Effective RSS data procurement for Crowdsensed Fingerprints for Indoor Localization

Abstract—**Crowdsourcing is currently one of the most prevailing methodology used in the received signal strength (RSS) fingerprinting based Indoor localization. The quality of the RSS data collected from the crowds is crucial to the accuracy of the localization system. While efforts have been dedicated to the incentive mechanism for the crowdsourcing platform, the problem that how to judge whether the data we should use and how to economically get access to these data that we want still remains unknown. In this paper, we give a quantitative measurement of the quality of data through the probabilistic model and propose a pricing mechanism to economically acquire the data given a limited budget under the basic framework of online machine learning. Our mechanism achieves the best performance in data purchasing than the state of the art method. And we further gives the theoretical analysis of the best quality of the data we can get access through the purchasing mechanism. Moreover, we give the alternative best money-saving strategy when the quality of data is required.(initial version)**

I. Introduction

A. Indoor localization

The past decade has witnessed a flourishing of indoor localization systems based on wireless techniques [1], where the fingerprinting based methodology has been widely adopted due to its convenient deployability [?], [?]. The fingerprinting based indoor localization system has two phases: In the offline phase, the site surveyor observes the received signal strength (RSS) of Wi-Fi access points (APs) termed as RSS fingerprints at each reference point, and submit the fingerprints and the location information of the reference point to the localization database; in the online phase, a user needs localization service could submit the observed fingerprints to the database, which then returns the location of the reference point that matches the fingerprints best as the estimated location of the user.

The fingerprinting based method utilizes Wi-Fi APs widely existing in buildings and has no need for other dedicated infrastructure; however, the site survey in the offline phase requires substantial efforts, which is hardly accomplished by any single entity. The recent advances of fingerprinting localization systems utilize mobile crowdsensing approach to collect fingerprints [?], [?], [?], [?], [?], [3]. Mobile crowdsensing is a cost-effective approach to collect large scale data for mobile applications, where individuals with handheld mobile devices collectively contribute sensing data so that information of certain events could be retrieved [?], [?]. Although sensing participants could receive certain rewards for the efforts and resources spent on the sensing activity, the cost of mobile crowdsensing is still much lower than deploying the dedicated sensing networks [?].

As the crowdsensing data are collected by unprofessional participants with non-dedicated equipment, the sensing data obtained are usually with considerable noise. The quality of the sensing data is the crux for evaluating contribution of the participants, which is the vitally important for effective utilizing rewards to incentivize participants to accomplish sensing tasks satisfactorily. However, how to evaluate the quality of the crowdsensing data is a challenging issue, because there is no ground truth for the collected data to be compared with. Efforts have been made to evaluate the crowdsensing data quality [?], and the task allocation scheme [?], [?]. and incentive mechanisms considering the data quality are proposed.

While the efforts have been made for the evaluation of the quality of the data, the RSS data procurement still remains not fully studied yet. Some quality-driven incentive mechanism[?], [?], [?], [?], [?] were proposed, however, the state of the art method for crowdsensing data collection still focus on the incentive of workers and the utility of the platform. The economical problem is considered in [?], however, the budget constraint of the platform is not included. Besides, all the work listed above do not consider the situation when data is coming in a sequential order and only available in each round. How to acquire the high-quality data that is in a sequential order given the limited budget still requires more thorough investigation, which is the focus of this work. Our motivation is two-fold. On one hand, the existing work for sequential data procurement in the literature [12]do not work well for the situation of indoor localization; on the other hand, we want to build a concrete measurement of RSS data specifically for both the accuracy of the localization and the active learning mechanism.

In this paper, we propose a pricing mechanism that can get higher quality of RSS data within limited budget. Using the high quality data we procure, the localization system could set a localization with higher accuracy. Our contributions are as following.

- We design an effective way to measure the what kind of RSS data should we purchase. In most cases, the collected RSS data is not idealy in the exact position, to design an effective way to measure the impact of those imperfect data is crucial to our system. We make a thorough analysis of the impact that imperfect data may exert on the result of localization through the probability model.
- We give the pricing strategy for the mechanism to acquire the high quality data. The mechanism has a theoretically better performance than the classical one proposed in **??**. The mechanism is robust in most indoor-localization

situations, even the prior knowledge of the costs is not well understood and the noise in the crowdsensing data is rather arbitrary.

