Improving IoT Data Quality in Mobile Crowd Sensing: A Cross Validation Approach

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***Abstract*—Data quality, or sometimes referred to as data credibility, is a critical issue in mobile crowd sensing (MCS) and more generally Internet of Things (IoT). While candidate solutions, such as incentive mechanisms and data mining have been well explored in the literature, the *power of crowds* has been largely overlooked or under-exploited. In this paper, we propose a cross validation approach which seeks a *validating crowd* to ratify the *contributing crowd* in terms of the sensor data contributed by the latter, and uses the validation result to reshape data into a more credible posterior belief of the ground truth. This approach consists of a framework and a mechanism, where the framework outlines a four-step procedure and the mechanism implements it with specific technical components, including a weighted random oversampling (WRoS) technique and a privacy-aware trust-oriented probabilistic push (PATOP^2) algorithm. Unlike most prior work, our proposed approach augments rather than redesigning existing MCS systems, and requires minimal effort from the crowd, making it conducive to practical adoption. We evaluate our proposed mechanism using a real-world MCS IoT dataset and demonstrate remarkable (up to 475%) improvement of data quality. In particular, it offers a unified solution to reconciling two disparate needs: reinforcing obscure (weakly recognizable) ground truths and discovering hidden (unrecognized) ground truths.**

***Index Terms*—Chance-constrained programming, crowdsourcing, data quality, exploration-exploitation tradeoff, Internet of Things (IoT), Kullback–Leibler divergence, privacy, trust.**

I. Introduction

MOBILE crowdsensing (MCS) is a key enabler of the Internet of Things (IoT) by connecting physical objects or "things" to the cyberspace via the medium of "humans-as-sensors." By leveraging personal sensing devices, such as smartphones, wearables, car-borne, and soon drone-borne sensors, MCS significantly accelerates the permeation of IoT as compared to the alternative of dedicated sensor deployment by governments and businesses.

However, the issue of *data quality*, or sometimes referred to as *data credibility*, presents a fundamental challenge to MCS and IoT in general. The challenge arises from the fact that the data sources—the *contributing crowd* who own the IoT devices—are barely controllable, unevenly skilled, and hardly accountable. In the literature, a wide variety of candidate solutions have been proposed, taking approaches, such as incentive mechanism design [1]–[7], quality and trust assessment [8]–[12], truth finding [13]–[15], and so on. What is in common is that these approaches all introduce some *exogenous* forces or tools while having overlooked the "power of crowds" per se [16], which could otherwise be exploited to a fuller extent.

In this paper, we propose a cross validation (CV) approach to address the data quality issue from a perspective different than prior work. This approach seeks a *validating crowd* to ratify the *contributing crowd* in terms of the sensor data contributed by the latter, and uses the validation result to reshape data into a more credible posterior belief of the ground truth. It comprises a CV framework and a CV mechanism, where the framework outlines a four-step procedure with objectives and requirements, and the mechanism fulfills the framework with specific and concrete technical components. In particular, the mechanism uses a weighted random oversampling (WRoS) technique to enable truth discovery, and a privacy-aware trust-oriented probabilistic push (PATOP^2) algorithm that we propose based on the exploration-exploitation principle [17] and stochastic optimization.

One key motivation of our CV approach is to leverage the "side information" possessed by people, which includes (diversely) people's domain knowledge, professional expertise, news learned from their social networks or public media, and so forth. This opens a much broader and powerful channel for acquiring information besides directly sensing the physical phenomenon or targets, thereby offering a more comprehensive perspective for improving IoT data quality.

Our CV leads to two key consequences. First, it relaxes the *spatio-temporal constraints* of direct and physical sensing, which requires IoT devices to be at specific locations within specific time windows and hence is rather restrictive. Second,

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it relieves the necessary burden of consuming sensing-related resources (especially energy) which can be substantial, and is less prone to privacy leakage via sensing devices.

This paper makes the following contributions.

- We introduce a CV approach which offers a new perspective to improve IoT data quality by exploiting the power of crowds to a fuller extent.
- We present a framework that outlines the general procedure and requirements of performing CV, and design a mechanism that substantiates the procedure and fulfills the requirements. In particular, using a WRoS technique and a PATOP^2 algorithm that we propose, the mechanism not only fulfills, with guaranteed success rate, the "hard" constraints imposed by the time-sensitivity of IoT applications, but also satisfies "soft" constraints on the trustworthiness of validation which concerns competency, honesty, and bias.
- Our proposed approach is conducive to practical adoption: a) unlike most prior work, it does not lead to redesigning existing MCS/IoT systems (which otherwise jeopardizes prior investments), but rather *augments* such systems with a lightweight plug-in; b) it requires minimal effort from the validating crowd and zero user intervention when executing the mechanism, and is simple to implement; c) it does not assume any distribution of the underlying sensing phenomenon as in Bayesian approaches, nor make any assumption on strict human rationality as in game-theoretical studies; and d) it is robust to common security threats such as collusion and Sybil attacks.
- Using a real-world IoT dataset, we demonstrate that the proposed CV mechanism leads to remarkable (up to 475%) improvement of data quality, which we quantify using both belief contrasts and the *Kullback–Leibler divergence*. In particular, our proposal offers a unified solution to reconciling two disparate needs: a) reinforcing obscure (weakly recognizable) ground truth and b) discovering hidden (unrecognized) ground truths.

II. Related Work

Data quality as a crucial issue in MCS and IoT in general, has attracted a large body of research work that tackles it from different angles.

A. Incentive Mechanisms

This line of research designs incentive mechanisms in order to influence worker behaviors so that workers will produce high-quality data. Typical incentive mechanisms include auctions [2], [3], lotteries [6], trust and reputation systems [18], bargaining games [19], contracts [20], and market mechanisms [21]. For example, Jin *et al.* proposed Thanos [2] that incorporates quality of information (QoI) into an incentive mechanism based on reverse combinatorial auctions to achieve near-optimal social welfare. A simple endorsement Web (SEW) [18] connects workers into a socioeconomic network using a trust-based relationship, using both social and economic incentives to encourage high-quality contributions. Theseus [22] is a payment mechanism that improves data quality by counteracting workers' strategic behavior of reducing sensing effort, so that the aggregated results calculated by truth discovery algorithms are more accurate. Kamar and Horvitz [7] used a consensus prediction rule to induce truthful reporting by comparing each worker's report against the consensus of the other workers' reports to calculate the payment for that worker. However, consensus-based methods have inherent bias and [7] only applies to single-truth applications. On the other hand, Bayesian truth serum [4], [5] removes the bias by using a scoring method, and can apply to multitruth applications with subjective answers. However, it requires each worker to explicitly predict the distribution of all the other workers' reports, which restricts its practicality. For a survey on incentive mechanisms, the reader may refer to [1].

B. Quality Assessment

Unlike incentives, this line of work takes the contributed data as given, and focuses on evaluating the quality of data or the trustworthiness of workers so as to make informed decisions such as which data or workers to trust. Kantarci *et al.* [8] assessed the trustworthiness of both workers and their contributed data by combining centralized reputation value with individual vote-based collaborative reputation values. Wu *et al.* [9] proposed an EndorTrust system that not only assesses but also predicts the trustworthiness of workers without requiring prior contributions from them. This is achieved by using a trust-based worker relationship together with the machine learning technique of collaborative filtering. Huang *et al.* [11] used the Gompertz function to calculate device reputation scores as a reflection of the trustworthiness of data contributed by that device. Amintoosi and Kanhere [12] proposed a trust framework that uses fuzzy logic to combine two quantities to obtain a final quality assessment of each contribution. One is the quality estimate of the sensor readings contributed by each worker, and the other is the trust score of each worker which is calculated using their social attributes.

C. Truth Finding

Like quality assessment, this thread of research also takes the indigenous data as given, but it focuses on finding the real truth from the large amount of noisy data, typically using data mining techniques. For example, Wang *et al.* [13] uses the expectation-maximization algorithm to obtain the maximum likelihood estimate of the probability that a MCS measurement is true, where the measurement must be *binary*. Davami and Sukthankar [14] aimed to predict the true occupancy of parking lots based on crowdsourced data, by combining multiple trust-based data fusion techniques using AdaBoost. Gisdakis *et al.* [15] proposed a framework called SHIELD to perform outlier detection, which is essentially the opposite of truth finding. It combines Dempster–Shafter theory and data mining to achieve desirable accuracy in the presence of a significant portion of outliers. However, the used complex machine learning model requires a large amount of training data as well as cumbersome private key configuration and operation.

D. Our Approach

Our proposed approach does not belong to any of the above categories. Instead, on top of the original crowdsensing, it introduces another layer of crowdsourcing which exploits the power of crowds [16] to a fuller extent. This approach does not have to replace or preclude existing solutions, but rather allows them to achieve better result by reshaping the original (possibly obscure or misleading) data into a more trustworthy representation of the reality, before applying existing methods. Meanwhile, it can also work as a standalone solution without relying on exist methods.

Regarding applicability and assumptions, unlike most work such as [7], [13], and [14] our approach applies to sensor measurements regardless of whether they are binary or multi-valued, discrete or continuous, and whether there are a single or multiple ground truth(s). Moreover, it does not assume the distribution of underlying sensing phenomena, nor any common prior held by crowdworkers like in Bayesian approaches, nor strict human rationality as in game-theoretical studies (e.g., [4] and [5]).

Our approach is also different from peer rating as used by some online Q&A and product review platforms. This will become evident in Section III (step 1).

A preliminary version of this work appeared at [23].

III. Cross Validation Framework

This framework describes a four-step procedure for performing CV.

A. Step 1: Data Presentation and Form of Verification

The objective of this step is to determine a proper form for presenting the original sensor data to the validating crowd, and a proper form of verification to be performed by the crowd. The following requirements need to be satisfied.

- Due to the nature of crowdsourcing, both data presentation and verification forms must to be easy to comprehend and handle by the validating crowd.
- The forms should *enable* timely verification due to the *time-sensitivity* of MCS and many other IoT applications, where the value of sensor data decays over time.

