making for optimal budget allocation in crowd labeling. *Journal of Machine Learning Research*, 16(1):1–46, 2015.

[4] Anirban Dasgupta and Arpita Ghosh. Crowdsourced judgement elicitation with endogenous proficiency. In *Proceedings of the 22nd International Conference on World Wide Web*, WWW '13, page 319–330, New York, NY, USA, 2013. Association for Computing Machinery.

[5] Saurabh Ganeriwal, Laura K. Balzano, and Mani B. Srivastava. Reputation-based framework for high integrity sensor networks. *ACM Trans. Sen. Netw.*, 4(3), June 2008.

[6] Nicholas J. A. Harvey, Richard E. Ladner, László Lovász, and Tami Tamir. Semi-matchings for bipartite graphs and load balancing. *J. Algorithms*, 59(1):53–78, April 2006.

[7] Nolan Miller, Paul Resnick, and Richard Zeckhauser. Eliciting informative feedback: The peer-prediction method. *Management Science*, 51:1359–1373, 09 2005.

[8] Nolan Miller, Paul Resnick, and Richard Zeckhauser. Eliciting informative feedback: The peer-prediction method. *Management Science*, 51:1359–1373, 09 2005.

[9] Moin Moti, Dimitris Chatzopoulos, Pan Hui, and Sujit Gujar. Farm: Fair reward mechanism for information aggregation in spontaneous localized settings (extended version), 06 2019.

[10] Moin Hussain Moti, Dimitris Chatzopoulos, Pan Hui, Boi Faltings, and Sujit Gujar. Orthos: A trustworthy ai framework for data acquisition, 2020.

[11] Goran Radanovic and Boi Faltings. Incentive schemes for participatory sensing. In *Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems*, AAMAS '15, page 1081–1089, Richland, SC, 2015. International Foundation for Autonomous Agents and Multiagent Systems.

[12] Vikas C. Raykar and Shipeng Yu. Eliminating spammers and ranking annotators for crowdsourced labeling tasks. *J. Mach. Learn. Res.*, 13(1):491–518, February 2012.

[13] Sasank Reddy, Deborah Estrin, and Mani Srivastava. Recruitment framework for participatory sensing data collections. volume 6030, pages 138–155, 12 2010.

[14] Victor Shnayder, Arpit Agarwal, Rafael M. Frongillo, and David C. Parkes. Informed truthfulness in multi-task peer prediction. *CoRR*, abs/1603.03151, 2016.

[15] Bo Waggoner and Yiling Chen. Output agreement mechanisms and common knowledge. In Jeffrey P. Bigham and David C. Parkes, editors, *Proceedings of the Seconf AAAI Conference on Human Computation and Crowdsourcing, HCOMP 2014, November 2-4, 2014, Pittsburgh, Pennsylvania, USA*. AAAI, 2014.

[16] C. Zhang, K. P. Subbu, J. Luo, and J. Wu. Groping: Geomagnetism and crowdsensing powered indoor navigation. *IEEE Transactions on Mobile Computing*, 14(2):387–400, 2015.

[17] D. Zhang, L. Wang, H. Xiong, and B. Guo. 4w1h in mobile crowd sensing. *IEEE Communications Magazine*, 52(8):42–48, 2014.

[18] Qi Zhang, Yutian Wen, Xiaohua Tian, Xiaoying Gan, and Xinbing Wang. Incentivize crowd labeling under budget constraint. *2015 IEEE Conference on Computer Communications (INFOCOM)*, pages 2812–2820, 2015.

[19] Yudian Zheng, Guoliang Li, and Reynold Cheng. Docs: A domain-aware crowdsourcing system using knowledge bases. *Proc. VLDB Endow.*, 10(4):361–372, November 2016.