PISCES: Participatory Incentive Strategies for Effective Community Engagement in Smart Cities

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Abstract

A key challenge in participatory sensing systems has been the design of incentive mechanisms that motivate individuals to contribute data to consuming applications. Emerging trends in urban development and smart city planning indicate the use of citizen reports to gather insights and identify areas for transformation. Consumers of these reports (e.g. city agencies) typically associate non-uniform utility (or values) to different reports based on the spatio-temporal context of the reports. For example, a report indicating traffic congestion near an airport, in early morning hours, would tend to have much higher utility than a similar report from a sparse residential area. In such cases, the design of an incentive mechanism must motivate participants, via appropriate rewards (or payments), to provide higher utility reports when compared to less valued ones. The main challenge in designing such an incentive scheme is two-fold: (i) lack of prior knowledge of participants in terms of their availability (i.e. who are in the vicinity) and reporting behaviour (i.e. what are the rewards expected); and (ii) minimizing payments to the reporters while ensuring that the desired number of reports are collected. In this paper, we propose STOC-PISCES, an algorithm that guarantees a stochastic optimal solution in the generalized setting of an unknown set of participants, with non-deterministic availabilities and stochastically rational reporting behaviour. The superior performance of STOC-PISCES in experimental settings, based on real-world data, endorses its adoption as an incentive strategy in participatory sensing applications like smart city management.

Introduction

In recent years participatory sensing has evolved into a scientific paradigm that empowers citizens with mobile devices, embedded with a plurality of sensors, to contribute to micro and macro-scale urban sensing applications (Ganti et al. 2013; Chon et al. 2013; Campbell et al. 2008; Mukherjee et al. 2014). The effectiveness of personal sensing systems such as PEIR (Mun et al. 2009) and CenceMe (Miluzzo et al. 2007), as well as community-based participatory sensing systems, such as the Favela Project (Maps 2012), heavily rely on the engagement of reporters contributing with data sensed from their devices. Prior work (Koutsopoulos 2013; Jaimes, Vergara-Laurens, and Labrador 2012; Lee and Hoh

2010) corroborates the fact that participants get motivated to submit data (reports) if they are appropriately incentivized (rewarded) by the requesters (e.g. city agency). However, approaches proposed erstwhile heavily rely on either auction-based or utility-based incentive mechanisms, that in no way guarantee that a requester will receive the desired number of reports, for a specific region or time period of interest. Further, these approaches do not address the problem of minimizing payments for a requester, while ensuring these payments are commensurate with the utility of reports. More importantly, prior art assumes knowledge of reporter availability as well as reporting behaviours (often in the form of bids). This assumption, however, does not hold in dynamic real-world scenarios, where reporters can be highly mobile and hence their availability can be non-deterministic.

Typically, for a participatory sensing application, requesters have a higher value (or *utility*) for events pertaining to certain spatio-temporal regions of interest over others. For instance, traffic reports during peak hours from a business district are of greater value compared to reports from a residential area, or reports during off-peak hours. A parking lot violation report at a busy city intersection may have greater utility to a city agency compared to such a report from a low-congestion area. In real-world settings, this implies that a higher number (or *demand*) of unique reports are warranted due to the higher utility of these events to a requester. Therefore, *we consider the utility as the demand, in terms of the number of unique reports, for an event.* We refer to the *context* of a report as the spatio-temporal event that influences the utility of the report.

Variations in demand of heterogeneous events can be modelled in terms of a configurable parameter, namely the *desired number of reports*. We use the terms *demand of a report* and *desired number of reports*, for any spatio–temporal event, interchangeably in the rest of the paper. As mentioned earlier, the demand is a direct function of the context of the report – i.e. events with higher utility (e.g. a parking violation in down town during office hours) have much higher demand for reports, than lower utility ones (e.g. a similar violation in a housing area at midnight). Additionally, independent of the utility of a report (event) to a requester, the severity of the event is associated with a certain desired number of reports received, which is empirically determined based on ground work done by the requesters themselves. For in-

stance, for a transit agency, non-availability of buses during peak hours maybe of high utility. However, the agency may not identify the issue to be severe based on a single report, as opposed to getting a significant number of reports. Therefore, in order to ascertain the severity of events, especially those of higher utilities to the requester, it is natural for the requester to desire a larger number of reports on these issues.

In order to meet the demand, requesters are constrained by the cost incurred by payments made to the reporters. In fact, an optimal incentive mechanism must guarantee the desired number of reports (demand) to a requester, while minimizing the total payment made to the reporters. Further, this needs to be accomplished in an environment where there is little or no prior knowledge about the availability of reporters, as well as their expectations in terms of payments (rewards) for these reports. We propose *PISCES*–a novel framework for designing incentive strategies in a participatory sensing system, that is geared towards increasing citizen engagement under dynamic and (previously) unknown conditions. In specific, the proposed framework strives to address the following challenges:

- *Non-uniform requester demand*: Different spatio-temporal events have different utilities to the requester. Hence, the demand for the number of reports is also different for varying contextual scenarios. The incentive mechanism should be able to produce a guaranteed supply of reports that (closely) follows the demand distribution of these reports.

- *Non-deterministic availability of reporters*: Maintaining and updating the specific location (mobility) of each prospective reporter maybe practically infeasible in an urban setting. For example, in an application targeted at commuters in office cabs, even if routes are determined a-priori, unforeseen traffic congestions, roadblocks etc. can cause reporters to be available well beyond the "interest" window of certain reports. Maintaining this information at a massive scale can cause huge operational overhead.

- *Unknown and stochastic reporting behaviour*: Each reporter is assumed to have an expectation in terms of the payment (reward) she receives for a report. As in the case of availability, it might not be feasible to maintain and update the expectations of each reporter. Further, it is possible that a reporter may not always report even if the payment exceeds her expectations. For example, Joshua might usually report a traffic condition for 1$ (or equivalent reward points), but may not report on a day when he is in a hurry to attend a client meeting. However, given a large enough pool of reporters and an appropriate reward announced for the event, it might still be possible to satisfy the demand. It is this non-deterministic nature of reporting behaviour that makes the problem both interesting and challenging.