It is instrumental to look at a few candidate solutions for a more concrete understanding. One solution is to publish the dataset in the raw (e.g., text or tabulated) form or a summarized (e.g., graphic) version at a public venue such as a website, and request visitors to assess in a certain way (e.g., write a review or vote a poll). This is most common and has been adopted by many review platforms (e.g., Amazon, TripAdvisor, Yelp, and Glassdoor) and online Q&A forums (e.g., Stackoverflow and Quora). However, such an opportunistic and ad hoc method is not compatible with the time-sensitivity of MCS/IoT, and its open nature also hinders quality control.

A variation is to present the same form of data to a dedicated group of "elite users" who may be able to provide timely and qualified validation. However, the sheer size of a dataset would still be overwhelming to each validator, letting alone how difficult and costly the recruitment of elite users would be. In addition, this and the previous methods are both prone to a *range-bias* problem: when facing a set of data for evaluation, people tend to favor majority values, or prefer intermediate over boundary values.

Another remedy is to partition the original dataset into smaller subsets for validators to evaluate one subset each, and then aggregate the evaluation results into an overall assessment of the original dataset. For each validator who is given a subset, she may be asked to: 1) assign a proper score to each value; 2) rank all the values; or 3) pick the "best" value. For this method, first note that option: 1) is a generalized (and hence harder) version of 2) and 3). Second, aggregating the evaluation results for 2) or 3) is in fact the classic *preference aggregation* problem in social choice theory [24]. Unfortunately, although decades of research has achieved promising accomplishments such as *Borda count* and *Condorcet winner*, this problem still remains largely open. For example, finding a Kemeny optimal ranking over m complete ranked lists of n candidates is NP-hard [25], and in our case, it is even harder because we need to aggregate *incomplete* ranked lists (over subsets). Moreover, there is no immediate answer to how to partition a dataset so that the subsets can properly represent the original dataset. Finally, the range-bias issue still exists, albeit milder.

B. Step 2: Quest for Validation

The objective of this step is to recruit a validating crowd and solicit for their assessment on the sensor data (presented in a form determined by step 1).

Implementing this step needs to address the following issues tactically.

- How to *perform* timely verification, i.e., quickly recruit a validating crowd and obtain a sufficient number of validation results, to satisfy the time-sensitivity?
- How to ensure good quality of the validation results? The "quality" can have comprehensive semantics as to cover competency, honesty, bias, etc.
- How to handle privacy and security aspects given that interacting with people is susceptible to these concerns?

C. Step 3: Consolidation

Given the validation results acquired in step 2, and the original IoT sensor data, this step is to consolidate these two heterogeneous datasets to obtain a better representation of reality, for example a more credible posterior belief of the ground truth.

This is analogous to the preference aggregation problem discussed in step 1. But due to the NP-hardness, one needs to devise a feasible solution.

D. Step 4: Compensation

Essentially, the proposed CV approach overlays an additional layer of crowdsourcing over the original crowdsensing.

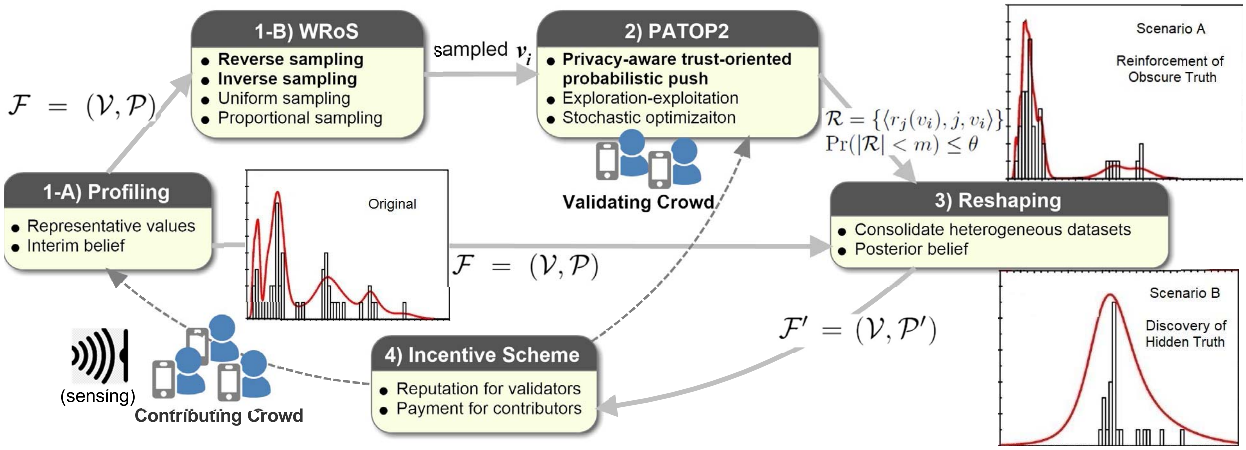

Fig. 1. Overview of our proposed CV mechanism. The input is the original crowdsensed data which will first be profiled as $\mathcal{F}$, depicted by the plot "original." The output is an improved profile $\mathcal{F}'$ illustrated by the plot "Scenario A" or "Scenario B": the former reinforces the ground truth when obscure (albeit weakly recognizable) in original, and the latter scavenges the ground truth when unidentifiable in original due to being hidden by noise. Our mechanism works for both scenarios without being told which it is in.

Therefore, incentives as a crucial element in crowdsourcing [26] need to be handled, and this last step is meant to close this loop.

However, besides addressing this issue for the validating crowd, note that the original contributing crowd is also affected. This is because the final outcome of MCS as obtained in step 3 would be different from the original sensor data, which means that we would have a better estimate of the quality of contributed data after CV. Therefore, a re-evaluation of the contributing crowd is also necessary.

IV. Cross Validation Mechanism

In this section, we design a CV mechanism that implements the framework outlined above, and fulfills the requirements the framework stipulates. An overview of this mechanism is given in Fig. 1.

A. *Profiling (Step 1-A)*

As explained in Section III-A, a massive crowdsensed dataset would be overwhelming to validators. Therefore, we first create a profile that can concisely represent the original dataset without loss of critical information. Then in Section IV-B, we apply a special sampling technique to this profile to extract values to present to validators.

The said profile, denoted by $\mathcal{F} = (\mathcal{V}, \mathcal{P})$, consists of a set $\mathcal{V}$ of representative values and a probability distribution $\mathcal{P}$ of those values. To create this profile, the IoT cloud (or server) which stores the crowdsensed dataset $\mathcal{O}$ first creates a histogram of $\mathcal{O}$ with an appropriate resolution (bin width) determined by the specific application. For instance, a traffic monitoring application may use a bin width of 3 mph while a noise mapping application may find 5 dB suitable. Let us index these bins by $i = 1, 2, \ldots, n$.

Next, the cloud designates for each bin i a representative value v_i, which can be the mean or median of the bin, or any other quantile when the resolution is sufficiently high. Thus, we obtain the representative value set $\mathcal{V} = \{v_i | i = 1, 2, \ldots, n\}$.

Finally, the cloud computes a probability measure $p_i = \kappa_i / \sum_{j=1}^{n} \kappa_j$ for all i, where κ_i is the volume of, or the number of data points in, bin i. Hence, we obtain the probability distribution $\mathcal{P} = \{p_i | i = 1, 2, \ldots, n\}$.

Sometimes we also refer to $\mathcal{P}$ as the *interim belief* to differentiate from *prior belief* which is a presumed distribution before observing the sensed data. Correspondingly, we refer to the final, consolidated distribution as the *posterior belief*.

B. *Sampling (Step 1-B)*

Given the profile $\mathcal{F} = (\mathcal{V}, \mathcal{P})$, we need to determine how to present it to validators. Based on our deliberation in Section III, we eventually take up a minimalist design: pick a *single* representative value from $\mathcal{V}$, show it to a validator and ask her to give a single rating, by choosing one out of a few options such as {"Agree," "Disagree"}. This method requires little effort from a validator and circumvents NP-hardness when consolidating results. It also facilitates quality and time control as will be elaborated in Section IV-D.

This section deals with how to pick representative values from $\mathcal{V}$, for which we use a WRoS technique. This technique samples $\mathcal{V}$ with replacement using a weights vector $S = \{s_i | i = 1, 2, \ldots, n\}$ such that each $v_i \in \mathcal{V}$ is sampled with a probability proportional to its weight s_i. The sample size m will be much larger than the population size $n = |\mathcal{V}|$, hence "oversampling."

The reason for using WRoS is that it gives an MCS/IoT system flexibility to configure S to meet different needs. For example, we are particularly interested in discovering *hidden* truth or "scavenging outliers." That is, conventional statistical methods generally ignore minority events or classify them as outliers, but this is risky as data is often insufficient for us to draw such conclusions with confidence. Furthermore, even a large number of observations can sometimes be fallacious, for example due to sensor drift or miscalibration [27], environmental causes (e.g., urban canyon and tunnel shadowing), or large-scale security breach [28]–[30].

Therefore, minority events should not be "conveniently" ignored and they could have contained the ground truth. In

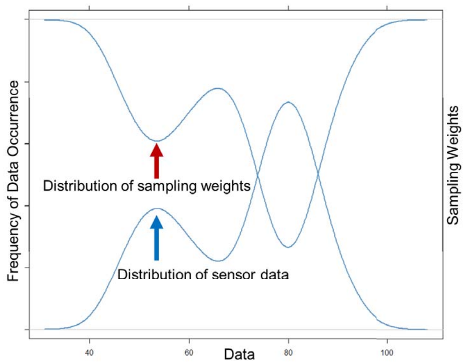

Fig. 2. WRoS allows for prioritizing over majority and minority events to meet different needs.

this regard, WRoS allows us to make a discovery, by assigning higher priority to minority events so as to expose them to more validation opportunities. Specifically, we use two weight configurations as follows.

