Incentive allocation function for mobile community sensing with smallholder farmers in a developing nation.

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Abstract

Eliciting effort from smallholder farmers for mobile crop sensing always requires careful consideration of the incentives and a mechanism that adaptively caters for their utility within crowdsourcer's budget. Community sensing with volunteers as in seen in the pilot use case of mobile ad hoc surveillance, *AdSurv*, for crop health surveillance, basically presents three problems; (1) the farmers need to complete as much of the surveillance task, (2) make above minimum submissions with some desired regularity, and (3) be motivated to explore areas within and outside their localities. Incentive mechanisms are necessary to provide participants with some compensation for their participation costs and reward efforts that source complete submissions from specific areas of interest or regions of high uncertainty.
This research presents an payment function for incentive allocation for mobile community sensing with smallholder farmers using *AdSurv* application for all year round real-time monitoring of cassava viral diseases and vector-pests in a developing nation.

1 Introduction

Adequate user participation and quality reporting are the most critical factors determining whether a mobile crowd sensing application, as seen in case for mobile ad hoc Surveillance (*AdSurv*), can achieve good service quality in monitoring and real-time surveillance of crop viral disease and pest. Sensing for real-time surveillance data using mobile phones has recently proved as an emerging approach effective for crop health monitoring and disease surveillance in the developing world.[17] Crop surveillance using the *AdSurv* application in Uganda, is based on voluntary participation of farmers, extension service and cassava experts reporting geo-tagged data from their disparate areas across the country to generate a cassava health situation map. While participating, the smartphone users consume their own resources such as battery and computing power, and expose their locations with potential privacy threats. *AdSurv* follows a game setting where; the main objective of the agricultural research centre is to obtain many complete submissions from areas of interest on regular basis, while the smallholder farmers in disparate locations around the country aim at maximising the rewards from their participation. Some nature of incentives are necessary to keep the participants interested in reporting to the crowdsourcer and motivated enough to submit the complete reports to update the cassava health situation map. A mechanism for direct monetary incentives is needed to reward participating smallholder farmers, based on their quantity and completeness of reports; providing better incentive for agents to report from areas of interest or areas of high uncertainty.
This paper presents an incentive mechanism with a pay function that is sensitive to report completeness and location from which the submission was sourced.

1.1 Related Work

The results in designing optimal pricing policies and mechanisms for allocating tasks to workers is central to online crowdsourcing markets by [1] provide ground evidence for practical applicability of budget-feasible mechanisms for realistic crowdsourcing markets on the web.
Three online incentive mechanisms based on online reverse auction were designed in [14]. Low participation levels of smartphone users due to various resource consumptions, and pursue platform utility maximisation.
Part of the research work presented here is based on the research done by [12] focusing on incentive mechanism design for mobile phone sensing for incentive mechanisms that can attract more user participation. To address this issue, they designed incentive mechanisms for mobile phone sensing, considering two system models: the platform-centric model where the platform provides a reward shared by participating users, and the user-centric model where users have more control over the payment they will receive. For the platform-centric model, they focused to design an incentive mechanism using a Stackelberg game, where the platform is the leader while the users are the followers.
Mechanisms presented in [6, 7] in which all of participating users report their types, including the tasks they can complete and the bids, to the crowdsourcer (campaign organiser) in advance, the crowdsourcer selects a subset of users after collecting the information of all users to maximise its utility (e.g., the total value of all tasks that can be completed by selected users).

In community sensing for air pollution in [2], the field agents submit reports to a centre, and the quality of reports sent is driven entirely by the utility of individual agents. Estimation maps are published by the centre that may be used as a public prior for individual agents, and later integrates the reports from the agents with an environmental model to produce a posterior map.
To Counter Bias in Human Computation, [8] investigates the use a Peer Truth Serum applied to the online labor platforms such as Amazon Mechanical Turk, to exploit the wisdom of the crowd. They use a game-theoretic bonus scheme, called Peer Truth Serum (PTS), to overcome systematic biases in human computation and increase the answer accuracy.
The work [13] investigates how to implement truthful Incentives in crowdsourcing tasks using regret minimisation mechanisms. The research is based on certain questions that are focused on designing the optimal pricing policies for monetary incentives to interest and motivate smallholder farmer crowds in sensing for their crop health.