The remaining of the paper is organized as following. The system structure and settings are given in section III. The measurement of the RSS data quality is presented in Section **??**. SectionV gives the abstract definition for the online data procurement mechanism. Section VI presents a pricing mechanism for the RSS data procurement to get the data with best quality give the limited budget. Section VI presents an alternative senario for the mechanism to achieve the least purchasing cost when the quality of data is given. Section VIII gives our simulations and experiments for the mechanism we given before.

II. Related Work

A. Indoor localization with crowdsourcing

In fingerprinting based indoor localization, one of the common approaches to collect fingerprints is crowdsourcing, in which any user with a mobile device like smart phone can acquire data while walking freely, without the requirement for users to have any technical training []. Wu *et al.* design a localizing system LiFS, combining indoor localization with crowdsourcing and bypassing the conventional site survey process [**?**], [**?**]. They initially place several landmarks in the physical space, and then harness information from user motions and pinned sensors in smart phone to set up a sample space with high dimension, with which approximates the user's location. Moreover, Shen *et al.* present a crowdsourcing based system *Walkie-Markie* [**?**] to generate indoor pathway maps from the user contributed data. and Luo *et al.* propose a self-calibrating participatory indoor localization system [**?**], which requires no prior knowledge about the building and user intervention including the floor planning.

Nevertheless, the above work has not placed a premium on the fingerprint procurement phase. In fact, concentration is needed in this part. For instance, we need to hire samplers to collect fingerprints to construct our database with limited budget practically, therefore probably we cannot buy all sampled fingerprints. How should we offer our price to fingerprints from each sampler, maximizing localizing accuracy? Perhaps samplers come in a batch or a queue, so what is the optimal purchasing strategy for these two conditions respectively? Zhang *et al.* cope with the situation where the goal is to incentivize a batch of workers to label some binary tasks with a budget constraint [**?**], while in our work we shed light on the scenario that samplers come in a queue with fingerprints, with budget constraint concerned as well.

B. Incentive meachnism design for crowdsourcing

In realistic situations, data providers are not always willing to sell their data to us for reasons like dissatisfying with the price we offer or worrying about data privacy. To cope with this problem, the incentive mechanism should galvanize them to supply us with their data, with means like offering them compensation. Furthermore, given that the data we need are required to be accurate enough, incentive mechanism should assure good quality of them.

With regard to data quality, Jin *et al.* introduce a key metric, quality of information(QoI), which evinces the quality of users sensory data[**?**]. Taking QoI into consideration, the incentive mechanism can acquire data with higher quality [**?**].Tham and Luo take timeliness of data into consideration of quality[**?**]. They assume that the quality of data contributed will go downhill with time. By incorporating the temporal factor, they render the mechanism more analogous to realistic scenes such as employees will get salaries a month later. Kawajiri *et al.* provide a novel framework, which aims to level up the quality of data directly rather than the data size, pinpointing the problem that monetary pressure and time consumption may ascend to an unbearable extent when the quantity of data is up-scaled [**?**].

However, the work mentioned above in this subsection except [**?**] does not fit the incentive mechanism into indoor localization. How can incentive mechanism be properly utilized in our context? Wen *et al.* tailors quality-based incentive mechanism into a Wi-Fi fingerprint-based indoor localization system [**?**]. Moreover they present a stochastic model to assess the reliability of sensed data, crystallizing the way to measure data quality in localization. This probabilistic model is contained within their mechanism. Kawajiri *et al.* also test their framework under the background of indoor localization [**?**]. However, their models function in offline conditions, differing from our online ones.

C. Online learning

There are assorted theoretical studies pertinent to online learning. Shalev-Shwartz summarizes classical methods such as Follow-the-Regularized-Leader(FTRL) and Online-to-Batch Conversions(OBC) in online learning [11]. Zinkevich introduces an effective algorithm: Generalized Infinitesimal Gradient Ascent (GIGA), which formulates a common form of online optimization algorithm [10].