- *Reverse Sampling ($s_i = d - p_i$):* where d is a constant that ensures $s_i \geq 0$. It is tempting to choose $d = 1$ since it seems to be most natural. However, a closer look reveals that it will blunt the multiplicative difference between s_i's for small p_i's. For example, $p_i = 0.2$ is twice of $p_i = 0.1$ but the corresponding $s_i = 0.8$ is close to $s_i = 0.9$ as sampling weights. Hence, the best reverse-weight vector S is one that "mirrors" $\mathcal{P}$ with respect to its "waistline" $(\min \mathcal{P} + \max \mathcal{P})/2$, which translates to $d = \min \mathcal{P} + \max \mathcal{P}$. This configuration is illustrated in Fig. 2.
- *Inverse Sampling ($s_i = 1/p_i$):* This results in a greater differentiation between majority and minority events. Events of $p_i = 0$ ($\kappa_i = 0$) are excluded.

In addition, we also include the following two configurations for comparison.

- *Uniform Sampling ($s_i = 1$):* Hence, all the v_i will be validated equally likely.
- *Proportional Sampling ($s_i = p_i$):* Under this setting, more frequently appeared values will be validated more times.

C. Quest for Validation: Stochastic Optimization (Step 2-A)

Recall that step 2 deals with the most critical problem: recruiting a validating crowd and soliciting for assessments (ratings).

Definition 1 (Problem Statement): The objective is to collect no less than m effective ratings below a shortfall probability θ by a deadline T_0. Here, m is a number typically much larger than $n = |\mathcal{V}|$, an effective rating is one that is either positive or negative but not neutral, and shortfall means less than m (i.e., not successful).

On top of these quantitative (hard) requirements, it is also desirable to have the following qualitative (soft) properties.

- *Competency:* Each effective rating should come from a competent validator, i.e., one who possesses the relevant information or domain knowledge.
- *Honesty:* A validator's rating should truly reflect her opinion.
- *Bias:* While humans are inevitably biased in general, such effect should be curbed as much as possible.

In a word, we aim to only collect *trustworthy* ratings.

To obtain an analytical solution to the above problem (with the hard constraints), suppose we had access to the conditional probability of obtaining an effective rating from an arbitrary validator who has been recruited. Denote this probability by ξ which we assume to be a random variable rather than a constant in order to capture the heterogeneity among workers. Then, we transform the above problem into one that aims to find the minimum number of workers, y, to be recruited such that the shortfall probability of obtaining m effective ratings is no greater than θ. Formally

$$\begin{aligned} &\min_{0 \leq y \leq |\Psi|} \; y \\ &\text{s.t.} \quad \Pr(\xi y < m) \leq \theta \end{aligned} \tag{1}$$

where Ψ is the set of all the workers available for recruiting (e.g., all the users registered on a crowdsourcing platform such as Amazon Mechanical Turk [31]).

Problem (1) is a stochastic optimization problem because the constraint contains a random variable, ξ. We solve it using chance constrained programming (CCP) [32].

First, we rewrite the constraint of (1) as

$$F_\xi\left(\frac{m}{y}\right) \leq \theta \tag{2}$$

where $F_\xi(\cdot)$ is the cumulative distribution function (c.d.f.) of ξ. Next, we introduce the *quantile function* of ξ, which is defined as

$$Q_\xi(\theta) = \inf\{x \in \mathbb{R} : F_\xi(x) \geq \theta\}. \tag{3}$$

Since $F_\xi(\cdot)$ is a monotone increasing function, it follows that $m/y \leq Q_\xi(\theta)$, i.e., the solution is given by

$$y^* = \frac{m}{Q_\xi(\theta)}. \tag{4}$$

To have an explicit form of (4), consider two common cases. If ξ follows a Beta distribution parameterized by α and β, i.e., $\xi \sim \mathcal{B}e(\alpha, \beta)$, then its c.d.f. is the *regularized incomplete Beta function*, i.e., $F_\xi(x) = I_x(\alpha, \beta)$. In this case, the optimal solution to (1) is

$$y^*_{\text{beta}} = \frac{m}{I_\theta^{-1}(\alpha, \beta)} \tag{5}$$

where $I_\theta^{-1}(\alpha, \beta)$ is the inverse of the regularized incomplete Beta function and can be computed by tools such as MATLAB using the `betaincinv` function, or Mathematica using the `InverseBetaRegularized` function. For example, Fig. 3 plots $I_\theta^{-1}(\alpha, \beta)$ versus θ (x-axis) for ($\alpha = 2, \beta = 8$) and ($\alpha = 8, \beta = 2$), respectively.

If ξ follows a Gaussian distribution as $\xi \sim \mathcal{N}(\bar{\xi}, \sigma^2)$ where $\bar{\xi} \in (0, 1)$, then since $(\xi - \bar{\xi})/\sigma \sim \mathcal{N}(0, 1)$, a similar derivation as from (2) to (4) yields $([m/y] - \bar{\xi})/\sigma \leq \Phi^{-1}(\theta)$, or equivalently $y \geq m/(\sigma \Phi^{-1}(\theta) + \bar{\xi})$. Here, $\Phi^{-1}(\cdot)$ is the *probit function* which is the quantile function for standard normal

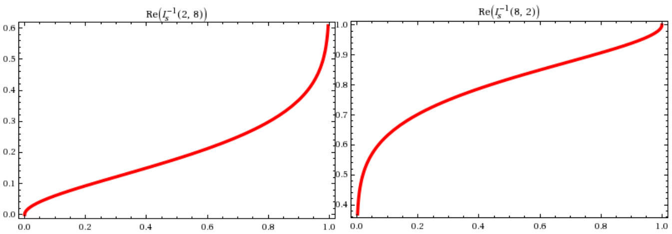

Fig. 3. Left: $I_\theta^{-1}(\alpha = 2, \beta = 8)$. Right: $I_\theta^{-1}(\alpha = 8, \beta = 2)$.

distribution. Hence, the optimal solution to problem (1) is given by

$$y^*_{\text{gauss}} = \frac{m}{\sigma \Phi^{-1}(\theta) + \bar{\xi}}. \tag{6}$$

The probit function $\Phi^{-1}(\theta)$ can be computed using Z-table [33]. For example, $\Phi^{-1}(0.05) = -1.65$, $\Phi^{-1}(0.1) = -1.28$.[1]

While having an analytical solution is desirable, the assumption of having precise knowledge of the distribution of ξ (i.e., type and associated parameters α, β, or $\bar{\xi}, \sigma$) limits practicality. Therefore, in the next section, we provide a more practical solution to the problem in Definition 1. In addition, it also satisfies the three soft constraints.

D. Quest for Validation: Heuristic Solution (Step 2-B)

This heuristic takes an *exploration-exploitation* approach[2] to predict and also leverage the conditional probability ξ. During the exploration phase, it "probes" a crowd and uses regression analysis to predict ξ by learning from the interaction with the probed crowd. During the exploitation phase, it launches another, more targeted, round of interaction with crowd based on the predicted ξ and other exploration results. Both of the interaction processes employ a "push" model (as opposed to the "pull" model used by most websites), which proactively approaches a tactically selected group of workers to seek their validation (i.e., ratings). The entire procedure is formulated as a PATOP^2 algorithm (see Algorithm 1 for pseudo code), and is elaborated below.

1) Exploration: Crowd behaviors are highly dynamic and uncertain when it comes to reacting to unsolicited requests. One may dismiss (decline) a request or may fail to notice it, and if she does respond, the response may be delayed arbitrarily and may not be an effective rating. Furthermore, we need to collect at least m effective ratings by a certain deadline T_0, without abusing the crowd by simply bombarding the entire or an arbitrarily large crowd with the requests.

To overcome this challenge, we use an exploration phase to learn the crowd behaviors online, in order to reduce the uncertainty. Unlike most exploratory online algorithms, where an initial set of data has to be sacrificed to establish a reference for comparison and cannot be utilized, our exploration process

Algorithm 1: PATOP^2

Input: All crowdworkers $\mathcal{U}$, contributors $\mathcal{C}$, profile $\mathcal{F} = (\mathcal{V}, \mathcal{P})$, target m, deadline T_0
Output: Effective ratings $\mathcal{R} = \{\langle r_j(v_i), j, v_i\rangle | r_j(v_i) \neq 0, j \in \mathcal{U}, v_i \in \mathcal{V}\}$

```
   // Initialization:
1  t ← 0, Ψ ← U\C, R ← ∅, D ← ∅
   // Exploration:
2  Select a set M_1 of m workers from Ψ using Eq. (10)
3  for each j ∈ M_1 do
4      Sample one v_i ∈ V using a predetermined WRoS
       method (Section IV-B)
5      Wrap v_i in a rating task and push it to worker j to
       seek rating r_j(v_i)
6  while t ≤ T_0/2 do
       // collect effective ratings:
7      R ← R ∪ {⟨r_j(v_i), j, v_i⟩ | r_j(v_i) ≠ 0}
       // construct regression dataset:
8      if t mod τ = 0 then
9          D ← D ∪ {⟨t, |R|⟩}
10     t++
11 m_Y(T_0/2) ← |R| // no. of effective ratings
       at t = T_0/2
12 Predict m_Y(t = T_0) to be m̂_Y(t = T_0) using function
   m̂_Y(t), which is the estimate of the target function m_Y(t)
   and is obtained via regression over D
   // Exploitation:
13 Ψ ← Ψ \ M_1
14 Compute m_exploit using Eq. (9)
15 Select a set M_2 of m_exploit workers from Ψ using (10)
16 for each j ∈ M_2 do
17     the same as Lines 4–5
18 while t ≤ T_0 do
19     the same as Line 7
20     t++
21 return R
```

is fully efficient in the sense that no data collected from it will be discarded.

We designate the period $[0, t^*]$ as the exploration phase and $[t^*, T_0]$ the exploitation phase. At time $t = 0$, we select m workers and send each of them a rating task. How the m workers are selected and what a rating task looks like will be described in Section IV-D3. For now, let us focus on the regression-based prediction.