1.2 Mobile ad hoc surveillance *AdSurv*

AdSurv is a mobile crowdsourcing application used in Uganda for all year round real-time surveillance and monitoring for the cassava crop viral disease and pest spread [17]. *AdSurv* collects reports from community agents engaged in agriculture across the country, who have access to a mobile smartphone.

Surveillance task The national agriculture research centre broadcasts a task to the farmers with the *AdSurv* app. The surveillance task includes four micro-tasks;

- Take images from the garden in situ.
- Label it as one of the following categories(disease, pest, anomaly, other)
- Write an observation/diagnosis/comment
- Tag a geo-coordinates to the report and submit it to an online server.

The reports are mapped in real-time, as shown in figure 1. The nature of this kind of sensing task requires the farmers to explore a spatial area of the crowdsourcer's interest, collect and submit reports on a regular time basis, for example, the research centre requests the farmers to submit at least 20 geotagged images per week.

2 Mechanism for incentives

In this section, we present a formal model for the *AdSurv* setting and consideration for the mechanism design. The non-trivial challenges to be optimised in the design of the pay function are; (1) evaluate completeness submissions of surveillance task, (2) batch processing of submissions per week, and (3) encourage exploration within and outside farmer locality.

We adopt a special solution of a weighted generalised bonus-and-compensation mechanism: a truthful implementation of the Vickrey-Clarke-Groves (*VCG*) type mechanism [11]. In this scenario, we consider a reverse auction of micro surveillance tasks to farmers, interested farmers submit their reports, and get rewarded according to their effort.

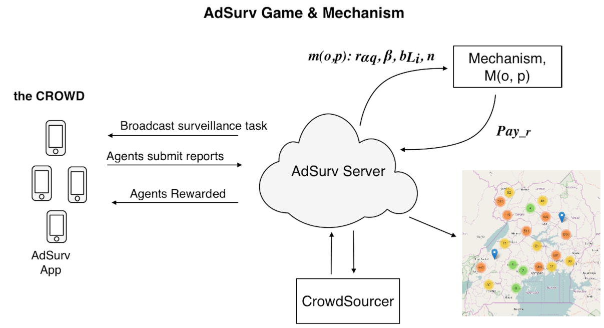

Figure 1: Game scenario of AdSurv crowdsourcing platform

2.1 Game setting on *AdSurv*

While the national agricultural research centre is interested in understanding disease/pest incidence and severity within a given region, the farmers on *AdSurv* are interested in maximising their monetary pay-offs. So farmers tend to put it the least effort that helps them maximise their rewards. The crowdsourcer needs a mechanism that calculates reward based on the completeness of submissions, the number of reports submitted, a compensation for the effort of participation and a bonus awarded for the location from which report was collected.

Here, is the formal reporting game;

1. The agent, i, represents a farmer, where $i = (1, ..., n)$ a network of farmers on *AdSurv*.
2. The choices available to each of the agents, A_i, an agent i can choose $a_i \in A_i$.
The agents may strategise on how they complete the surveillance task, by choosing which of the micro-tasks to complete.
3. The outcomes $a = (a_1, ..., a_n)$ where $a_i \in A_i$ for each possible i
4. Utilities $U_i(a)$ as known as desired payoffs
Note:
Agent i wants to choose his actions a_i to maximise (a_i, a_{-i}).
Agent i has no control over a_{-i}

Objectives of the incentive mechanism
Compensate the agent for the basic effort and costs incurred in participating by sending reports. The mechanism should encourage; reports which have as many competed micro-tasks and exploration by giving a bonus for reports collected outside your locality.
The mechanism is thus based on 4 factors;

1. A compensation as a base report price awarded to an agent participating. When an agent has sent in reports, crowdsourcer need to cover the agent's effort to participate which includes their participation time, internet data airtime, battery.