Execution of online learning theory in realistic models has been materialized. Abernethy *et al.* embed the theory into online data procurement [12].Specifically the situation is that a learner with a limited budget purchases data from agents coming in an online way, and the learner needs to propose a hypothesis and a price in each round to get accesss to the data. However, they only describe parameters abstractly in their work. In more specific work like indoor localization the concrete meanings of data, loss and so on should be clarified.

In our work we carry out some adjustments over the framework of [12] to fit into indoor localization background. We inject particular meanings to parameters, for instance data is RSS offered by signal samplersand loss is the localizing error we suffer using data purchased, thus we can derive our solution with more specific forms. Deeper technical modifications of the model in [12] will be displayed in the next subsection.

III. System Model

In this section we describe our system model and give out the problem formulation.

We present a mobile crowdsensing system consisted of *RSS Procurement mechanism*. For the purpose of performing accurate indoor localization in region $\mathcal{V}$, the data purchaser has to build the corresponding *Fingerprint Database* of *Received Signal Strength*(RSS). Therefore the data purchaser releases tasks of collecting data–RSS value on the platform. For a specific location $s \in \mathcal{V}$, we use $\mathbb{W}_s = \{w_1, w_2, ..., w_{N_s}\}$ to denote the corresponding applicants set. To simplify the notation, we omit the identification of s in almost all the rest of this paper. Without loss of generality, we mainly focus on workers with the same location's data. It's rational that data purchaser need to buy several data points at one location since the RSS value is not constant, in fact it obeys some probability distribution, we assume that its probability density function is $\mathcal{D}(\cdot)$. Consequently, we need several amounts of samples to learn the distribution, more specifically, to estimate the mean value of RSS.

At the very beginning, the data purchaser needs to submit his *Pricing Mechanism* $\mathbb{M}$ to the platform. Here we consider the most nature trading scenario: these N workers arrive in a sequential way with his data x_i. Once agents i arrives, he submit his bid c_i to the platform and the platform compute its price p_i using a mechanism $\mathbb{M}$. If $p_i \geq b_i$ then agents w_i accept this transaction: the platform pays b_i to worker i and receives data x_i, otherwise the worker reject the transaction and the platform receives null signal.

IV. Analysis of two dimension localization

A. Probability Model of Localization Error

The RSS value in the environment is hard to know, however, some research **??** has shown that the mean value and variance of the RSS follows a relative stable variety. Thus it is proper for us to make the assumption that the value of RSS P in position $\vec{r}$ follows a continuous probablity distribution $f_{\vec{r}}(P)$, the Gaussian distribution,e.g. Since that some experiment result show that the RSS value may actually follow other form of distribution,e.g. a two-mode Gaussian. For a more general manner, we may assume that the probability density function(PDF)$f_{\vec{r}}(P; h(\vec{r}))$ of the RSS value is arbitrary and is determined by parameter $h(\vec{r})$ that is a continuous function of the mean value of RSS data in location $\vec{r}$, $\mu(\vec{r})$. As shown

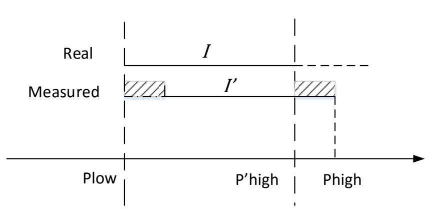

Fig. 1. Description.

in Figure **??**, we devide the physical space into many small circles each centered at $\vec{r}$ with radius $\vec{\delta}$. We assume that within each block we have a threshold P_{high} and P_{low} for the RSS value$P$. According to the MLE principle used in **??**, which means that the probablity that the RSS falls into the ideal region must higher than the adjacent reigon, P_{high} and P_{low} should satisfy that

$$\begin{aligned} f_{\vec{r}-\delta}(P_{high}; h_{\vec{r}-\delta}) &= f_{\vec{r}}(P_{high}; h_{\vec{r}}) \\ f_{\vec{r}+\delta}(P_{low}; h_{\vec{r}+\delta}) &= f_{\vec{r}}(P_{low}; h_{\vec{r}}) \end{aligned} \tag{1}$$

. Thus we may define the reliability as the probability of the system correctly estimate the user's location,

$$R = \int_{P_{low}}^{P_{high}} f_r(P; h(r))dP \tag{2}$$

which means the probablity of RSS value tested in position r lies within the interval $[P_{low}, P_{high}]$ However, in real circumstnaces, the P_{high} and P_{low} are acquired through the training process, during which may recieve the imperfect data and thus cause the result to be inaccurate.The speculated location of the RSS value may migrate from the original one, causing that the RSS value from one certain region may falsely be recognized to other area.