The response dynamics of the m workers under exploration can be characterized by two nondecreasing functions (with unknown forms) depicted in Fig. 4. During the exploration phase, we construct a regression dataset $\mathcal{D}$ by uniformly picking k samples over $[0, t^*]$, as $\mathcal{D} = \{\langle t_i := i \cdot t^*/k, m_Y(t_i)\rangle | i = 1, 2, \ldots, k\}$, where $m_Y(t_i)$ is the number of workers who have responded with an effective rating by time t_i. We can then recover a function $\hat{m}_Y(t)$ via nonlinear regression over $\mathcal{D}$, which approximates the target function $m_Y(t)$, and thus predict

[1] σ is sufficient small so that $\sigma\Phi^{-1}(\theta) + \bar{\xi} > 0$.

[2] While it may sound resemblant to reinforcement learning and particularly multiarmed bandits (MAB), we will explain in Section IV-D4 that the MAB model does not fit our problem.

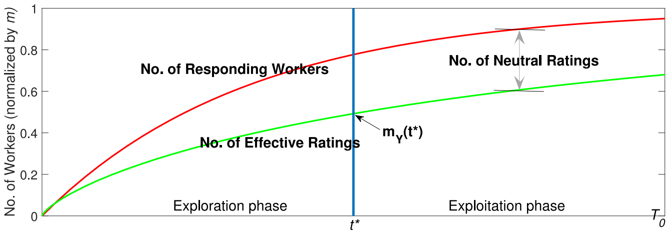

Fig. 4. Modeling crowd dynamics for workers under *exploration*.

(extrapolate) the target function value at the deadline to be $\hat{m}_Y(T_0)$.[3]

2) Exploitation: The exploration phase tells us two things. First, in expectation, we will be in short of $m - \hat{m}_Y(T_0)$ effective ratings by the deadline T_0. Second, the "conversion rate" from approached workers to effective ratings at the end of a time window $[0, t]$ is

$$\hat{\xi}(t) := \hat{m}_Y(t)/m$$

which is actually an estimate of the conditional probability ξ as a function of elapsed time t.

Thus, for the exploitation phase which starts at t^*, we can determine the expected size of the crowd to approach as

$$\bar{m}_2 = \frac{m - \hat{m}_Y(T_0)}{\hat{\xi}(T_0 - t^*)}. \tag{7}$$

To cater for the randomness of $\xi(\cdot)$ with respect to the shortfall probability θ, we use the CCP method introduced in Section IV-C to determine the actual size of crowd to approach, which we denote by m_2, as follows. Assuming that the prediction error is Gaussian as is most common, we can directly apply (6) where y^*_{gauss} corresponds to m_2, and on the right hand side of (6), we substitute m by $\bar{m}_2$, $\bar{\xi}$ by $\hat{\xi}(\cdot)$, and

$$\sigma \leftarrow \sqrt{\chi^2/(k-1)}$$

which is the *corrected* sample standard deviation [34] where

$$\chi^2 = \sum_{i=1}^{k} |m_Y(t_i) - \hat{m}_Y(t_i)|^2, \quad t_i \in \mathcal{D} \tag{8}$$

is the sum of squared errors of regression. Thus, putting all together, we have

$$m_2 = \frac{m\left(m - \hat{m}_Y(T_0)\right)}{\hat{m}_Y(T_0 - t^*)\left(\sqrt{\frac{\chi^2}{k-1}}\Phi^{-1}(\theta) + \hat{m}_Y(T_0 - t^*)\right)}. \tag{9}$$

Choice of t^*: t^* is the delimiter of the exploration phase and the exploitation phase. It affects the accuracy of m_2 as given by (9) as follows.

- In general, the larger t^* is, the more accurate $\hat{m}_Y(T_0)$ is. This is because $\hat{m}_Y(T_0)$ is an extrapolation of data collected over $[0, t^*]$ where $t^* < T_0$.
- A larger t^*, however, does not improve the accuracy of $\hat{m}_Y(T_0 - t^*)$ when $t^* \geq T_0/2$. This is because $\hat{m}_Y(T_0 - t^*)$ can be *measured* (rather than predicted) during the exploration phase when $t^* \geq T_0/2$.

Moreover, a larger t^* will lead to a shorter exploitation phase, which means that more responses (ratings) are more likely to arrive *after* deadline T_0 and hence be wasted.

Based on the above three considerations, we choose $t^* = T_0/2$ which strikes a reasonable tradeoff. It also allows us to use in (9) the measured $m_Y(T_0/2)$ rather than a predicted $\hat{m}_Y(T_0/2)$ via $\hat{m}_Y(t)$, which (the latter) is more prone to inaccuracy.

3) Validator Recruitment: Now we explain how we select the m workers in the exploration phase, whom we collectively denote by $\mathcal{M}_1$, and the m_{exploit} workers in the exploitation phase, denoted by $\mathcal{M}_2$. This worker selection process is also called validator recruitment.

To recruit a set of validators $\mathcal{M}$ from a pool of available workers Ψ, we assign each worker $j \in \Psi$ a weight

$$q_j(t) = \frac{1 - e^{-\lambda_j\left(t - t_j^-\right)}}{1 + e^{-wR_j}} \quad \forall j \in \Psi. \tag{10}$$

With this assignment, we perform a *weighted sampling without replacement* over Ψ to obtain $|\mathcal{M}|$ validators, and push to each $j \in \mathcal{M}$ a rating task at time t. In the above

$$\begin{cases} \Psi = \mathcal{U} \backslash \mathcal{C}, & \mathcal{M} = \mathcal{M}_1, \ \text{if } t = 0 \\ \Psi = \mathcal{U} \backslash \mathcal{C} \backslash \mathcal{M}_1, & \mathcal{M} = \mathcal{M}_2, \ \text{if } t = \frac{T_0}{2} \end{cases} \tag{11}$$

where $\mathcal{U}$ is the entire population of all the workers, and $\mathcal{C}$ is the contributors of the original crowdsensed data.

Equation (10) is the product of logistic function $1/(1 + e^{-wR_j})$ and $1 - e^{-\lambda_j(t - t_j^-)}$, which represent a trust component and a privacy component, respectively. Let us explain below.

Trust Oriented: Every worker $j \in \mathcal{U}$ is associated with a reputation score $R_j \in \mathbb{R}$, which characterizes how reliable j as a validator is, based on the credibility (accuracy) of her past ratings. The logistic function (where $w > 0$ is a constant) makes it such that more reputable workers will have higher chance to receive rating tasks, in order to collect higher quality of ratings overall.

A rating task (Fig. 5) consists of a single representative value $v_i \in \mathcal{V}$ sampled using WRoS, a task description, and a list of rating options such as {"Agree," "Unsure," "Disagree"}.

Now, let us recall the three soft properties about trustworthiness: competency, honesty, and bias. We approach competency and honesty using R_j as part of our incentive scheme (Section IV-F): R_j only increases if j's rating is consistent with the belief adjustment (toward the real truth), which requires the validator to be competent at this particular rating task *and* rate honestly; otherwise, R_j would decrease, constituting a *penalty*. The reputation R_j is initialized as 0 for new workers, and can go both positive and negative.

If a validator is not competent at a rating task but she is honest, she can choose the neutral rating to avoid being penalized. This is why our rating task should always keep a neutral rating option no matter how many (e.g., 3 or 5) options will be offered.

On the aspect of human bias, we incorporate two countermeasures. First, we exclude $\mathcal{C}$ from $\mathcal{U}$. This eliminates contributors' biases toward their own respective contributions.

[3]This can be done using, for example, the SciPy function `curve_fit()` or the MATLAB function `interp1()`.

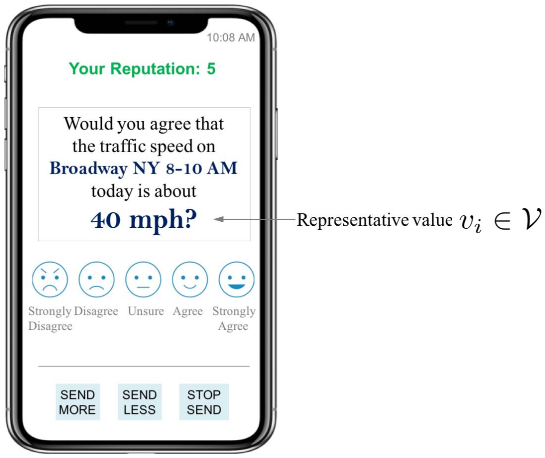

Fig. 5. Rating task illustrated on a user interface.

Second, we ensure that no validator can provide more than one rating (to minimize the effect from any validator who does have bias), by sampling *without replacement* over Ψ to obtain $\mathcal{M}$ and pushing each $j \in \mathcal{M}$ a single rating task.

Privacy Aware: We have employed a proactive push model in order to suit the time-sensitivity of MCS/IoT and to have better quality control (as we can select validators). But on the other hand, a push model can be potentially *privacy-intrusive* if the push frequency is too high or not properly aligned with validators' personal preferences. We address this issue using two elasticity elements, one global and one individual.

The global elasticity element is the exponent $t - t_j^-$ in (10), where t_j^- is the last time when j received a rating task, or when she was enrolled as a worker if never received a rating task before. Hence, those who just received rating tasks will be much less likely to be pushed again; for those who did not, $q_j(t)$ does increase but the marginal increase is diminishing. Hence, the overall effect is that the pushes to any one worker is naturally *spaced out* on the timeline.

The individual element is realized by a personal preference indicator λ_j. It is initialized as a constant (e.g., 1) and then updated as $\lambda_j \leftarrow \min(\lambda_j + \delta, \lambda_{\max})$, $\lambda_j \leftarrow \max(\lambda_j - \delta, \delta)$, and $\lambda_j \leftarrow 0$, respectively, when the validator j (optionally) chooses "Send me more," "Send me less," and "Stop sending" (see Fig. 5). Here, δ is the step size (e.g., 0.2), $\lambda_{\max}$ is a cap (e.g., 2) which prevents malicious users from abusing λ_j to offset their low reputation R_j.[4]

4) Comparison With MAB: Our exploration-exploitation approach may be reminiscent of the multiarmed bandit (MAB) problem [35]. However, there are key differences that set our problem apart from the MAB model, making its existing solutions not applicable.

