Course Project Report

Incentive Mechanism Design

for crowdsensing based indoor localization

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1. Crowdsensing

First, I will introduce a new and promising paradigm in environmental data collection, called crowdsensing. It utilizes the ubiquitous mobile devices with enhanced sensing capabilities to gather, analyze, and share their local information, such as position, noise, air pollution, traffic congestion, and so on.

In recent years, crowdsensing has gained increasing interest from research community. Many novel works have been proposed for various scenarios, *e.g.*, on-street parking [12], environmental monitoring [11], in-door localization [14, 16], floor plan reconstruction [6], real-time image search [18], scalable sound sensing [9], sociable sensing [13], mobile video streaming [7], and traffic estimation [10].

2. Motivations

As we know, the success of crowdsensing based services critically depends on sufficient and reliable data contributions from individual participants, *i.e.*, we hope to attract large-scale, sustained, and high quality participations to support the high quality of data services.

But, the reality is that the collected sensing data items are of diverse qualities. One possible reason is that the mobile users are rational, and only consider their own profits. Since performing sensing tasks requires time, battery consumption, storage space, and computation resources, mobile device users may not be willing to participate in the sensing campaign, if and only if they receive proper and enough compensations. In addition, the different levels of personal efforts may also influence the data qualities. Take the noise monitoring on campus for instance. The correct measurement approach is to let the phone exposed in the air, rather than putting them on a busy road, or into the pocket.

In a word, to bridge the gap between the vision and reality, it is of great necessity to incorporate the considerations of data quantity and data quality, when designing an incentive mechanism.

3. Online Fingerprints Collection

As shown in Figure 1, we focus on a concrete crowdsensing model, called online fingerprints collection. To perform the accurate indoor localization for a specific region, *e.g.*, a library, the data purchase first has to build the corresponding fingerprinting database of received signal strength (RSS). Then, she releases the sensing tasks through the trading platform. We note that the data purchaser also needs to submit her pricing strategy $\mathbb{M}$ for different types of data points to the trading platform. Regarding the data procurement, we here consider that the

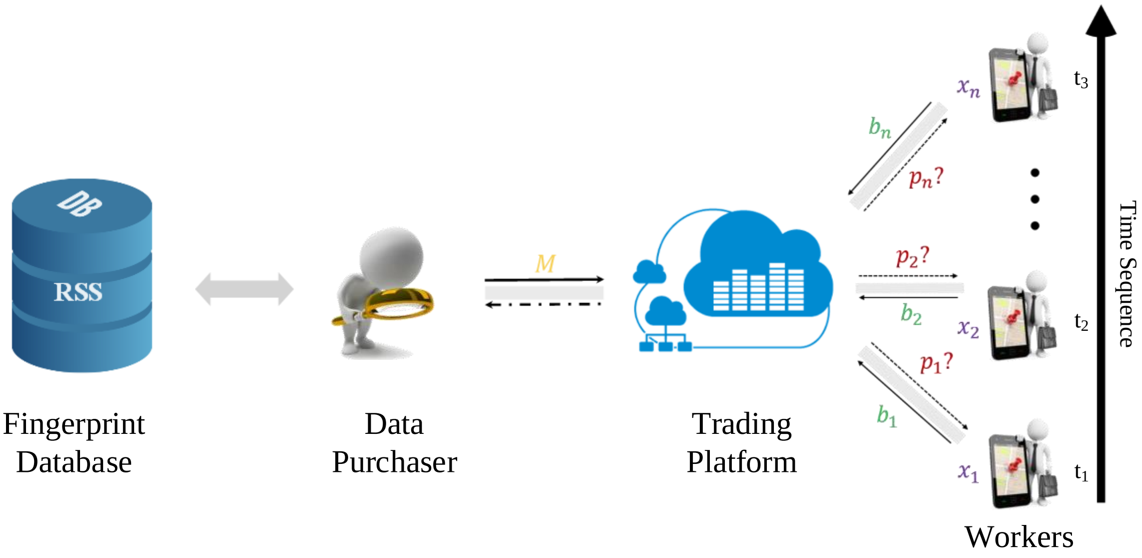

Figure 1: Online Fingerprints Collection.

interested workers arrive in a sequential way. Once a worker w_i arrives, she first submits a bid b_i to platform, and then receives a claimed payment p_i. If $p_i \geq b_i$, then the worker will accept the transaction, undertake the sensing tasks, and forward his data point x_i to the platform. Otherwise, she will reject the transaction, and the trading platform gets null signal. Finally, all the collected data items will be sent to the data purchase, which may facilitate the construction of database.