- *Payment constraints*: To ensure that a desired number of reports is received, appropriate rewards need to be determined for each event. However, to ensure economic viability for the requester, any reward-based mechanism must minimize the overall payment made to reporters. The cost optimization, under dynamically varying apriori

unknown conditions, is a novel aspect of the incentivization problem addressed in this paper.

Contributions: *PISCES* is a closed-loop incentive framework that computes the reward (or payment) declared for each report in a participatory system, where the reporters are mobile and expect a (non-zero) payment for each report. Each report is associated with a demand (i.e. number of unique reports that need to be collected) and the framework attempts to meet this demand, while minimizing the total cost incurred by payments to reporters. At a high level, *PISCES* employs an explore-exploit technique–(i) it declares a reward for each report at the beginning of a trial; (ii) observes the number of reports gathered at the end of the trial; and (iii) tunes the reward for the next trial in order to obtain the desired number of reports. Our objective is to converge to a reward value that minimizes the total payments over a small number of trials.

We propose STOC-PISCES, an algorithm to determine the minimum reward for each report, where the availability and reporting behaviour of the participants can change in every trial. This generalized setting allows us to consider any participant who is in the spatio-temporal region of interest for a report. Further, we assume that each participant will report for each declared reward value with a non-zero probability specific to the $(reporter, reward)$–tuple. The proposed strategy, STOC-PISCES, combines a Multi-Armed Bandit (MAB) framework for adaptive learning, with binary search, to converge to the (stochastic) optimal rewards in a polynomial number of trials. *To the best of our knowledge, this is the first algorithm that provides optimality guarantees on the expected outcome (i.e. number of reports generated) in the stochastic setting of the cost minimization problem.* We show that the number of trials is determined by the deviation from the expected number of reports that can be tolerated by the requester and a desired confidence level specified by the requester.

Finally, empirical results from extensive simulations, conducted using real-world mobility traces and realistic reporting behaviours, demonstrate that: (i) STOC-PISCES ensures significantly low payments for requesters with guarantees on the expected number of reports; and (ii) STOC-PISCES scales efficiently with increased number of users as well as variations in reporting behaviors of participants.

Related Work

There has been a plethora of work in participatory sensing systems (Chon et al. 2013; Mun et al. 2009; Campbell et al. 2008). This section specifically addresses those pertaining to incentive mechanisms in such systems. None of these works address the problem of spatio-temporal variance in utility of reports and unknown reporter profiles, either independently or jointly. Most importantly, prior work completely overlook the stochastic behaviour of participants in real-world scenarios.

Reverse auction and utility based mechanisms: (Koutsopoulos 2013) proposes an optimal incentive scheme, which maximizes individual user payments based on bidding profile history. (Krontiris and Albers 2012) optimizes

Figure 1: Illustrative example of a participatory sensing system

Figure 2: Overview of $PISCES$ framework

a reporter-centric multi-attribute utility function; while in (Jaimes, Vergara-Laurens, and Labrador 2012), a reverse auction based mechanism with a greedy algorithm is proposed to improve the coverage of reports. In (Lee and Hoh 2010), a Reverse Auction based Dynamic Price (RADP) mechanism is presented with Virtual Participant Credit to ensure reporter engagement. (Biswas et al. 2015) proposes a mechanism that learns the stochastic qualities of the crowd-workers, and proposes an auction-based payment rule which is individually rational, truthful, budget feasible and computationally efficient. (Yang et al. 2012) frames the incentive design problem as a Stackelberg game that maximizes platform utility and also proposes a user-centric model with an auction-based scheme. In (Feng, Zhu, and Ni 2013), a strategy-proof incentive mechanism is proposed based on the Vickrey-Clarke-Groves (VCG) mechanism to stimulate strategic smartphone users to truthfully disclose their real costs. Three online incentive mechanisms based on online reverse auction are also proposed in (Zhou et al. 2014). All these mechanisms either assume apriori knowledge of reporter profiles or fail to guarantee a desired number of reports under stochastic conditions.

All-pay auctions based schemes: In (Sun 2013), a behaviour-based incentive mechanism with budget constraints applies sequential all-pay auctions in mobile social networks. (Zhao, Li, and Ma 2014) additionally considers the time availability of reporters. (Zhao, Ma, and Liu 2014) proposes a solution to minimize the payment while laying a constraint on the number of tasks that will be completed within a deadline. Although these works recognize the online arrival pattern of reporters, they primarily focus on the quality of reports with no guarantees. They further require a non-scalable handshaking of user bids and choose only a certain number of reporters depending on the budget.

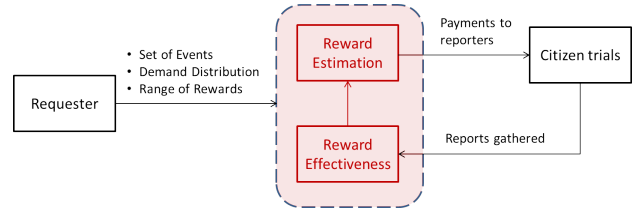**Adaptive learning schemes**: Probably Approximately Correct-Multi-Armed Bandit (PAC-MAB) algorithms have been used to learn true participant behaviours in crowd-sensing scenarios. (Jamieson et al. 2013) finds the near-optimal arm and theoretically proves an upper bound on the number of samples or trials required. (Karnin, Koren, and Somekh 2013) studies the problem of finding the best arm in minimum number of trials for a given confidence; and with a high confidence for a fixed number of trials. A MAB mechanism is also proposed in (Jain, Narayanaswamy, and Narahari 2014) for demand response, which makes monetary offers to strategic requesters who have unknown response characteristics. However, these techniques require a large number of trials to achieve performance bounds with a high confidence and ignore the cost associated with each trial. To the best of our knowledge, there exists no result around minimizing the total cost incurred, subject to the constraint that the value obtained from the trials is greater than a given threshold.