In an MAB setting, there are multiple arms each associated with a random reward following an unknown and different distribution. An agent pulls an arm each time to receive a reward, and aims to maximize the total reward (or minimize the regret as compared to the optimal reward). Thus, the agent faces an exploration-exploitation dilemma: whether to explore (try) more arms or each arm more times in order to find the best arms, or to exploit (concentrate on) the seemingly most rewarding arms so far.

In an attempt to frame our problem under MAB, it seems plausible to model each worker or each group of workers as an arm. However, an arm like this does not have *repeatability*, and hence leaves no opportunity for exploitation after being explored. In addition, exploration on this type of arm does not reveal the outcome until the deadline, which also leaves no room for exploitation. Therefore, existing solutions do not apply and we must devise our own, as provided above.

E. Consolidation: Reshaping (Step 3)

Thus far, we have obtained a profile $\mathcal{F} = (\mathcal{V}, \mathcal{P})$ of the original MCS/IoT data, and a collection of effective ratings $\mathcal{R} = \{\langle r_j(v_i), j, v_i \rangle\}$. The next step is to consolidate these two heterogeneous datasets into a (better) posterior belief of the ground truth.

To do so, we assign each rating option a score of $-L, -L+1, \ldots, -1, 0, 1, \ldots, L-1, L$ corresponding to its position in the list of the $2L+1$ rating options, where 0 corresponds to the neutral rating. Then for each v_i, we separately aggregate positive scores and negative scores in terms of their absolute value normalized by L, as

$$g_i = \frac{1}{L} \sum_j r_j(v_i) \mathbb{1}_{r_j(v_i)>0}$$

$$b_i = -\frac{1}{L} \sum_j r_j(v_i) \mathbb{1}_{r_j(v_i)<0}. \tag{12}$$

Here, we slightly abuse notation by using $r_j(v_i)$ to denote both a rating score and a rating option (e.g., "Agree").

Recall from Section IV-A that $p_i = \kappa_i / \sum_{j=1}^n \kappa_j$ is the interim belief of how likely v_i is the ground truth (κ_i is the bin volume of i). It can be interpreted as κ_i out of $\sum_{j=1}^n \kappa_j$ contributors have "voted" for v_i to be the ground truth. Similarly, we can interpret (12) as, during CV, another g_i out of $g_i + b_i$ validators voted for v_i. Thus, the interim belief p_i can be reshaped to

$$\tilde{\hat{p}}_i = \frac{\kappa_i + \eta \times g_i}{\sum_{j=1}^n \kappa_j + \eta \times (g_i + b_i)} \quad \forall v_i \in \mathcal{V}$$

which aggregates the two groups of votes. Here, an additional factor η is introduced to allow for weighing a (full-score) rating against a direct data contribution. For example, one can set $\eta = 0.5$ if sensors are generally reliable, and $\eta = 1$ otherwise.

However, the above $\tilde{\hat{p}}_i$ is dominated by the larger of the contributing crowd and the validating crowd if they are very different in size. Therefore, we need another factor for *balancing* purposes, which leads to

$$\hat{p}_i = \frac{\kappa_i + \eta \times \frac{g_i}{|\mathcal{R}|} \sum_{j=1}^n \kappa_j}{\sum_{j=1}^n \kappa_j + \eta \times \frac{g_i + b_i}{|\mathcal{R}|} \sum_{j=1}^n \kappa_j}$$

$$= \frac{p_i + \eta \times \frac{g_i}{|\mathcal{R}|}}{1 + \eta \times \frac{g_i + b_i}{|\mathcal{R}|}} \quad \forall v_i \in \mathcal{V}. \tag{13}$$

[4]One could use a more sophisticated method such as a gradient-descent-like algorithm (which is still empirical) to adjust λ_j. However, we keep it simple for practicality and also because obtaining the "optimal" value or updating-model (if ever exists) of user preference is not critical to our problem.

The final posterior belief, p_i', is then calculated by normalization

$$p_i' = \hat{p}_i \Big/ \sum_{i=1}^{n} \hat{p}_i. \tag{14}$$

Thus, we have obtained the reshaped profile $\mathcal{F}' = (\mathcal{V}, \mathcal{P}')$, where $\mathcal{P}' = \{p_i' | i = 1, 2, \ldots, n\}$.

Robustness Control: A subtle issue to address is the *imprecision of human perception*. That is, unlike sensor readings which are precise (if the sensors are reliable), human ratings are largely based on their estimation which is generally imprecise. As a result, values near ground truth v^* are likely to receive similar positive ratings as v^*, which will create "humps"—blunt peaks that make ground truths less distinguishable—in a profile.

To be robust to human imprecision, we add a rectifying procedure before applying (13). First, construct a vector $\vec{\gamma} = (\gamma_i := [g_i/(g_i + b_i)] | i = 1, 2, \ldots, n)$ and detect humps in $\vec{\gamma}$ by looking for sequences of *prominent local maxima*.[5] Second, for each hump represented by a sequence $(\gamma_i | i = i_l, \ldots, i_r)$, designate its gravity center as $i_c = \arg\max_{i \in \{i_l, \ldots, i_r\}} \gamma_i$ (breaking tie using the mean). Third, for each hump, update g_i where $i = i_l, \ldots, i_r$ to

$$g_i' = \begin{cases} g_i a_i^l, \ \text{where } a_i^l = \frac{i_c - i}{(i_c - i_l + 1)^2}, & \text{if } i \in [i_l, i_c) \\ g_i a_i^r, \ \text{where } a_i^r = \frac{i - i_c}{(i_r - i_c + 1)^2}, & \text{if } i \in (i_c, i_r] \\ g_i + \sum_{j=i_l}^{i_c - 1} g_j \left(1 - a_j^l\right) & \\ \quad + \sum_{j=i_c+1}^{i_r} g_j \left(1 - a_j^r\right), & \text{if } i = i_c. \end{cases} \tag{15}$$

The ratios a_i^l and a_i^r serve the purpose of shifting a major portion of each g_i to the "gravity mass" g_{i_c}, where the portion size is larger if i is closer to i_c (because the votes for such a v_i are more likely due to its closeness to v_{i_c}). On the other hand, b_i is kept unchanged because a negative vote means that the validator disagrees with this particular v_i and does not indicate what other value she would agree with. Hence, eventually, we substitute g_i with g_i' when applying (13).

F. Compensation: Incentive Scheme (Step 4)

As pointed out by the framework in step 4, we need to both compensate the validating crowd and re-evaluate the compensation for the contributing crowd. Below, we provide such an incentive scheme to close the loop.

Validating Crowd: Given the reshaped profile $\mathcal{F}' = (\mathcal{V}, \mathcal{P}')$, we update the reputation R_j of each validator j who gave an effective rating $r_j(v_i) \neq 0$ on v_i, as

$$R_j' = R_j + \begin{cases} \frac{p_i' - p_i}{1 - p_i} \times \frac{r_j(v_i)}{L}, & \text{if } p_i' > p_i \\ \frac{p_i' - p_i}{p_i} \times \frac{r_j(v_i)}{L}, & \text{if } p_i' < p_i. \end{cases} \tag{16}$$

The gist of (16) is twofold. First, whether a validator j will gain or lose reputation is determined by whether her rating r_j is *consistent* with the belief adjustment $p_i' - p_i$, which can be positive or negative. Second, the amplitude of reputation gain or loss is determined by: 1) the normalized belief adjustment (against p_i or $1 - p_i$), which measures the *impact* of CV and 2) her normalized rating score r_j/L, which measures how much her rating has contributed to the above impact.[6]

We remark that reputation has been widely adopted in practice as an incentive in the form of "digital currency." On top of that, it can also be assigned monetary value such as vouchers or coupons, or other tangible benefits such as entitling users to privileged services or the access to more profitable sensing tasks.

Contributing Crowd: Denote by $\pi_c(u_c, \mathbf{u}_{-c})$ the payment to a contributor $c \in \mathcal{C}$ as stipulated by the original incentive scheme (without CV),[7] where u_c is the quality of c's contribution, and $\mathbf{u}_{-c}$ are the qualities of all the other contributors' contributions. Suppose the data point contributed by c is represented by v_i (i.e., her contribution falls in the ith bin in our profiling step). Then after CV, her payment π_c is revised to

$$\pi_c' = \pi_c \left(u_c \frac{p_i'(c)}{p_i(c)}, \mathbf{u}_{-c}' \right) \tag{17}$$

where

$$\mathbf{u}_{-c}' = \left\{ u_{\tilde{c}} \frac{p_{\tilde{i}}'(\tilde{c})}{p_{\tilde{i}}(\tilde{c})} \middle| \tilde{c} \in \mathcal{C} \backslash \{c\} \right\}$$

$p_i(c)$ and $p_i'(c)$ are just p_i and p_i' (14) with associated contributor explicitly indicated, and $p_{\tilde{i}}(\tilde{c})$ and $p_{\tilde{i}}'(\tilde{c})$ are defined similarly, in which $\tilde{c}$ is the contributor of $v_{\tilde{i}}$. Hence, (17) means that the original incentive scheme π is treated as a black box (which gains us maximal generality) while only its input u_c is substituted by $u_c(p_i'(c)/p_i(c))$ for all $c \in \mathcal{C}$. The rationale is that, since $p_i(c)$ and $p_i'(c)$ are the likelihoods of v_i being the ground truth before and after CV, respectively, $(p_i'(c)/p_i(c))$ rescales u_c according to c's validated (and presumably more accurate) quality of contribution.

Note that the revised payment π_c' (17) does not guarantee the same *total* payment. Hence, if there is a fixed *budget constraint* to satisfy, one can simply normalize π_c' (17) to

$$\pi_c'' = \frac{\pi_c'}{\sum_{\tilde{c} \in \mathcal{C}} \pi_{\tilde{c}}'} \sum_{\tilde{c} \in \mathcal{C}} \pi_{\tilde{c}} \quad \forall c \in \mathcal{C}. \tag{18}$$

V. Performance Evaluation

We evaluate our proposed CV mechanism using a real dataset from a transportation MCS application called *Mobile Century* [41] built by UC Berkeley. To date, this dataset remains one of the most comprehensive public GPS datasets for traffic monitoring research [42].