Using the terminology from game theory, the data procurement process is a defacto reverse auction.

4. Design Goals

In this section, we identify requirements on the design from two aspects, *i.e.*, game theory and machine learning.

On one hand, we illustrate some desirable economic properties, including truthfulness, budget constraint, and individual rationality.

- *Truthfulness:* The worker's bid is consistent with her sensing cost c_i, *i.e.*, $b_i = c_i$. Here, c_i denotes the reserve price for the worker to undertake the sensing tasks.
- *Budget Constraint:* Budget constraint is specific to the trading platform or the data purchaser, which indicates that the total payments should be within a threshold, *i.e.*, $\sum_k p_k \leq B$.
- *Individual Rationality:* Individual rationality means that the selected worker should be rewarded no less than her sensing cost, *i.e.*, $p_i \leq c_i$.

On the other hand, we present the solution concepts in terms of machine learning, whose roadblock is to deal with biases.

- *Online:* Online data procurement implies the sequential data arrivals. In other words, the trading platform has no future information. Furthermore, the update of *hypothesis* h in the online learning algorithm should also be taken into account.

- *Regret Minimization:* Regret minimization is related to loss function $\ell(\cdot)$. In particular, regret is defined as the difference between the current loss and globally optimal loss, *e.g.*, at a time period t,

$$loss = \sum_{t} \ell(h_t, x_t), \tag{1}$$

$$regret = loss - \sum_{t} \ell(h_t^*, x_t), \tag{2}$$

  where h_t^* represents the globally optimal hypothesis function under the condition that the trading platform knows all the future information.

5. Candidate Solutions

In this section, I clarify our candidate solutions, which were derived using the enlightenment from the previous top works. Here, for brevity, I will only show the design ideas, and may not elaborate on the details.

First, we plan to preserve the property of truthfulness by employing the posted-price model [1, 15]. Under such model, the payment is bid-independent, and thus truthfulness can easily be guaranteed. Another appealing property of this model is it gives *take-it-or-leave-it* price offer. Hence, individual rationality can also be achieved.

Second is about the tradeoff between budget feasibility and regret minimization. To the best of my knowledge, there exist at least two suitable techniques. One is called the importance weighted regret bound [3], which was originally published in the proceeding of *ICML*. Furthermore, it was utilized in a paper, called "Low-cost learning via active data procurement" [1], which has been accepted by the proceeding of *EC* last year. In this work, Abernethy *et al.* propose a model of online learning with purchased data: T arriving data points and a budget B. They finally show regret on order of $T/\sqrt{B}$ and lower bounds of the same order. The other idea comes from Multi-armed bandit (MAB) problem. Its intention is to seek for a tradeoff between exploration and exploitation. In addition, some related work may also target on the property of truthfulness [4,5], or budget constraint [2,8,15].

6. Future Work

Regarding the future work, we shall first instantiate above general techniques with our concrete scenario, *i.e.*, indoor localization. Specifically, we may employ the maximum likelihood estimation (MLE) with imperfect information to draw the predicative error for different types of data points. Then, we can derive the concrete and accurate data qualities, and thus construct the definite data pricing strategy. In fact, this fundamental work has been done by Wen *et al.* [17]. Second, since I am more familiar with cryptography, it is still a good idea to achieve the strict truthfulness of the *EC* paper as mentioned above by employing some authentication schemes. In particular, [1] has a seemly strong assumption, *i.e.*, the trading platform needs to obtain both an arriving data point and her cost c_i, where the cost is used to importance-weigh the data based on the probability of picking a payment larger than that cost. It is worth noting the the requirement of truthfulness is $b_i = c_i$. To explore a strictly truthful implementation, the arriving worker can commit to her bid, which could be a message authentication code or signature on the cost c_i, for non-repudiation. Moreover, she can still employ a order preserving encryption (OPE) scheme to preserve her cost for privacy, while maintaining the functionality of the online pricing algorithm. If the worker accepts the transaction, she reveals her data point and her cost, verifying the validity of the authenticator. It is strictly truthful for the worker to commit to her true cost.