A very obvious situaiton as shown in Figure**??**. We assume that the deviation of the RSS value is d, and the current collected RSS data is P. We use P'_{high} to denote the threshold deduced by R and P_{high} to denote the ideal threshold. Obviously, $P_{high} = P'_{high} - d$. The probability that the user can be mistakenly located using the data P equals the probability that the user's RSS data x lies within the interval of $[d, P'_{high}]$. We thus give this probability to define the error of the RSS data we collected.

$$Pr_{\vec{r}}(error) = \int_{P'_{high}-|d|}^{P'_{high}} f_{\vec{r}}(x; h(P))dx \tag{3}$$

B. The analysis of the loss

We can observe from **??** that the error is a function of d, the deviation value of RSS, according to our assumption that the hypothesis h is continuous function of μ. We can rewrite the probability of error as the function of h

$$P_{\vec{r}}(error) = Err(|h_{\vec{r}}(P) - h_{\vec{r}}(\mu^*)|) \tag{4}$$

, where μ^* is the real mean RSS value and $h_{\vec{r}}(\mu^*)$ is the ideal hypothesis , e.g. the real mean value of RSS when $h(x) = x$. We then use h^* to denote $h_{\vec{r}}(\mu^*)$ and h to denote$h_{\vec{r}}(\mu)$ for simplicity. Obviously μ^* should satisfy that

$$\mu^* = arg \min_{mu \in R} E_P(Err(|h(P) - h(\mu)|)) \tag{5}$$

, where we defnie the $|h(P) - h(\mu)|$ as $klnf(P; h))$. The following theorem shows the rationality for our definition of error.

Theorem 1. *The expectation of the error $Err(|h(P) - h(\mu)|)$ over P get its minimum when μ equals real RSS value μ^*.*

Proof:

$$E_P[Err(kln(f(P; h)))] \geq E_P[Err(-klnf(P; h^*))]$$

$$E_P[Err(kln(f(P,h)))] - Err(klnf(P;h*))] \geq 0$$

according to the Lagrange interpolation formula , there exists ξ,such that

$$E_P[Err(kln(f(P;h)))] - h(klnf(P;h^*))]$$
$$= E_P[Err'(\xi)kln(\frac{f(P;h)}{f(P;h^*)})]$$

obviously, $h(\xi)$ 0, consider the monotony and continuity of Err,there exists a minimum $m > 0$ of Err, thus we have

$$E[h'(\xi)kln\frac{f(P;h)}{f(P;h^*)}] \geq E_P[mkln\frac{f(P;h)}{f(P;h^*)}]$$

According to Jessen inequality

$$mkE_P[ln\frac{f(P;h)}{f(P;h^*)}] \geq mkln(E_P[ln\frac{f(P;h)}{f(P;h^*)})$$
$$= mkln(\int_P \frac{f(P;h)}{f(P;h^*)} f(P;h*)dP)$$
$$= mkln1 = 0$$

■

Assume that we sample N data $x_1, ..., x_N$, we let $h*$ be the value that that minimize the $\frac{1}{N}\sum_{i=1}^{N} f(x_i;h)$.The theorem **??** above shows that when the number of data we collected is enough, the $t*$ we obtain from the data will approximate to the real RSS value r. We will use Hoeffding inequality to show the performance of the approximation

Theorem 2. *The average error of $\hat{t}$ obtained from collected sample has at least $1 - 2e^{-\frac{2\epsilon^2}{N}}$ the probablity that is within ϵ close to the average error of real RSS data r, that is*

$$Pr(\frac{1}{N}\sum_{i=1}^{N} f(x_i;\hat{t}) - E[f(x_i;r)] \leq \epsilon) \geq 1 - 2e^{-\frac{2\epsilon^2}{N}} \quad (6)$$