Trust based schemes: The bi-directional relationship between trust models and incentive mechanisms have been identified in various domains. (Zhang, Cohen, and Larson 2012) proposes trust-based incentive mechanisms to promote honesty in electronic marketplaces. (Vu and Aberer 2011) studies the effect of various computational trust models on rational participants. (Wang et al. 2012) uses a Maximum Likelihood estimation approach to determine the trustworthiness of participants and veracity of observations reported by participants of unknown trustworthiness. Trust and veracity of reports is an important research direction in participatory sensing. However, the related techniques do not cater to the problem of designing incentives under dynamic variations in the demand for reports, as well as the availability/willingness of users to report.

PISCES Framework

In this section, we introduce the $PISCES$ framework for a typical participatory sensing system, illustrated in Fig. 1.

System Overview

Fig. 2 presents the overview of the $PISCES$ framework. Recall that the objective of the framework is to compute rewards for each event (report) in a participatory sensing application. The requester submits the following requirements to the framework:

- **Set of events to be reported**, i.e. the set of events for which reports are required;

- **Demand Distribution of reports**, i.e. the desired number of reports pertaining to each event and spatio-temporal

context;

- **Reward range**, the range of reward values that the requester is willing to pay for each event.

As illustrated in Fig. 2, $PISCES$ is a closed-loop system framework that works as follows. In each trial (e.g. during each day), a reward vector is estimated that constitutes the rewards for each event in the system. The rewards are declared to the participants. Note that for a particular event, any reporter reporting it is paid the same amount, corresponding to the reward declared for the event in that trial. At the end of the trial, $PISCES$ observes the number of reports that are gathered from the participants, for each event. Based on the observed effectiveness of the trial, the reward vector is updated for the consecutive trial and so on. This pricing mechanism is referred to as a *posted price mechanism* in literature (Hartline 2001; Singla and Krause 2013; Jain, Narayanaswamy, and Narahari 2014).

During the reward estimation step of each trial, our objective is to converge towards an optimal reward that guarantees the desired number of reports for each event. Note that, in each trial a participant is rewarded only once, i.e., even if a participant sends multiple reports of a particular event, she gets rewarded only once. Hence, assuming rational reporters, no reporter will report on an event more than once. However, for every unique report that is gathered for a particular event, a payment is made to the corresponding reporter. Finally, the rewards computed for each event can be very different depending on the relative utility of the events.

System Model and Requirements

Each report is associated with an event in our system. Fig. 1 depicts illustrative events in the context of traffic management in the city of Bangalore, India. Events are characterized by the triple: $<place, time, category>$. Let $\mathcal{T}$ represent the set of events (triples consisting of place, time and type of the event) and for each event $j \in \mathcal{T}$ let d_j denote the number of unique reports required for the event.

As noted earlier, the demand, d_j, differs across events and represents the inherent utility of reports for the specific event. For example, in Fig. 1, a report on the wait times during rush hours (9 AM) at Hoodi traffic signal have a higher utility and demand compared to off-peak hours (e.g. 2 PM) at the same location. Similarly, reports regarding illegal diggings on the Outer Ring Road (a critical highway across the business district) is deemed to be of higher value than any of the traffic signal reports. We assume that the requester (e.g. the Bangalore Traffic Police) is allowed to express the demand, d_j, as the desired number of reports for event j, depending on the spatio-temporal event corresponding to the report(s). Intuitively, a requester would like to pay higher rewards for the valuable, in-demand events to encourage larger number of unique reports for such events. More reports are desirable for increased accuracy w.r.t. actionable insights that are drawn from these reports. However, at the same time, the requester would like to minimize the total payment for getting the required number of reports for each event. Finally, for every event j, the associated reward r_j is bounded as $r_{min} \leq r_j \leq r_{max}$.

Reporter Profiles

The event-specific rewards are declared by the system to the participants beforehand. More importantly, the system is unaware of the payments expected by each reporter. Note that, the reporters are typically large in number, so instead of estimating the distribution of costs of each reporter, we propose a method to declare a posted price (or reward) and update the reward in each trial towards converging to the minimum reward required for getting the desired number of reports.

Reporter Mobility and Availability The availability of a participant in reporting an event depends on the match between the spatio-temporal context of the event and the participant, i.e., if a participant is present in the neighbourhood of the event location during the specified time interval, then she is considered available to report on the event. For example, any resident commuting through Hoodi signal between 9–11 AM becomes eligible to report wait times and collect the corresponding reward. In other words, given an event and its spatio-temporal context, anyone in the vicinity during the specified time is a potential candidate for reporting.

We assume that reporters have associated mobility patterns with some stochastic variability. Note that the stochastic nature does allow for chance occurrences resulting in reporter unavailability or deviation from regular mobility pattern, for example detours due to road blocks, delays or absence due to other reasons. Conversely, it also allows for unexpected reporter availability for events due to similar reasons.

The incentive strategy proposed in this paper does not depend on any specific mobility pattern, but rather is only aware of the fact that reporters have a stochastic mobility pattern (and hence availability) and does not presume any a-priori knowledge of the same.

Reporting behaviours Apart from non-deterministic availability, reporters may also have variable reporting behavior. For example, the reporter near Hoodi at 9 AM may not report traffic wait time even for a high reward, if she is running late for a meeting. Thus, similar to the above argument for mobility pattern, the reporting behaviors is assumed to have a stochastic pattern. In particular, each reporter has an associated probability $P_a(r)$ for each reward r ($P_a(r) <= 1$) with which they accept each reward r. $P_a(r)$ is further assumed to be a non-decreasing function of reward r, in other words, reporters are considered to be *stochastically rational*.

Irrespective of the rationality assumption, $P_a(r)$ allows us to capture the variability due to human behavior or chance occurrences, in reporting an event for a reward value even when the reporter is available to report it.

In a special case setting, where $P_a(r) = 1$ for a reward r, each reporter has a *fixed (deterministic)* cost threshold, above which she will always report an event.

In the following section, we present the proposed incentive strategy, which uses a Multi-armed Bandit (MAB) algorithm to estimate near-optimal rewards with a high confidence, with a reasonable convergence rate.