References

[1] J. D. Abernethy, Y. Chen, C. Ho, and B. Waggoner. Low-cost learning via active data procurement. In *EC*, 2015.

[2] M. Babaioff, Y. Sharma, and A. Slivkins. Characterizing truthful multi-armed bandit mechanisms: extended abstract. In *EC*, 2009.

[3] A. Beygelzimer, S. Dasgupta, and J. Langford. Importance weighted active learning. In *ICML*, 2009.

[4] A. Biswas, S. Jain, D. Mandal, and Y. Narahari. A truthful budget feasible multi-armed bandit mechanism for crowdsourcing time critical tasks. In *AAMAS*, 2015.

[5] W. Ding, T. Qin, X. Zhang, and T. Liu. Multi-armed bandit with budget constraint and variable costs. In *AAAI*, 2013.

[6] R. Gao, M. Zhao, T. Ye, F. Ye, Y. Wang, K. Bian, T. Wang, and X. Li. Jigsaw: indoor floor plan reconstruction via mobile crowdsensing. In *MOBICOM*, 2014.

[7] M. A. Hoque, M. Siekkinen, and J. K. Nurminen. Using crowd-sourced viewing statistics to save energy in wireless video streaming. In *MOBICOM*, 2013.

[8] S. Jain, S. Gujar, O. Zoeter, and Y. Narahari. A quality assuring multi-armed bandit crowdsourcing mechanism with incentive compatible learning. In *AAMAS*, 2014.

[9] H. Lu, W. Pan, N. D. Lane, T. Choudhury, and A. T. Campbell. Soundsense: scalable sound sensing for people-centric applications on mobile phones. In *MobiSys*, 2009.

[10] P. Mohan, V. N. Padmanabhan, and R. Ramjee. Nericell: rich monitoring of road and traffic conditions using mobile smartphones. In *SenSys*, 2008.

[11] M. Y. Mun, S. Reddy, K. Shilton, N. Yau, J. Burke, D. Estrin, M. H. Hansen, E. Howard, R. West, and P. Boda. Peir, the personal environmental impact report, as a platform for participatory sensing systems research. In *MobiSys*, 2009.

[12] S. Nawaz, C. Efstratiou, and C. Mascolo. Parksense: a smartphone based sensing system for on-street parking. In *MOBICOM*, 2013.

[13] K. K. Rachuri, C. Mascolo, M. Musolesi, and P. J. Rentfrow. Sociablesense: exploring the trade-offs of adaptive sampling and computation offloading for social sensing. In *MOBICOM*, 2011.

[14] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen. Zee: zero-effort crowdsourcing for indoor localization. In *MOBICOM*, 2012.

[15] A. Singla and A. Krause. Truthful incentives in crowdsourcing tasks using regret minimization mechanisms. In *WWW*, 2013.

[16] Y. Wen, J. Shi, Q. Zhang, X. Tian, Z. Huang, H. Yu, Y. Cheng, and X. Shen. Quality-driven auction-based incentive mechanism for mobile crowd sensing. *IEEE Transactions on Vehicular Technology*, 64(9):4203–4214, 2015.

[17] Y. Wen, X. Tian, X. Wang, and S. Lu. Fundamental limits of RSS fingerprinting based indoor localization. In *INFOCOM*, 2015.

[18] T. Yan, V. Kumar, and D. Ganesan. Crowdsearch: exploiting crowds for accurate real-time image search on mobile phones. In *MobiSys*, 2010.