2. The number of reports that the agents has collected.
3. The quality of the report which is noted by report completeness, shows how well an agent has completed the micro-tasks.
4. A Bonus is awarded for location from where the reports was taken and considers two things;
(i) The spatial quality of the reports i.e. the spatial spread of the reports from within field / locality where they were collected.
(ii) From which part of the country the reports were surveyed. More bonus is awarded for regions where we have little or no reports and bonus proportionally drops for places where crowdsourcer already has more than a given number of submissions.

The reward policy, has both compensation and bonus terms for the *AdSurv* incentive problem, and is constrained to a limited budget.

Since the agents' utilities on the AdSurv are influenced by direct monetary incentives, $v_i(a)$, denotes the value that agent i assigns to the effort, a.
In this case, the effort lay in completing the micro-tasks of the surveillance task, and collecting reports from specific area regions with varying bonus weights corresponding to the interest to the research centre.
If a is chosen, then agent i is additionally given some quantity of, I units of incentive, that should be more than the effort Thus the $i's$ utility is given by

$$U_i = v_i(a) + I - e \tag{1}$$

Generalising for all possible outcomes, we write

$$U_i = \sum_i v_i(a) + I - \sum_i e \tag{2}$$

where
$v_i(a)$, is the value an agent attaches to the outcome of reporting on a give surveillance task, and
I, the additional Incentive that is issued as compensation and/or bonus.
e, the effort expended by the agent to collect a report and complete micro-tasks. This is the utility that the agent on AdSurv wishes to maximise.

2.2 The Mechanism

Intuitively, when agents choose their strategies as to maximise their own selfish utilities, a mechanism assures that the required output occurs and are compatible with the algorithm.

The mechanism defines for each agent i a family of strategies A_i. The agent can chose to perform any $a_i \in A_i$.
A mechanism $m = (o, p)$ is composed of two elements:

The mechanism provides an output function $o = o(a_1, ..., a_n)$.
The second thing a mechanism provides is a payment $p_i = p_i(a_1, ..., a_n)$ to each of the agents.

Optimal Allocation on AdSurv

AdSurv system runs an optimal allocation, where the surveillance task is broadcast to all agents in the field. The agents can then decide how to participate and they are allocated monetary reward based on their effort calculated according to the payment function.

Payment Function on *AdSurv*

The payment function which consists of 2 terms; compensation and bonus terms, is as follows:

Compensation term

$$\beta + \sum_{j=1}^{J}(\alpha_j) \tag{3}$$

Bonus term

$$b_{L_i} \tag{4}$$

Combined into a payment function

$$Pay = (b_{L_i} + 1)(\beta + \sum_{j=1}^{J} \alpha_j) \tag{5}$$

where
J, is the micro-task, where $j \in J$ b_{L_i}, is the bonus for reporting from location of interest L_i and $b_{L_i} \propto (1/n_{L_i})$
β, is the compensation reward for participating: here indicated as a base report price for each of the reports submitted.
α_j, is the price micro-task, j, of the surveillance task

Generalising the Payment function for a given period (e.g week) for rR number of reports, is as follows ;

$$Pay = \sum_{n=1}^{N}(b_{L_i} + 1)(\beta + \sum_{j=1}^{J} \alpha_j)) \tag{6}$$

where
n, is the number of reports. $n \in N$

Theorem In the *AdSurv* game setting, there exists a pay function which presents a dominant strategy profile for agents that complete surveillance many micro-tasks and explore areas of high bonus reward.

proof The Expected Reward of an agent i is given by :

$$E[Pay_r] = (b_{L_i} + 1)(\beta + \sum_{i=1}^{J} \alpha_j) \tag{7}$$

where, $b(L_i)$ is bonus price for location, and α_j is the price of a completed micro-task.
The Expected Value is maximised when $b_{L_i} = 1$ and α_j for all $j \in J$ are fulfilled, each of the n reports submitted.