Incentive Strategy

As mentioned in the previous section, we assume the reporters are rational and the mobility pattern to be independent of rewards for events. The availability of a reporter for an event depends solely on the stochastic mobility pattern of the reporter and is independent on the rewards for the event. We make the following observation from these assumptions.

Observation 1. *The expected number of reports that can be obtained for an event cannot decrease as the reward increases.*

We propose a MAB algorithm in the *posted price setting* (Hartline 2001; Singla and Krause 2013; Jain, Narayanaswamy, and Narahari 2014).

The basic idea behind the algorithm for estimating the right incentives or reward vector runs in parallel for every event, and for any given event, it conducts a certain number of trials to converge to the right reward. In a trial, any reporter reporting an event is paid the same amount corresponding to the posted reward for that event in that iteration. The reward estimate for each event is updated after observing the reporting behaviors for a particular posted reward vector. The update step employs binary search on the reward range with resolution of ϵ. The number of trials n run for every event (parallelly) is determined by the desired confidence level and the extent of *deviation* from the desired number of reports d_j that can be tolerated by the requester. Based on the observations of the actual behaviour in the reward trials, the rewards are updated. We show that the proposed scheme will converge in at most $n \cdot \log_2 \left(\frac{r_{max} - r_{min}}{\epsilon} \right)$ iterations. Algorithm 1 presents the STOC-PISCES algorithm describing the procedure in detail.

Algorithm 1 STOC-PISCES for an event $j \in \mathcal{T}$

Input: $r_{max}, r_{min}, \epsilon, d_j, \varepsilon_1, \varepsilon_2 < \varepsilon_1$ and δ.
Output: r_j.
Set $r_{j,max} \leftarrow r_{max}$ and $r_{j,min} \leftarrow r_{min}$.
Set $n \leftarrow \lceil \frac{1}{2\varepsilon_2^2} \cdot \ln\left(\frac{2}{\delta}\right) \rceil$, $k \leftarrow 1$, $r_j \leftarrow r_{j,max}$, and $v_{j,max} = 0$.
while $k \leq \log_2 \left(\frac{r_{max} - r_{min}}{\epsilon} \right)$ **do**
    Set $r_{j,k} \leftarrow \frac{r_{j,max} + r_{j,min}}{2}$ and $v_{j,k} \leftarrow 0$.
    for all $p \in \{1, \ldots, n\}$ **do**
        Run system trial with $\{r_{j,k} | j \in \mathcal{T}\}$.
        $P_{j,k,p} \leftarrow$ number of reports received.
        Compute $v_{j,k,p} \leftarrow \min\left(\frac{P_{j,k,p}}{d_j}, 1\right)$.
        Update $v_{j,k} \leftarrow v_{j,k} + \frac{v_{j,k,p}}{n}$.
    end for
    if $v_{j,k} \geq 1 - \varepsilon_1$ **then**
        Update $r_j \leftarrow r_{j,k}$, and $r_{j,max} \leftarrow r_j$.
    else
        Update $r_{j,min} \leftarrow r_{j,k} + \epsilon$.
        if $v_{j,max} < v_{j,k}$ **then**
            Update $v_{j,max} \leftarrow v_{j,k}$ and $r_j \leftarrow r_{j,k}$.
        end if
    end if
    $k \leftarrow k + 1$.
end while
Return reward r_j.

First, we determine the number of trials required for each reward value considered. Let the confidence level desired by the requester be $(1 - \delta)$, and the maximum deviation in the expected number of reports that the requester can tolerate

is $(1 - \varepsilon)$. Given the values of δ and ε, we choose ε_1 and ε_2, such that $\varepsilon_1 + \varepsilon_2 \leq \varepsilon$, and $\varepsilon_1 > \varepsilon_2$, and accordingly determine number of trials, $n = \lceil \frac{1}{2\varepsilon_2^2} \cdot \ln\left(\frac{2}{\delta}\right) \rceil$.

As already stated, each reward is tried n times. For every event j, for iteration k with reward $r_{j,k}$, and trial $p \in \{1, \ldots, n\}$, the value obtained from the trial is computed as $v_{j,k,p} = \min\left(\frac{P_{j,k,p}}{d_j}, 1\right)$, where $P_{j,k,p}$ is the number of reports obtained from that trial. This will be a function with range $[0, 1]$. Now, for a given $r_{j,k}$, if $\sum_{p \in \{1,\ldots,n\}} \frac{P_{j,k,p}}{n} < 1 - \varepsilon_1$, we reject the reward, and search in the upper half of the current reward range (by binary search), otherwise, we search in the lower range. This is done $\log_2\left(\frac{r_{max} - r_{min}}{\epsilon}\right)$ times for every event in parallel.

Theorem 1. *With probability $(1 - \delta)$, for any event j, the reward r_j, as computed by Algorithm STOC-PISCES is $r_j \leq r_{j,STOC-OPT}$, where $r_{j,STOC-OPT}$ is the minimum reward for which the expected number of reports is $\geq d_j$, if such a reward exists. Otherwise, with probability $(1 - \delta)$, r_j is the minimum reward for which the expected number of reports is the highest possible. Furthermore, the expected number of reports with r_j is $\geq (1 - \varepsilon_1 - \varepsilon_2) \cdot d_j \geq (1 - \varepsilon) \cdot d_j$ with probability $\geq (1 - \delta)$.*

Proof. Suppose that the estimated reward $r_j > r_{j,STOC-OPT}$. For this to happen, the estimated $v_{j,k}$ for a $r_{j,k} < r_j$ must have been underestimated as $< 1 - \varepsilon_1$ in an iteration k. Let the true expected value for $r_{j,k}$, be $\hat{v}_{j,k}$. From Chernoff-Hoeffding inequality (Hoeffding 1963), we know that for the given choice of n, the probability that $v_{j,k} < \hat{v}_{j,k} - \epsilon_2$ is $\leq \delta$. Therefore, with probability $\geq (1 - \delta)$, $v_{j,k} \geq \hat{v}_{j,k} - \epsilon_2$. Since $v_{j,k} < 1 - \varepsilon_1$, this implies that $\hat{v}_{j,k} \leq 1 - \varepsilon_1 + \epsilon_2$. Since we have chosen $\varepsilon_1 > \varepsilon_2$, it holds that $\hat{v}_{j,k} < 1$, and therefore $r_{j,k} < r_{j,STOC-OPT}$ with probability $(1 - \delta)$. In fact, this holds for every iteration where $v_{j,k'} < 1 - \varepsilon_1$, where we update the search space to higher reward values, including the iteration with reward $r_j - \epsilon$. Hence, it follows that with probability $\geq (1 - \delta)$, $r_j \leq r_{j,STOC-OPT}$.