A. Dataset

The Mobile Century application used cellphone-borne GPS sensors to measure vehicular speeds on the California I-880

[5]This can be done using, for example, the SciPy function `find_peaks()` or the MATLAB function `findpeaks()`.

[6]This does not imply that a higher rating is always advantageous, because it simultaneously bears the risk of losing more reputation if it is opposite to the belief adjustment. Therefore, one should always rate in accord with her confidence level.

[7]There is a rich literature on incentive mechanism design for MCS, for example [2], [7], [36], and [37]. For a comprehensive survey (see [1] and [38]–[40]).

highway. It accumulated 8 h of GPS trajectory data on a 10-mile stretch of I-880, and the dataset is accessible at [43].

Specifically, we use the virtual trip line (VTL) data which consists of 44 374 north bound (NB) speed records and 43 403 south bound (SB) speed records. Each such record contains a VTL ID, the timestamp of the GPS reading, the coordinate of the GPS sensor, and the vehicle speed (mph) when crossing the VTL.

B. Simulation Setup

Putting our experiment into perspective, one can imagine that there is a grand pool of workers $\mathcal{U}$ registered on Amazon mTurk, among which a set $\mathcal{C}$ has participated in Mobile Century to contribute their GPS data to the above NB and SB datasets. Now, we aim to collect $m = 2000$ effective ratings from $\mathcal{U}$ below a shortfall probability $\theta = 0.1$ within deadline $T_0 = 1$ h, as per our problem statement given in Definition 1.

We use the following user model to simulate worker behaviors. A worker reacts to a validation request with a delay that follows the exponential distribution with a 10-min mean. Whenever a worker j reacts, she dismisses (declines) the request with probability $1 - a_j$ and responds with probability a_j, where $a_j \sim \mathcal{B}e(2, 10)$ and hence the mean is 0.2. To respond (by giving a rating), she compares the value v_i contained in the task (e.g., 40 mph as in Fig. 5) with her estimated or believed truth v_j, and rates "Agree" $(+1)$ if $|v_i - v_j| < 0.2v_j$ and Disagree (-1) otherwise $(L = 3)$. Here, $v_j \sim \mathcal{N}(v^*, (0.15v^*)^2)$ where v^* is the ground truth, which means that 95% of the estimates v_j are within $\pm 30\%$ of the ground truth v^* (negative v_j will be regenerated). Workers who give such $-1/+1$ ratings only constitute 80% of all the workers who respond; the other 20% give the neutral rating (Unsure) because they either do not have a clear estimate v_j or are simply not sure of what to rate.

In the consolidation or reshaping step (Section IV-E), $\eta = 0.75$ [see (13)].

C. Result of Profiling

We first profile the NB and SB datasets by following the procedure described in Section IV-A. We set the number of bins to 40 for a sufficiently fine-grained resolution (bin width is 2.175 mph for NB and 2.025 mph for SB traffic). The resulting profiles are presented in Fig. 6, which shows that the NB traffic has some ambiguity while the SB traffic is rather clear. Thus, we will focus on the NB dataset henceforth. Furthermore, for a more meaningful evaluation, we further obscure the data slightly by pruning the highest bin (at about 65 mph) down to the average height of its two adjacent bins. Fig. 7 shows the final profile, where extreme values (above 80 mph) are cleaned. This profile will go through the rest of the procedure of our CV.

D. Main Result

Apart from visual comparison, we also use the *Kullback–Leibler divergence* to characterize the change of belief (from interim to posterior) due to CV. The KL divergence measures the difference between two probability distributions, and in

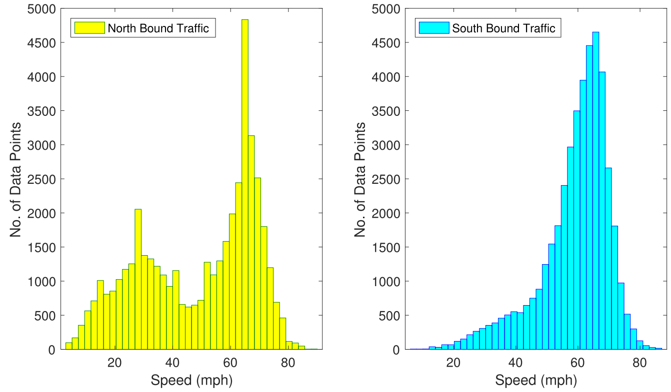

Fig. 6. Profiling the original mobile century traffic data.

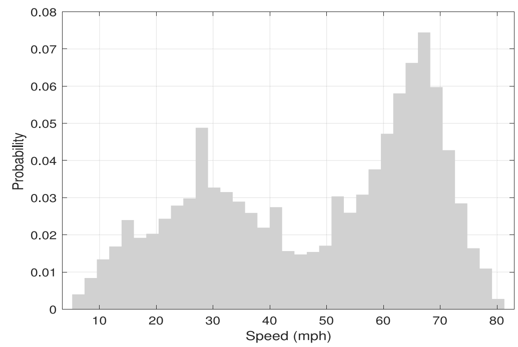

Fig. 7. NB traffic profile after pruning and cleaning.

fact is the only measure of such difference that satisfies a set of desired canonical properties [44]. It is defined as

$$D_{KL}(\mathcal{P}'||\mathcal{P}) = -\sum_{i=1}^{n} p_i' \log \frac{p_i}{p_i'} \tag{19}$$

where we adopt the same notation as of our case, so $\mathcal{P}$ is the interim belief (based on original crowdsourced data) and $\mathcal{P}'$ is the posterior belief (after CV). A larger value of D_{KL} indicates a larger information gain (hence a bigger change of belief).

1) Scenario A—Reinforcing Obscure Truth: We consider two typical scenarios. In Scenario A, the ground truth is obscure despite being somewhat recognizable. This corresponds to Fig. 7 where, even though 67 mph may indeed be the ground truth, we would not be confident enough to draw that conclusion because its surrounding neighbors have similar probabilities too, and 28 mph seems to be a promising truth as well.

After we carry out CV, the result is presented in Fig. 8. We see that the originally obscure truth is evidently reinforced: the interim belief about 67 mph is increased from 0.0744 to the posterior belief of up to 0.1575 under different sampling methods, tantamount to a substantial increase of up to 111.7%, as tabulated in Table I. Meanwhile, the other competitor, 28 mph, becomes less salient, which further corroborates the prominence of 67 mph as the ground truth.

Among the four WRoS methods, `Proportional` performs the best. This is because the interim belief about the truth 67 mph is (indistinctly) the highest, so proportional

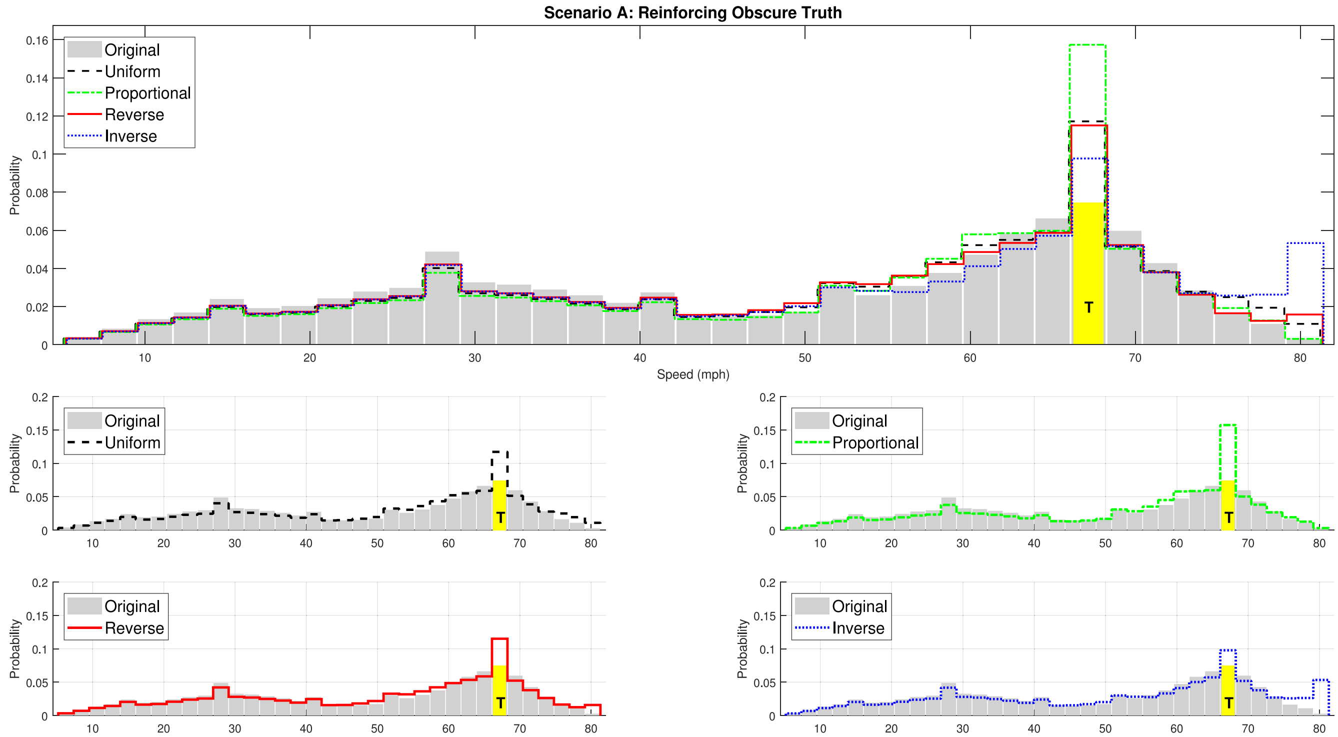

Fig. 8. Reinforcement of obscure truth (Scenario A). The top figure gives the overall comparison, and the four subfigures provide individual comparisons for better clarity. The yellow bar with letter "T" indicates the ground truth.