Proof: We use $Err(P;h)$ to represent $Err(klnf(P;h))$ Assume that $Err(P;h) \in [m, M]$, and in fact $0 \leq m \leq M \leq 1$ according to Hoeffding inequality, for any t

$$Pr(|\frac{1}{N}\sum_{i=1}^{N} Err(P;h) - E_P[Err(P;h)]| \geq \epsilon) \leq e^{-\frac{2\epsilon^2}{N}}$$

Assume that $\hat{h}$is our speculated hypothesis, and $h^*$is the real hypothesis, thus

$$Pr(\frac{1}{N}\sum_{i=1}^{N} Err(P;\hat{h}) \leq E_P[Err(P;\hat{h}) + \epsilon) \geq e^{-\frac{2\epsilon^2}{N}}$$
$$Pr(\frac{1}{N}\sum_{i=1}^{N} Err(P;h^*) \geq E_P[Err(P;h^*)) - \epsilon) \geq e^{-\frac{2\epsilon^2}{N}}$$

Considering that those two events in $Pr(\dot{)}$ is independent to each other

$$Pr(\frac{1}{N}\sum_{i=1}^{N} Err(P;\hat{h}) \leq E_P[Err(P;\hat{h} + \epsilon,$$
$$\frac{1}{N}\sum_{i=1}^{N} Err(P;h^*)) \geq E_P[Err(Ph^*)) - \epsilon)$$
$$\geq (1 - e^{-\frac{2\epsilon^2}{N}})^2 \geq 1 - e^{-\frac{2\epsilon^2}{N}}$$

Since that when

$$\frac{1}{N}\sum_{i=1}^{N} Err(P;\hat{h}) \leq -E_P[Err(P;\hat{h} + \epsilon$$
$$\frac{1}{N}\sum_{i=1}^{N} Err(P;h^*) \leq -E_P[Err(P;\hat{h}) - \epsilon)$$

We have that

$$0 \leq \frac{1}{N}\sum_{i=1}^{N} Err(P;\hat{h}) \leq -E_P[Err(P;\hat{h}$$
$$\leqq \frac{1}{N}\sum_{i=1}^{N} Err(P;\hat{h}) - Err(P;h^*) + \epsilon$$
$$\leq \epsilon$$

Combining the equation IV-B, we thus have

$$Pr(\frac{1}{N}\sum_{i=1}^{N} f(x_i;\hat{t}) - E[f(x_i;r)] \leq \epsilon) \geq 1 - 2e^{-\frac{2\epsilon^2}{N}} \quad (7)$$

■

The result shows that when N is big enough, the probability that the $\hat{h}$ is close to h^* will approximate to 1.

C. Example of Gaussian Distribution

We may now give a more specific example of the theories we deduce above.We assume that the RSS value P folllow the Gaussian distribution with mean value of μ_r and varianceσ. In this case, the hypothesis h is exactly the mean value μ. According to many previous studies**??**, we assume that the $\mu_{\vec{r}}$ is coninuous over $\vec{r}$. Given the fact that the δ is far smaller than $|\vec{r}|$, we may make an approximation that, for any position $\vec{r'}$ on the circle centered at A with arbitrary radius δ in Figure **??**

$$\mu(\vec{r'}) = \mu(r) + \nabla\mu(\vec{r})\delta cos(\phi) \quad (8)$$

, where ϕ is the angle between $\vec{r}$ and $\nabla\mu(\vec{r})$. Now we consider the threshold of the RSS value. We can see from Firgure **??** that the threshold of the RSS is corresponding to the physical boundrary of the circle, the point B,C,D,E. Thus we can give the specific form of these two threshold.

$$P_{high} = \mu(\vec{r}) + \frac{\nabla\mu\delta\min\{\cos\phi, \sin\phi\}}{2}$$
$$P_{low} = \mu(\vec{r}) - \frac{\nabla\mu\delta\min\{\cos\phi, \sin\phi\}}{2} \quad (9)$$

Thus we may deduce the specific form of the error we defined above

$$Pr_{\vec{r}}(error) = \int_{\mu(\vec{r}) + \frac{\nabla\mu\delta\min\{\cos\phi, \sin\phi\}}{2}}^{P(\vec{r}) + \frac{\nabla P\delta\min\{\cos\phi, \sin\phi\}}{2}} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-P)^2}{2\sigma^2}} dx \quad (10)$$

Further, we can derive the form

V. Low-cost data purchasing problem

In this section, we will give some preliminary about the task of our mechanism and prevailing principle used in statistical machine learning. We abstractly define the problem of the designing of the effective mechanism to acquire the RSS information collected by the crowds.