If $r_j < r_{j,STOC-OPT}$, then $\hat{v}_j$ must be < 1, where $\hat{v}_j$ is the true expected value for r_j. However, we had estimated $v_j \geq 1 - \varepsilon_1$, and from our choice of n, it follows from Chernoff-Hoeffding inequality, that $v_j \leq \hat{v}_j + \varepsilon_2$. Therefore, $\hat{v}_j \geq v_j - \varepsilon_2 \geq 1 - \varepsilon_1 - \varepsilon_2$. Since $\varepsilon_1 + \varepsilon_2 \leq \varepsilon$, it follows that with probability $\geq (1 - \delta)$, the true expected number of reports corresponding to reward r_j is $\geq (1 - \varepsilon) \cdot d_j$. $\square$

Optimality of STOC-PISCES: Informally, Theorem 1 states that the algorithm $STOC-PISCES$ is near optimal (in the expected sense), with a high (desired) confidence. An optimal algorithm would minimize the total reward for which the expected number of reports is at least the minimum required for each event. However, such an optimal algorithm would need to be *omnipotent*, i.e., it needs to know the exact stochastic nature of mobility patterns and reporting behaviors. However, in reality, since the stochastic nature of the mobility patterns or reporting behaviors are *unknown*, and need to be estimated, in a reasonable number of exploration rounds or trials, one can only hope to achieve

a guarantee on the quality (near optimality) of the solution with a high desired probability (where the probability can be specified as an input to the system). STOC-PISCES achieves this while ensuring that the expected number of reports obtained for any event are within a certain bound of the desired number of reports.

Note that, optimality can indeed be guaranteed (i.e., providing minimum reward while ensuring that desired number of reports are received) in certain simplified situations. In particular, consider the scenario where—(i) the set of users available for reporting a particular event is fixed in each trial; and (ii) users are rational with a fixed threshold or cost, where a rational reporter *always* reports for a reward r as long as $r \geq c$, where c is the cost of reporting [1]. We show that under such assumptions, there exists a simplified algorithm, referred to as OPT-PISCES, that can be used to compute the optimal rewards for each event. Specifically, this leads to the following observation.

The main assumptions for OPT-PISCES are that the reporters have deterministic availability and deterministic reporting behaviours, i.e., (i) the set of reporters available for reporting a particular event are the same in every trial (e.g. every day), and secondly, (ii) reporters are rational with a fixed threshold or cost, such that if the reward for a particular event for which the reporter is eligible to report is higher than that threshold, then the reporter will report the event. Specifically, this leads to the following observation.

Observation 2. *As the reward for a particular event increases, the number of reports obtained can not decrease.*

The algorithm runs in parallel for every event, and for any given event, it employs binary search on the reward range with resolution of ϵ, and based on observations of actual behavior in the reward trial, updates the rewards, thereby converging to optimal rewards for every event in at most $\log_2 \left(\frac{r_{max} - r_{min}}{\epsilon} \right)$ iterations. Algorithm 2 depicts the OPT-PISCES algorithm describing this procedure in detail.

Theorem 2. *Algorithm OPT-PISCES gives the optimal set of rewards for all the events in $\mathcal{T}$, with a time complexity of $O \left(\log_2 \left(\frac{r_{max} - r_{min}}{\epsilon} \right) \right)$ in parallel for every event.*

Proof. Suppose for a particular event j, for which there exists a feasible optimal solution, the estimated reward $r_j > r_{j,OPT}$, where $r_{j,OPT}$ is the minimum reward for which the number of reports received is $\geq d_j$. Since we chose r_j, and employed binary search over the entire range in ϵ granularity, it must hold that the number of reports received for $r_j - \epsilon$ was $< d_j$. From Observation 2, therefore, for every $r \leq r_j - \epsilon$, the number of reports received by any solution would be $< d_j$, which implies that $r_{j,OPT} \geq r_j$, which contradicts the assumption that $r_j > r_{j,OPT}$. For an event, for which there is no feasible solution, in other words, the maximum number of reports $P_{j,max}$ that can be received is $< d_j$, we find the minimum r_j for which we can still get $P_{j,max}$ reports, by the same argument as above. Specifically, in this case, r_j will only get updated

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[1]Unlike in bidding systems, the notion of truthfulness of costs does not arise here as our solution does not require reporters to bid their expected costs.

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if the number of reports received (while still less than d_j) increases on increasing the reward. The time complexity is clearly $O \left(\log_2 \left(\frac{r_{max} - r_{min}}{\epsilon} \right) \right)$, since the update steps take constant time, and we run the iterations in parallel for every event. □

Algorithm 2 OPT-PISCES for an event $j \in \mathcal{T}$

Input: $r_{max}, r_{min}, \epsilon, d_j$.
Output: r_j.
Set $r_{j,max} = r_{max}$ and $r_{j,min} = r_{min}$.
Set $k \leftarrow 1$ and $r_j \leftarrow r_{j,max}$, and $P_{j,max} = 0$.
while $k \leq \log_2 \left(\frac{r_{max} - r_{min}}{\epsilon} \right)$ **do**
    Set $r'_j \leftarrow \frac{r_{j,max} + r_{j,min}}{2}$.
    Run system trials with $\{r'_j | j \in \mathcal{T}\}$.
    $P_j \leftarrow$ number of reports received.
    if $P_j \geq d_j$ **then**
        Update $r_j \leftarrow r'_j$, and $r_{j,max} \leftarrow r_j$.
    else
        Update $r_{j,min} \leftarrow r'_j + \epsilon$.
        if $P_{j,max} < P_j$ **then**
            Update $P_{j,max} \leftarrow P_j$ and $r_j \leftarrow r'_j$.
        end if
    end if
    $k \leftarrow k + 1$.
end while
Return reward r_j.