TABLE I
IMPROVEMENT OF BELIEF IN GROUND TRUTH: SCENARIO A

Interim belief	0.0744			
WRoS method	Uniform	Proportional	Reverse	Inverse
Posterior belief	0.1175	0.1575	0.1155	0.09875
Enhancement	57.9%	**111.7%**	55.2%	32.7%

TABLE II
IMPROVEMENT OF BELIEF IN GROUND TRUTH: SCENARIO B

Interim belief	0.016			
WRoS method	Uniform	Proportional	Reverse	Inverse
Posterior belief	0.08	0.06	0.092	0.0815
Enhancement	400%	275%	**475%**	409%

sampling will allocate most validation opportunities to that value, which in turn receives most positive ratings to boost its prominence. By the same reasoning, `Inverse` allocates the least validation opportunities to the truth and thus receives the least boost. Moreover, we notice that `Inverse` creates a "heavy tail" near the right end. This is because those low-probability values were allocated many validation chances and, as they are also near the truth value, they received a good number of positive ratings too.

2) Scenario B—Discovering Hidden Truth: In Scenario B, the ground truth is buried among much noise and thereby become unidentifiable under conventional statistical methods. This corresponds to Fig. 7 when the ground truth is, for example, 45 mph. In practice, such a scenario could be caused by low-quality or faulty sensors, unskilled or malicious contributors, sensor drift or miscalibration [27], environmental causes, security breach [28]–[30], etc.

CV has the capability of discovering such hidden truth, as demonstrated by the results shown in Fig. 9. The interim belief about the hidden truth 45 mph is boosted significantly from 0.016 to the posterior belief of 0.06–0.092, which is equivalent to a remarkable increase of 275%–475% as shown in Table II. Meanwhile, the two originally ostensible truth candidates (due to their prominence), 28 mph and 67 mph, are also mitigated to becoming even lower than the probability of 45 mph (except for proportional sampling).

Among the four methods, `Reverse` performs the best. This is because it allocated more validation opportunities to the hidden truth than the ostensible truths (28 and 67 mph), which enabled the ramp-up that "unearthed" the buried truth. Similarly, this explains why `Proportional` has the lowest improvement among the four methods. On the other hand, it is not intuitive why `Inverse` does not top all the methods, since it can be considered an "exaggerated" version of `Reverse`. The reason is that it wasted a lot of validation opportunities on very low-probability values (such as those near 4 and 80 mph), thereby leaving relatively less opportunities for the real hidden truth.

3) Choice of WRoS Method: In practice, the challenge is that we do not have prior knowledge of what scenario we are facing when choosing the best sampling method. A trial-and-error approach (trying each method and picking the best) is not viable because each trial inevitably entails a large-scale outreach to crowd, which violates our objective of minimizing it. Therefore, we need to make the best choice in advance.

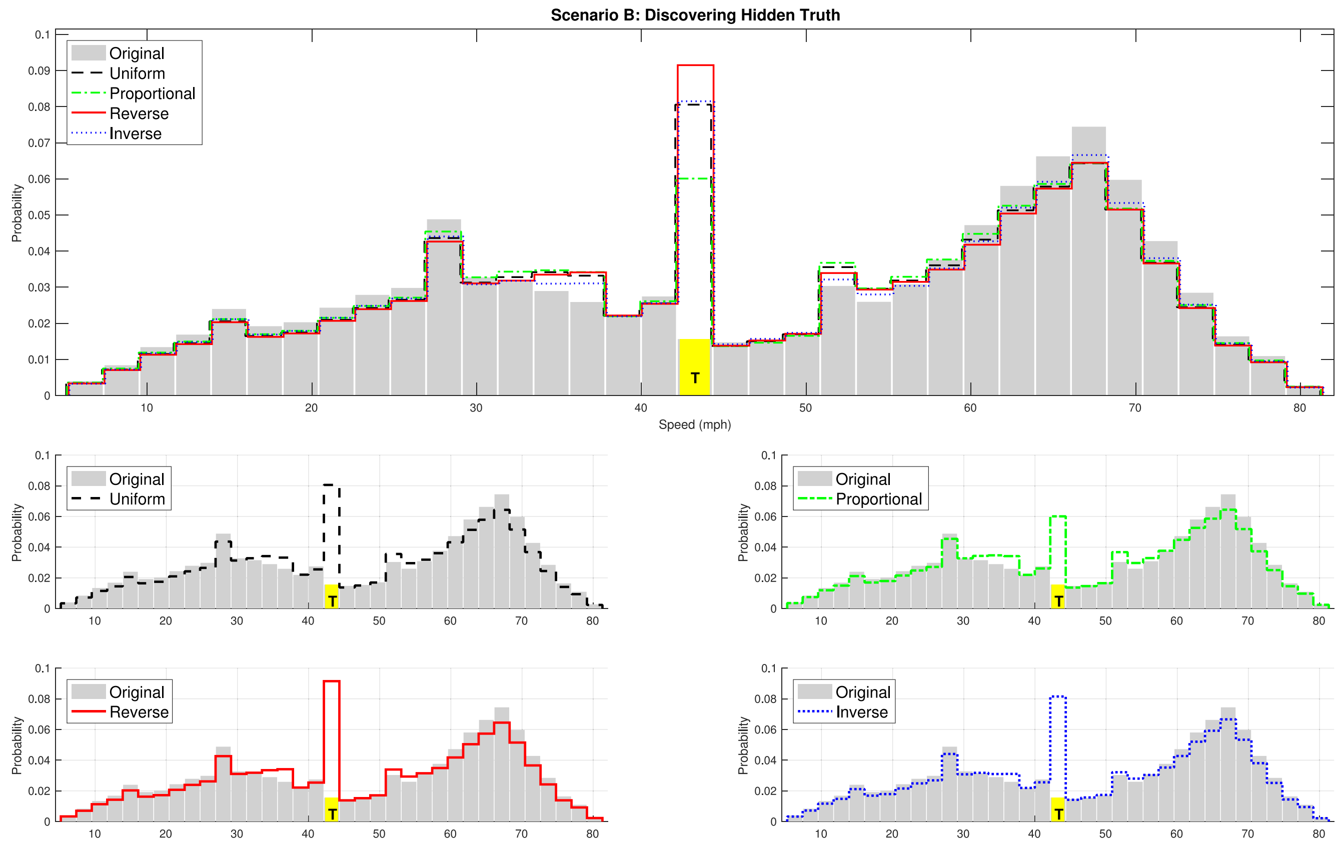

Fig. 9. Discovery of hidden truth (Scenario B). The top figure gives the overall comparison, and the four subfigures provide individual comparisons for better clarity. The yellow bar with letter "T" indicates the ground truth.

TABLE III
KULLBACK–LEIBLER DIVERGENCE

WRoS method	Uniform	Proportional	Reverse	Inverse
D_{KL} **(A)** $\times 100$	3.14	4.91	3.22	12.87
D_{KL} **(B)** $\times 100$	7.50	4.35	9.45	7.37

Our recommendation is `Reverse`, based on the tradeoff as follows. First, it has the most superior discovering capability as demonstrated in Scenario B. Second, its reinforcement effect as demonstrated in Scenario A is good enough, which we quantify below.

- The relative strength of the obscure truth (67 mph) against the most salient competitor (28 mph) after reinforcement is $0.1155/0.0425 = 2.72$, which means that the true signal is nearly triple the second strongest signal, making it well distinguishable from noise. In comparison, the relative strength as in the original dataset is $0.0744/0.0488 = 1.52$ only.
- The KL divergence, which measures the information gain, is higher for `Reverse` (3.22×10^{-2}) than for `Uniform` (3.14×10^{-2}), as tabulated in Table III. Note that the KL value for `Inverse` (12.87×10^{-2}) is an outlier, because it is due to the heavy tail explained in Section V-D1. Moreover, the KL divergence for Scenario B is also provided in Table III for completeness, which corroborates the superiority of `Reverse`.

VI. DISCUSSION

A. Multiple Truths

Our CV approach is agnostic to the number of truths. While we demonstrate its performance with a single truth for clarity, it should have been evident that it applies to multitruth applications as well. This is because we do not make any single-truth assumptions like in maximum likelihood estimation (MLE) and many other truth-finding studies in the literature.

On another note, the proposed approach also applies to both continuous and discrete types of data, which are unified by the profiling step (Section IV-A).

B. Resistance to Security Attacks

Due to the close interaction with people, a CV approach as such may be subject to the following security attacks. However, our mechanism is robust to them.

- *Collusion Attack:* User rating systems commonly face this security threat where individual raters collude with product providers (in our case data contributors) to give unfair (usually higher) ratings; or in another case, a group of raters collaborate to give adverse or favorable ratings to a specific (set of) product(s). However, our proactive and probabilistic push combined with the randomness of WRoS, ensures that no one knows for sure who will be selected as raters and which product (data v_i) will be pushed to which rater. This makes it practically not feasible for the above collusion to succeed, whether individual or group based.

- *Sybil Attack:* This refers to the case where a user creates or controls multiple accounts to gain unwarranted benefits, such as increasing the chance of being selected as a validator. However, our reputation-based recruitment grants Sybil accounts little chance, and even if one such account happens to be selected, it will be made worse off under our trust-oriented design if it provides biased or dishonest validation (see Section IV-D3). Moreover, the stochasticity of our push and sampling method makes it improbable for a Sybil account to validate its intended targets (e.g., friend or foe's contributions).

In any case, one cannot rate her own contributions because one of our anti-bias measures excludes contributors from the candidate pool of validators. This in effect disincentivizes most security attacks in the first place.

VII. Conclusion

In essence, the CV approach proposed in this paper overlays another layer of crowdsourcing (for metadata) on top of the original crowdsensing (for raw data). This offers a new perspective to tackle the long-standing data quality challenge for MCS-based IoT applications. By leveraging the diverse side information people possess, it alleviates the strict spatio-temporal constraints and the resource-consuming burden imposed by direct and physical sensing.