2.3 Crowdsourcing under budget constraints

Participation constraints on *AdSurv*

The incentive mechanism for *AdSurv* satisfies participation constraints if whenever an agent is truth-telling, its utility is non-negative.

Consider an agent i who submits two reports as follows;
Report 1 : contains 1 image and GPS geo-coordinate for region A
Report 2 : contains 1 image, a comment and GPS geo-coordinate for region B

Location Bonus b_{L_i} : Region A attracts a bonus reward of 0.4 i.e $b_{L_A} = 0.4$, Region B attracts a bonus reward of 0.7 i.e. $b_{L_B} = 0.7$
Compensation Reward $\beta = 2$
The micro-tasks and their respective prices : Image $\alpha_I, q_I = 6$, Comment $\alpha_{cmt}, q_{cmt} = 2$, GPS geo-coordinates $\alpha_{gps}, q_{gps} = 4$

$P_{r_1} = (0.4 + 1) * (2 + (6 + 4))$
$P_{r_1} = 16.8$ units of money

$P_{r_2} = (0.7 + 1) * (2 + (6 + 2 + 4))$
$P_{r_2} = 23.8$ units of money

For an agent that has not participated by submitting no reports, their payment is as follows;
$P_r = (0 + 1) * (0 + (0 + 0 + 0))$
$P_r = 0$ units of money

Thus for a truth-telling agent, their utility is non-negative and satisfies the condition for participation constraints $p_i(t, \tilde{t}) + v_i(x(t), \tilde{t}) \geq 0$.

Limited Budget for *AdSurv* payments

Let the Budget, B be the as follows:
$B = (max b_{L_i} + 1) * (\beta + q_I + q_{cmt} + q_{gps})$
$B = ((1 + 1)(2 + 6 + 2 + 4))$
$B = 28$ units of money

Note: The payouts for each report, $P_i(r_1) \leq B$ and $P_i(r_2) \leq B$, are within the limits of the budget per report.
Thus, this incentive scheme is a $B - constrained$ Revelation Mechanism.

3 Contribution

This research presents a framework for studying the maximisation problems of incentives as applied to mobile community sensing with smallholder farmers for crop health surveillance campaigns. The paper presents a reporting under incentives problem in game theoretic setting, and provides a mechanism solution based on a weighted generalised compensation-and-bonus mechanism, built on *VCG* as the main model.
The model can be expanded to cater for more factors affecting the agent utilities.

This work presents pay function that may be used to elicit for sensing effort from agents in an ad hoc manner under budget constraints, as seen in the use case for monitoring crop health and pest. The work further shows proof of its robustness and the dominant strategy profile it fulfils through the two constraints of participation and budget.

4 Limitations of the Study

The mechanism presented here is geared towards a participation objective. The crowdsourcer cares for many submissions of completed micro-tasks from areas of interest, and the volunteer smallholder farmers are already a trusted cohort of contributors because the agents participating on this exercise are relatively more exposed and learned on the crop health subject matter. A cohort of 29 participants on the *AdSurv* pilot spatially spread around the country is optimal to draw behavioural insights and reactive mechanism strategies, however it is still relatively small a pool sample to draw generalisations for a greater mass of farmer and extension agents.

5 Conclusion

We have demonstrated a game-theoretic setting to study the reporting problem in community crop sensing using volunteer farmers that are local to the disparate areas.
We go ahead to present a $B - constrained$ revelation mechanism for incentives suited for adaptively motivating participants to collect images, complete micro-tasks and submit from locations of high interest.
We foresee the work here contributing important results towards enhancing efforts for mobile community sensing under budget constraints. Community sensing is vital part to early warning systems in low-resource settings, that need real-time surveillance for timely interventions in; viral crop disease outbreaks, massive pest infestation and humanitarian response efforts.

Future Work This work could be extended in several interesting avenues. Many of the mechanism design aspects are available to be studied as machine learning problems, in which cases more sophisticated active learning methods will be required.
Further, our on-going research is looking at incentive mechanisms for scaled crowdsourcing, learning to reward, and optimise within incentive budgets for large crowds.

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