The "deterministic" assumptions (in OPT-PISCES) on availability and reporting behaviour are mostly violated in practice. Reporters cannot be expected to be in the same spatio-temporal neighbourhood during each trial, nor compelled to report at the same reward value during each trial. However, OPT-PISCES provided an interesting baseline for our empirical analysis. In particular, we demonstrate how STOC-PISCES performs in real-world (dynamic) conditions w.r.t a baseline approach that is provably optimal, however, less suitable for pragmatic real-world environments.

Experimental Evaluation

Experimental Set-up

In this section, we show the performance of STOC-PISCES experimentally. We first describe the reward acceptance profiles and mobility model of the reporters used in our experiments. Multiple experiments are then conducted to evaluate STOC-PISCES. Since STOC-PISCES is a first-of-a-kind algorithm, we use OPT-PISCES as the baseline since it guarantees the theoretical optimal under a simplified scenario. In a realistic set-up with stochastic reporter mobility and behavior, STOC-PISCES is more effective.

Reward Acceptance Profile of Reporters In practice, one would expect these profiles to be observed/learnt from user studies, historical data etc. At the time of writing this paper, we do not have sufficient real-word data to infer these profiles. At the same time, there is little or no prior art that has studied reward acceptance profiles in participatory systems. Consequently, we have opted for realistic simulations of user profiles, described below.

As mentioned in the previous sections, we assume the reporters to be stochastically rational. i.e., the probability
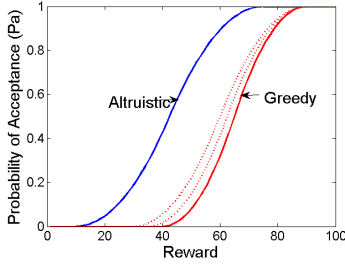
Figure 3: Reward acceptance profile of reporters

Figure 4: Percentage of employees commuting during a typical day

of acceptance would either increase or remain constant as the reward increases. Specifically, the probability of acceptance for low rewards would tend towards zero, while the probability of acceptance for high rewards would tend towards 1. For our experiments, we have therefore chosen a sigmoidal acceptance model to capture the this stochastic behavioural pattern[2]. Fig. 3 depicts the stochastic reward acceptance profile used in our experiments. The leftmost profile corresponds to an altruistic participant while the rightmost one corresponds to a greedy participant, each reporting in a probabilistic manner. Naturally, a greedy reporter reports with higher probabilities for higher incentives and may not report at all for lower values. In Fig. 3, a greedy reporter is not probable to report for 30 reward points, while reporting with a probability of 90% for 80 reward points (or more). An altruistic reporter, on the other hand, is probable to report even when incentives are low.

Reporter Population & Mobility Model We have considered real mobility traces of 143 employees commuting to and from a 24×7 BPO office facility in Bangalore, India. We collected the GPS traces of the office cabs, which these employees avail at different times of day depending on their shifts, for a month. Table 1 shows a summary of different parameters inferred from the dataset. Depending on the shifts and mobility patterns, the hours of the day are categorized into "peak" or "off-peak" hours. The thirty-day average, in terms of percentage of employees, commuting during different times of the day is depicted in Fig. 4. For the given data and set of participants, one can observe that during a typical day, the off-peak hours (considered to be hours where less than 20% of participants are mobile) fall during 12 AM -7 AM, 9 AM - 1 PM, 7 PM - 10 PM; while peak hours are during 7 AM - 9 AM, 1 PM - 6 PM, 10 PM - 12 AM.

The dispersion of spatial coordinates during the three "off-peak periods" is more than during peak periods. From Table 1 one can note that, while peak and off-peak travel times differ by approximately 10 minutes; the standard deviation is as high as 30 minutes for both these categories. The observations highlight that the underlying mobility model is bound to lead to *non-deterministic* availabil-

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[2]Note that, the set of experiments in this work can also be performed with any other acceptance model that captures the aforementioned stochastic reporting behaviour (since STOC-PISCES is agnostic of any specific behavior but only assumes stochastic rationality of reporters).
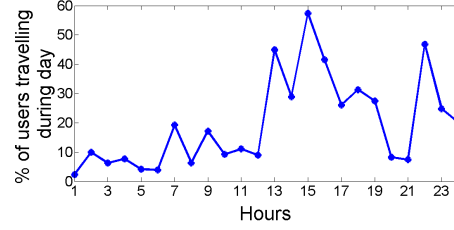
ity. We further enhance the basic model to increase the population of reporters in the system for studying scalability of STOC-PISCES when number of available reporters increases. Specifically, the spatio-temporal distribution of reporters in the basic model (with x reporters, where $x = 143$) is uniformly scaled up for $2x$, $3x$ and $4x$ reporters. For example, in the basic model, if there are 5 reporters available at a location at a particular time, then for the enhanced model of $2x$ reporters, there would be 10 reporters available at the same location co-ordinate at the same time.

Table 1: Mobility Data.