A. Preliminaries

We first give the concept of loss and regret. The loss function that reflects the data quality is defined in the space $H \times Z \to R$, where H is the hypothesis class and Z is the space of the objects. We expect the loss function to get its minimum value when the data is exactly the ideal data. The above theorem **??** has shown that the error of localization caused by the imperfect data we defined in**??** is the ideal choice. In our setting, the hypothesis h is the parmeter of the probability distribution function of the RSS data in location $\vec{r}$, which is the function. For simplicity, we denote that in each time t at location $\vec{r}$

$$L_t(h_t) = Err_{\vec{r}}(|P - h|) \tag{11}$$

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

$$R(T) = \sum_{t=1}^{T} L_t(h_t) - \min_{h^* \in H} \sum_{t=1}^{T} L_t(h_t^*) \tag{12}$$

where h^* is the optimal choice, causing the least loss in our solution space H. The regret function reflexes how the data deviate from the desired value, the real mean and variance of RSS. We also make some assumptions for this problem

1) the costs of the RSS data is arbitrarily given and have nothing to do with the data quality
2) the agents do not fabricate the data
3) the meachnism only pay at most M to each data

The reason that we make such assumptions are rather straightforward, since most people in the crowdsensing acquire the data through unprofessional devices and they do not have the ability to know the quality of their data, so they may give the price at their will.

B. Online Gradient Descent

Online learning is a widely used learning paradign. The goal of online learning is to produce the best hypothesis when data is in sequential order We here use the classical Online Gradient Descent(OGD) algorithm to work as the Online Algorithms. It has been proved that the OGD has an upper bound of regret of $O(\sqrt{T})$, which ensures that the average regret tends to zero when T goes to infinite. There are also many kinds of other Online Algorithms which can be found in refOLServey, etc. The OGD is described as following. In each time t, we obtain a h_t according to

$$h_t = h_{t-1} - \eta \nabla f_t(h_{t-1}) \tag{13}$$

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C. Importance Weighting technique

In tradational online learning problem, all the data will be used to produce the total regret. In our low-cost purchasing problem, the mechanism do not get access to data and obtain a loss in each time t. the estimation of loss is $E(\sum_{t=0}^{T} \delta_t f_t) = \sum_{t=0}^{T} q_t f_t$, where δ_t is the function showing whether the data is procured. However, the definition of regret in (12) still includes all the loss in each time t, whether it has been used or not. In order to get an unbiased estimator of the regeret, we define

$$\hat{f}_t(h) = \begin{cases} \frac{f_t(h_t)}{q_t} & data \quad access \quad to \quad RPM \\ 0 & else \end{cases} \tag{14}$$

.With the unbiased estimator acquired, we can consider the mechanism as an OGD that recieves $\hat{f}$ in each round t.

D. Problem definition

We consider that the data collected through crowdsensing coming in a sequence of $d_1,,,d_T$, with each of them contains a cost $c_1,,,c_T$. We should design a pricing mechanism that can choose how much we should pay for the data. However, we have no means to know either the quality of data is good enough for localization or there will be a better one coming in the sequence. Under the framework of online machine learning, we formally define our RSS data Procure Mechanism (RPM) is defined as following.

Definition 1. *Given a sequence of data $d_1,...,d_T$ coming in time $1,,,,,T$ with each data possessing a posted price c_t, $c_t \in [0, M]$.*

1) *The RPM post a hypthesis h_t from OGD*
2) *The RPM post a price p_t according to a distribution G_t over $[0, M]$.*
3) *If the $p_t > c_t$ agent accepted the price, the RPM send the loss function $f(h_t)/q_t$ back to the OGD and pay for the posted price p_t. If $p_t < c_t$the agent rejected the price, the mechanism send a null data to the OGD .*

The mechanism outputs a final hypothesis $\overline{h} \in H$

And clearly, our kernel problem is to find the best distribution G_t used for the mechanism to post its price

