# Low-Cost Crowdsensing for Indoor Localization

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***Abstract*—**

## I. Introduction

## II. Related work

Many related work have been done.[?] used the online learning algorithm to solve the problem and gives an upper bound of $1/\sqrt{B}$of the regret. [?] [?]propose the classical online learning algorithm. Importance weighting is also a important technique used in the field of active learning. [?] gives the importance technique in the binary classifiers problem. Other works to solve the data procurement have been done by [?]. However, this method is a offline algorithm. [?] considers the incentive of agents to provide higher quality of data, and[] proposed a mechanism optimizing the truthful, individual rationality, platform profitability, and social-welfare for the mobile crowd sensing. However, these models did not consider the situation of fixed- give budget problem.

Add:

Many related work about online learning has been done. [?] provided an introduction of online convex programming and an effective algorithm: Generalized Infinitesimal Gradient Ascent for this problem, making for the fundamental construction of online learning. However, it only derives a general model aiming at online convex optimization, with a number of details to be modified and renovated in specific situations. [?] comprehensively displayed online convex optimizing theory, on which our online learning researches are predicated.

With regard to our particular problem setting: minimizing the overall regret with a fixed upper limit of budget,[?] presented an all-round dissection on it. [?] firstly utilized the classical online learning algorithm: Follow the Regularized Leader(FTRL) to update steadily the hypothesis in every round the mechanism should give, in light of information the mechanism has acquired in previous rounds about offered hypotheses and suffered loss. Then they embedded FTRL in their main algorithm: Mechanism for no-regret data-purchasing problem, which resolved the problem with an upper regret bound $O(T/\sqrt{B})$ given.

In terms of concrete techniques applied in [?], importance weighting is an important one, playing a crucial role in estimating unbiasedly the cumulative loss suffered until the current round. This technique is also a research point in our work, where we focus on providing an alternative form of the unbiased estimator to reach better regret bound. One specific application of importance weighting methods–binary classification is shown and analyzed in [?].

Moreover, a bottleneck in solving our problem is the complex form of our objective function and budget constraint, with unknown distributions of costs in each round and an inequality containing integral. [?] made use of inequality zooming methods to clear the integral part in budget constraint, rendering a more computable convex optimizing problem. However, this method can only derive an approximated solution and the corresponding bound may not be tight enough. In our work we try to get access to the accurate solution of this problem, by means of calculus variation. [?] illustrates the applicability and methods of calculus variation in detail. A concrete specific example taking advantage of it lies in [?]. [?] dealt with the problem that minimizing the variance of estimator with a given price distribution and a fixed budget by calculus variation. Nevertheless, it concentrated on the offline situation, deviating from our online background.

## III. Localization Model

## IV. Low-cost data purchasing problem

In many situations, we could not get access to all the data for both the reason that the data has a cost and our budget is limited. In this section, we will define the problem of thedesigning of the effective mechanism to acquire the RSS information collected by the crowds. However, the mechanism have no means to know either the data is good enough for our localization or there will be a better one coming after. We implement the online machine learning algorithm in our mechanism.

### A. Preliminaries and basic assumption

We first define the loss function according to the localization model above.

$$f_t(h_t) =$$

After we acquire the loss function, we give the defininition of the regret function.

$$R(T) = \sum_{t=1}^{T} f_t(h_t) - \min_{h^* \in H} \sum_{t=1}^{T} f_t(h_t^*)$$

where $h^*$ is the optimal choice, causing the least loss in our solution space $H$. We also make some assumptions for this problem

1)
2)
3)

### B. Online Learning Algorithms

We will here use the classical Follow the Regularized Leader(FoRL) algorithm to work as the Online Algorithms. The FoRL has a upper bound of regret of $O(\sqrt{T})$, which ensures that the average regret tends to zero when.There are many kinds of other Online Algorithms which can be found in **??**, etc. The FoRL is described in **??**.

### C. Problem formulation

The problem can be described as follows.

1) a sequence of data $d_1, , , d_T$ coming in time $1, , , , , T$ with each data possessing a posted price $c_t$, $c_t \in [0, M]$.
2) The mechanism post a price $p_t$ according to a probablity $g_t(p_t)$.
3) If the $p > c_t$ agent accepted the price, the mechanism get the loss function and send it back to the OLA and the mechanism will pay for the posted price $c_t$. If the agent rejected the price, the mechanism would send a null data to the OLA .

### D. Importance Weighting technique

In tradational online learning problem, all the data will be used, and we can consider . In out low-cost purchasing problem, not all the loss function are used, and the estimation of loss is $E(\sum_{t=0}^{T} \delta_t f_t) = \sum_{t=0}^{T} q_t f_t$, where $\delta_t$ is the function showing whether the data is procured. Noticing that the definition of regret still includes all the loss, in order to get an unbiased estimator, we define

$$lf_t(h) = \begin{cases} \dfrac{f_t(h_t)}{q_t} & \text{if the is} \quad (1) \\ 0 & \text{else} \quad (2) \end{cases}$$

### E. online batch to conversion

We give our final results by averaging every hypothesis $h_t$ acquired in each Details will be added later.

## V. The regret minimization senario

In this senario, the mechanism has a fixed budget. The main purpose of the mechanism is to get a high accuracy of localization informaiton, which is consistent with our definition of loss function and regret.

### A. Upper bound of regret

We will first find the upper bound of the regret. [] gives a quite well estimation as shown in the following lemma

*Lemma 1:* The regret bound of problem **??** using the OLA of FoRL is bounded by

$$R(T) = \frac{\beta}{\eta} + E(\sum_{t=1}^{T} \frac{\Delta^2_{h_t, f_t}}{q_t})$$

### B. Randomized posted price setting

There still many details be determined here.

### C. The optmization problem

Now we can change the problem into a more single form.

$$\min \sum_{t=1}^{T} \frac{\Delta^2_{h_t, f_t}}{q_{c_t}}$$

$$s.t. \sum_{t=0}^{T} \int_{c_t}^{M} x dq(x) \leq B$$

## VI. The budget minimization senario

In this senario, the mechanism do not have a certain amount of budget, instead, an upper bound of regret $R_{min}$ is required as a constraint and the optimization target changes to the minimum of budget.

$$\min E(B)$$

$$s.t. R(T) \leq R_{min}$$

## VII. Experiments and Simulations

## VIII. Conclusion

The conclusion goes here.


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## References


[1]