Parameters	value
Total Participants	143
Distinct Locations	84
Routes	235
Landmarks	858
Average Distance	26 Kms
Average Peak travel time	42 min
Average OffPeak travel time	31 min
Standard Dev. in Peak travel time	35 min
Standard Dev. in OffPeak travel time	29 min

Events and Demands from Requesters For our experimental set-up, we consider twelve distinct events mapped to specific strategic locations and timings in the context of the Bangalore city. There are three locations, each of which has four different times when the event occurs. The events belong to different categories (i.e. wait time at traffic signal, potholes on roads, illegal parking, and uncleared garbage). In practice, these could be defined around any arbitrary points of spatio-temporal interest. We assume that the events are heterogeneous in terms of–(i) demands from requesters, i.e. the number of reports required, as well as (ii) availability and behaviour of reporters who can potentially participate. A reporter can independently participate in multiple events. For instance, a reporter can report on illegal parking (which has a lower demand) and simultaneously report on traffic congestion (which has a higher demand). To show the efficacy of the incentive strategy, we vary the demands (i.e. the number of desired reports) for each of these events, across the following categories: *low, normal, and high*. If there are x eligible reporters for an event, then based on the mobility model described above, these cate-

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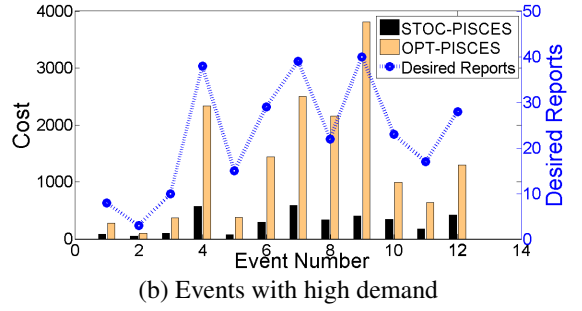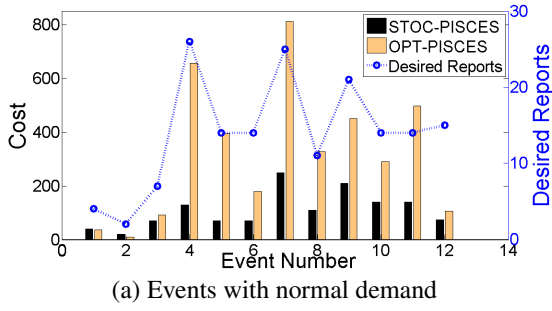(a) Events with normal demand (b) Events with high demand

Figure 5: Cost of STOC-PISCES and OPT-PISCES for stochastic settings. Events have independent demands in terms of number of required reports. Performance for each event depends on the demand (utility) and reward acceptance profiles of participants.
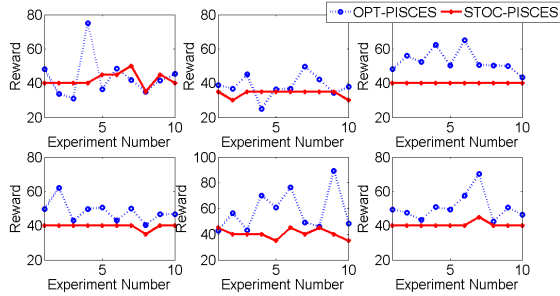

Figure 6: Rewards comparison of OPT-PISCES and STOC-PISCES for six representative events across 10 runs
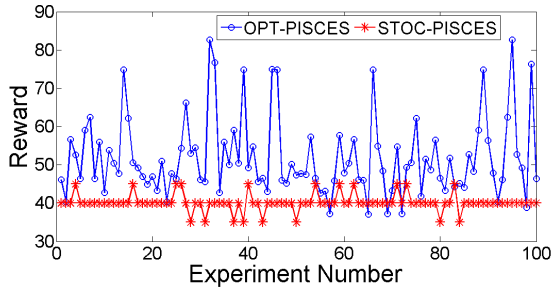

Figure 8: Reports acquired by STOC-PISCES in large trials

Figure 7: Comparison of rewards of STOC-PISCES and OPT-PISCES for a single event across 100 runs

gories translate to—-*low*, where number of reports $\leq \frac{x}{3}$; *normal*, where $\frac{x}{3} <$ number of reports $\leq \frac{2x}{3}$; and *high*, where number of reports $> \frac{2x}{3}$. Intuitively, our objective is to test the performance of the strategies for different demands.

Results and Insights

Comparison of OPT-PISCES and STOC-PISCES Fig. 5 shows the average payment (cost) for events when the demands for number of reports are normal and high, respectively. The key observation here is that STOC-PISCES always results in lower payments (where *total payment=number of reports × reward*) compared to OPT-PISCES. This is primarily due to the lower rewards deter-

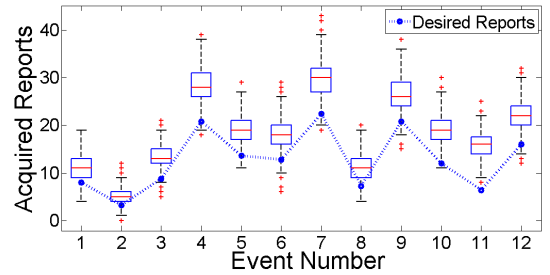mined by STOC-PISCES compared to OPT-PISCES. Interestingly, when the demand increases from normal to high, the differences in cost (total payment) between STOC-PISCES and OPT-PISCES become significant (Fig. 5(b)). Fig. 6 shows the reward values offered by OPT-PISCES and STOC-PISCES for reporting on a subset of events. Specifically, we highlight the variations in rewards by the two strategies for different runs of the same stochastic setting. Fig. 7 further shows this variation for a much larger number of runs (of the same stochastic setting) for a single event. STOC-PISCES not only provides lower rewards than OPT-PISCES, but it also provides consistent reward values with very little deviations across runs. However, in the case of OPT-PISCES, the reward values for reporting the same event vary drastically for different runs and fail to converge to a stable value. *The result clearly demonstrates why an optimal solution for deterministic setting does not work in real-world scenarios.*

Effectiveness of STOC-PISCES While it is true that STOC-PISCES converges to lower rewards and minimizes the cost for a requester, it is important to empirically validate the guarantees for actual number of reports received. Fig. 8 shows the reports acquired by STOC-PISCES. Specifically, 100 trials are performed for each event (i.e., $n = 100$ as per the formula in Algorithm 1) - where each trial constitutes declaring the "converged" reward computed by STOC-PISCES and observing the number of reports gathered. We observe that the lower (25%) and upper quartiles (75%) of

number of reports are always above the desired number of reports for each event.