The approach is embodied by a CV mechanism, which hinges on a number of key components such as oversampling with WRoS, stochastic information solicitation using PATOP^2, and vote-based reshaping. It satisfies the hard constraints due to the time-sensitivity of IoT applications, as well as the soft constraints on the trustworthiness of validation. Not built on premise of Bayesian or game-theoretical assumptions, it is conducive to practical adoption, by virtue of augmenting rather than redesigning existing MCS systems, minimal user effort requirement, as well as resistance to common security attacks.

Performance evaluation based on a real IoT dataset has demonstrated that CV provides a unified solution to two disparate scenarios: 1) reinforcement of obscure truth and 2) discovery of hidden truth. In particular, hidden truth commonly remains unidentified under conventional statistical and data mining methods. Quantitative measurements via posterior belief enhancement and KL divergence indicate remarkable improvement in data quality as well.

References

[1] T. Luo, S. S. Kanhere, J. Huang, S. K. Das, and F. Wu, "Sustainable incentives for mobile crowdsensing: Auctions, lotteries, and trust and reputation systems," *IEEE Commun. Mag.*, vol. 55, no. 3, pp. 68–74, Mar. 2017.

[2] H. Jin *et al.*, "Thanos: Incentive mechanism with quality awareness for mobile crowd sensing," *IEEE Trans. Mobile Comput.*, to be published.

[3] T. Luo, H.-P. Tan, and L. Xia, "Profit-maximizing incentive for participatory sensing," in *Proc. IEEE INFOCOM*, 2014, pp. 127–135.

[4] G. Radanovic and B. Faltings, "A robust Bayesian truth serum for non-binary signals," in *Proc. AAAI*, 2013, pp. 833–839.

[5] D. Prelec, "A Bayesian truth serum for subjective data," *Science*, vol. 306, no. 5695, pp. 462–466, Oct. 2004.

[6] T. Luo, S. S. Kanhere, H.-P. Tan, F. Wu, and H. Wu, "Crowdsourcing with Tullock contests: A new perspective," in *Proc. IEEE INFOCOM*, 2015, pp. 2515–2523.

[7] E. Kamar and E. Horvitz, "Incentives and truthful reporting in consensus-centric crowdsourcing," Microsoft Res., Albuquerque, NM, USA, Rep. MSR-TR-2012-16, 2012.

[8] B. Kantarci, P. M. Glasser, and L. Foschini, "Crowdsensing with social network-aided collaborative trust scores," in *Proc. IEEE Globecom*, 2015, pp. 1–6.

[9] C. Wu, T. Luo, F. Wu, and G. Chen, "EndorTrust: An endorsement-based reputation system for trustworthy and heterogeneous crowdsourcing," in *Proc. IEEE Globecom*, 2015, pp. 1–6.

[10] L. Zeynalvand, J. Zhang, T. Luo, and S. Chen, "MASA: Multi-agent subjectivity alignment for trustworthy Internet of Things," in *Proc. 21st Int. Conf. Inf. Fusion (FUSION)*, 2018, pp. 2013–2020.

[11] K. L. Huang, S. S. Kanhere, and W. Hu, "Are you contributing trustworthy data? The case for a reputation system in participatory sensing," in *Proc. ACM MSWiM*, 2010, pp. 14–22.

[12] H. Amintoosi and S. S. Kanhere, "A trust framework for social participatory sensing systems," in *Proc. Mobiquitous*, 2012, pp. 237–249.

[13] D. Wang, L. Kaplan, H. Le, and T. Abdelzaher, "On truth discovery in social sensing: A maximum likelihood estimation approach," in *Proc. ACM/IEEE IPSN*, 2012, pp. 233–244.

[14] E. Davami and G. Sukthankar, "Improving the performance of mobile phone crowdsourcing applications," in *Proc. AAMAS*, 2015, pp. 145–153.

[15] S. Gisdakis, T. Giannetsos, and P. Papadimitratos, "SHIELD: A data verification framework for participatory sensing systems," in *Proc. ACM Conf. Security Privacy Wireless Mobile Netw. (WiSec)*, 2015, Art. no. 16.

[16] P. Michelucci and J. L. Dickinson, "The power of crowds," *Science*, vol. 351, no. 6268, pp. 32–33, 2015.

[17] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*. Cambridge, U.K.: MIT Press, 1998.

[18] T. Luo, S. S. Kanhere, and H.-P. Tan, "SEW-ing a simple endorsement Web to incentivize trustworthy participatory sensing," in *Proc. IEEE SECON*, 2014, pp. 636–644.

[19] Y. Zhan, Y. Xia, Y. Liu, F. Li, and Y. Wang, "Incentive-aware time-sensitive data collection in mobile opportunistic crowdsensing," *IEEE Trans. Veh. Technol.*, vol. 66, no. 9, pp. 7849–7861, Sep. 2017.

[20] L. Duan *et al.*, "Motivating smartphone collaboration in data acquisition and distributed computing," *IEEE Trans. Mobile Comput.*, vol. 13, no. 10, pp. 2320–2333, Oct. 2014.

[21] C.-K. Tham and T. Luo, "Quality of contributed service and market equilibrium for participatory sensing," *IEEE Trans. Mobile Comput.*, vol. 14, no. 4, pp. 829–842, Apr. 2015.

[22] H. Jin, L. Su, and K. Nahrstedt, "Theseus: Incentivizing truth discovery in mobile crowd sensing systems," in *Proc. ACM MobiHoc*, 2017, Art. no. 1.

[23] T. Luo and L. Zeynalvand, "Reshaping mobile crowd sensing using cross validation to improve data credibility," in *Proc. IEEE Globecom*, Dec. 2017, pp. 1–7.

[24] C. List, "Social choice theory," in *The Stanford Encyclopedia of Philosophy*, E. N. Zalta, Ed. Stanford, CA, USA: Stanford Univ., 2013.

[25] J. Bartholdi, C. A. Tovey, and M. A. Trick, "Voting schemes for which it can be difficult to tell who won the election," *Soc. Choice Welfare*, vol. 6, no. 2, pp. 157–165, 1989.

[26] T. Luo, S. K. Das, H. P. Tan, and L. Xia, "Incentive mechanism design for crowdsourcing: An all-pay auction approach," *ACM Trans. Intell. Syst. Technol.*, vol. 7, no. 3, pp. 1–26, 2016.

[27] M. Holmberg and T. Artursson, "Drift compensation, standards, and calibration methods," in *Handbook of Machine Olfaction: Electronic Nose Technology*. Weinheim, Germany: Wiley, 2002, pp. 325–346.

[28] L. Kugler, "Why GPS spoofing is a threat to companies, countries," *Commun. ACM*, vol. 60, no. 9, pp. 18–19, Sep. 2017.

[29] M. Harris. (Sep. 2015). *Researcher Hacks Self-Driving Car Sensors*. [Online]. Available: https://spectrum.ieee.org/cars-that-think/transportation/self-driving/researcher-hacks-selfdriving-car-sensors

[30] N. C. Moore. (Mar. 2017). *Scientists Can Hack Sensors in Cars and Phones With a $5 Speaker*. [Online]. Available: https://www.futurity.org/sensors-accelerometer-hacking-sound-1379602-2/

[31] *Amazon Mechanical Turk*. Accessed: Apr. 2, 2018. [Online]. Available: http://www.mturk.com

[32] A. Shapiro, D. Dentcheva, and A. Ruszczynski, *Lectures on Stochastic Programming: Modeling and Theory*. Philadelphia, PA, USA: SIAM Math. Program. Soc., 2009.

[33] TIBCO Statistica. *Compare Distribution Tables*. Accessed: Apr. 2, 2018. [Online]. Available: http://www.statsoft.com/Textbook/Distribution-Tables
[34] *Bessel's Correction*. Accessed: Apr. 2, 2018. [Online]. Available: https://en.wikipedia.org/wiki/Bessel's_correction
[35] V. Kuleshov and D. Precup, "Algorithms for the multi-armed bandit problem," *J. Mach. Learn. Res.*, vol. 1, pp. 1–48, Oct. 2000.
[36] T. Luo, S. S. Kanhere, S. K. Das, and H.-P. Tan, "Incentive mechanism design for heterogeneous crowdsourcing using all-pay contests," *IEEE Trans. Mobile Comput.*, vol. 15, no. 9, pp. 2234–2246, Sep. 2016.
[37] T. Luo, S. S. Kanhere, S. K. Das, and H.-P. Tan, "Optimal prizes for all-pay contests in heterogeneous crowdsourcing," in *Proc. IEEE Int. Conf. Mobile Ad Hoc Sensor Syst. (MASS)*, 2014, pp. 136–144.
[38] X. Zhang *et al.*, "Incentives for mobile crowd sensing: A survey," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 1, pp. 54–67, 1st Quart., 2016.
[39] F. Restuccia, S. K. Das, and J. Payton, "Incentive mechanisms for participatory sensing: Survey and research challenges," *ACM Trans. Sensor Netw.*, vol. 12, no. 2, pp. 1–13, May 2016.
[40] L. G. Jaimes, I. J. Vergara-Laurens, and A. Raij, "A survey of incentive techniques for mobile crowd sensing," *IEEE Internet Things J.*, vol. 2, no. 5, pp. 370–380, Oct. 2015.
[41] J.-C. Herrera *et al.*, "Evaluation of traffic data obtained via GPS-enabled mobile phones: The *Mobile Century* experiment," *Transp. Res. C*, vol. 18, no. 3, pp. 568–583, 2010.
[42] *Dan Work*. Accessed: Apr. 15, 2018. [Online]. Available: https://my.vanderbilt.edu/danwork/open-data-2/
[43] *Mobile Century Data.* Accessed: Apr. 15, 2018. [Online]. Available: http://traffic.berkeley.edu/project/downloads/mobilecenturydata
[44] A. Hobson, *Concepts in Statistical Mechanics*. New York, NY, USA: Gordon and Breach, 1971.

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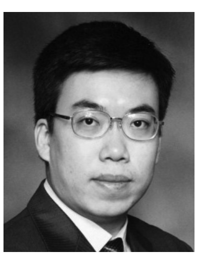

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