Due to the stochastic nature of the experimental settings, there are expected variations in the number of reports received across different trials. In fact there are a few rare outliers, where the number of reports are below the demand. Recall that, for the tunable parameter δ of STOC-PISCES, the requester obtains the desired number of reports with a confidence of $1-\delta$. In our experiments, we have set $\delta = 0.2$, with an expectation of obtaining the number of reports in at least 80% of the cases. While smaller values of δ increase the chances of obtaining the desired number of reports, significantly lowering this value can result in a large number of trials for convergence. Next, we show empirically that the number of trials, n, can however be reduced if there are higher number of reporters.

Scalability of STOC-PISCES The experiments till now have used $n = 100$ trials for x reporters under an equal mix of greedy and altruistic users. We now present the results from a set of experiments where we vary—(i) the number of reporters from x to $4x$ (where $x = 143$ as mentioned previously); and (ii) the mix of greedy and altruistic reporters. The purpose is to study how STOC-PISCES scales with increase in number of reporters, as well as the impact of different mix of reporters on the outcome of STOC-PISCES, under different demands. We further examine how these parameters affect the number of trials in STOC-PISCES.

Fig. 9 shows the cost for three representative events for a generalized setting of mixed population of altruistic and greedy reporters (50% each) under both normal and high demands. It is noted that the cost for any event converges to a stable value for lower number of trials when the number of users is higher. Since the supply increases with higher number of users, providing lower rewards leads to getting the required number of reports. Hence, lower number of trials is generally enough for STOC-PISCES to converge. However, for each event, as demand is increased from normal to high, the cost increases. The extent of this increase can be different for different events depending on the spatio-temporal variations of available altruistic and greedy reporters.

For our experimental set up, we see the increase of cost from normal to high demand is between 2 to 5 times. Interestingly, for high demand, it takes more trials to converge for $2x$ reporters. This is because as demand is high, the number of reporters needs to be considerably higher ($3x$ and $4x$) to converge in low number of trials. In summary, requesters' cost increases with increase in their demand. However, if there are enough supply of reports then cost becomes low. Notably, lower number of trials are required in STOC-PISCES to converge when the supply is higher.

Fig. 10 shows that for high demand, variations on the mixture of greedy and altruistic users, can impact number of trials required for convergence of STOC-PISCES. As expected, with increase in number of greedy users, the cost increases, since higher rewards are warranted to elicit the required number of reports. The number of trials needed to converge also increases for higher number of reporters. However, even for the scenario of $4x$ reporters (in our exper-
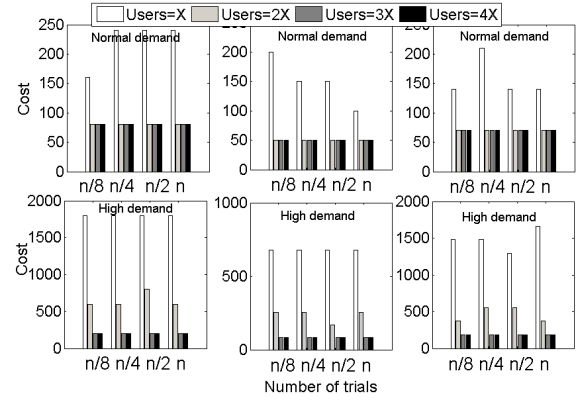

Figure 9: Cost for different number of trials and different number of users for three representative events under normal and high demands.
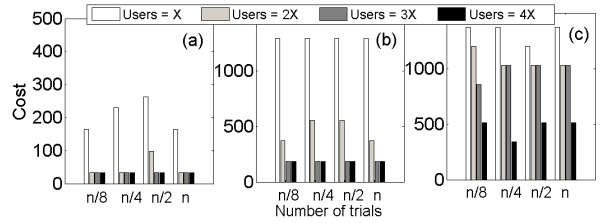

Figure 10: Cost (reward per report $\times$ total number of reports) for different number of trials for different number of users under different mix of altruistic and greedy users ((a) 25% greedy, 75% altruistic; (b) 50% greedy, 50% altruistic; (c) 75% greedy, 25% altruistic) for a representative event with high demand.

iments), which is more than 500 reporters, STOC-PISCES needs only around 10 trials. This is a reasonable scalability result and for an even larger reporter pool, the number of trials required can not increase (as the trends in Figs. 9 and 10 suggest) because of larger supply.

It must be noted that, STOC-PISCES does better than our expectations in the reported settings. In fact, it mostly delivers the expected number of reports in very less number of trials; and even when it falls short, the difference is within tolerable limits as set by the parameter ε. Based on our experimental results, we advocate the suitability of STOC-PISCES to meet requester demands in a scalable manner at significantly lower costs in real-world scenarios.

Conclusions and Future Work

This paper proposed a closed loop incentive framework, $PISCES$, for participatory sensing systems. $PISCES$ meets requester demands in terms of the desired number of reports pertaining to a spatio-temporal region of interest, while minimizing the total cost incurred by payments to reporters. The framework provides incentive strategies for participants, with no apriori knowledge of their reporting profiles. To the best of our knowledge, the proposed algorithm,

STOC-PISCES, is the first algorithm that provides provably optimal guarantees on the number of reports in the stochastic setting of the cost minimization problem. Extensive simulations using real-world mobility traces and realistic reporting behaviours, demonstrate that STOC-PISCES consistently ensures significantly low payments for requesters with guarantees on the expected number of reports.

We recognize that one of the key extensions, needed for a participatory sensing system, is the incorporation of data veracity and reputation in deciding the incentives to reporters. From a requester point of view, it is critical to ensure that the reports are valid, timely, and from a trusted source. We are exploring enhancements to the stochastic framework by leveraging an estimation-theoretic approach for computing the veracity of reports as part of the incentivization process. It is also important for a requester that reporters do not collude and any incentive strategy should discourage same set of malicious reporters from sending multiple similar reports to meet the demand. Tuning the incentive mechanism to ensure data veracity and discourage such malicious behavior is an important future work that we are pursuing.

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