E. online batch to conversion

The meachanism and online learning algorithm produces a sequence of hypothesis $h_1,,,h_T$. The main goal of our algorithm is to get the best hypothesis $\overline{h}$, the mean value and variance of RSS, from the sequence. One simple aproach is to average every hypothesis h_t acquired in each time t.

$$\overline{h} = \sum_{t=1}^{n} h_t \tag{15}$$

It has been proved that**??**, the expectation of loss of $\overline{h}$ is less than the optimal h^* plus $R(T)/T$, that is

$$E_{f_1,,,f_T} Loss(\overline{h}) \leq L(h^*) + \frac{R(T)}{T}$$

This means that if $O(R(T)) < O(T)$, then the $\overline{h}$ will approximate to the optimal hypothesis h^* as T goes to infinite.

VI. The main setting: regret minimization senario

In this senario, the mechanism has a fixed budget. The target of the mechanism is that in each round t, the produce the minimum regret defined in 12 . In this section, we will give the exact form of the distribution G_t and the analysis of the regret bound according to this distribution.

A. Estimate the upper bound of regret

We will find the upper bound of the regret defined in (12) produced by RPM. In normal case, the regret bound of OGD is

$$\frac{||h||^2}{2\eta}+\eta\sum_{t=1}^{T}\nabla f_t(h_t)^2 \tag{16}$$

, which is a well known result. Under the importance weighting framework, we give the regret bound in the following lemma

Lemma 1. *The regret bound produced by RPM in 1 is bounded by*

$$R(h)\leq\frac{||h||^2}{2\eta}+\eta E(\sum_{t=1}^{T}\frac{\nabla f_t(h_t)^2}{q_t}) \tag{17}$$

. The 1 is quite easy to be proved under our setting that the loss function f_t is of strong convexity.

B. Derivation of the Regeret Minimization Problem

In each time t, the RPM need to post a price p according to a distribution g in order to get a minimum regret, we thus reduce the problem of designing a mechanism into an optimization problem

$$\begin{aligned}&\min\sum_{i=1}^{n}\frac{\nabla {f_i}^2}{1-F_i(c_i)}\\ s.t.\quad&\sum_{i=1}^{n}\int_{c_i}^{M}xdF_i(x)\leq B\end{aligned} \tag{18}$$

where $\forall c_i, 0\leq c_i\leq M$,and$F(0)=0, F(M)=1$

Theorem 3. *The optimal solution of the optimization problem [**??**] is in the form*

$$F_t(c)=\begin{cases}1-\frac{\nabla f_t}{\sqrt{\lambda c-\beta}} & c\in(\frac{\nabla f_t^2+\beta}{\lambda},M]\\ 0 & else\end{cases} \tag{19}$$

Proof: We first give our function space $V=\{y|y(0)=0,y(M)=1\}$. And we denote our cost function as

$$M(F_1,,,F_n)=\sum_{i=1}^{n}\frac{\alpha_i}{1-F_i(c_i)}.$$

Then the augmented Lagrange function is derived as

$$J(F_1,,,F_n,\lambda)=M(F_1,,,F_n)+\lambda(\sum_{i=1}^{n}\int_{c_i}^{M}xdF_i(x)-B)$$

According to the Gateaux Deravative, we obtain that for $\forall\hat{F}\in V$

$$\delta J|_{F_t}(\hat{F}_t-F_t)=\int_{c_t}^{M}(-\frac{\alpha_t}{(1-F_t(c_t))^2}+\lambda x)(\hat{f}(x)-f(x))dx$$

if $\overline{F}$ is the local minimum, then we have

$$\delta J(\hat{F}_t-\overline{F_t})\geq 0$$

holds for every $\hat{F}\in V$.Noticing that

$$\int_0^M f_t(x)-f(x)dx=0$$

We must have

$$-\frac{\alpha_t}{(1-F_t(c_t))^2}+\lambda x\geq 0$$

hold on every where on $[c_t,M]$ thus we obtain that

$$F_t(c)=\begin{cases}1-\frac{\nabla f_t}{\sqrt{\lambda c-\beta}} & c\in(\frac{\nabla f_t^2+\beta}{\lambda},M]\\ 0 & else\end{cases} \tag{20}$$

■

One major difficulty for the is the determination of the determination of β and λ Noticing that $F(x)$ is not continuous, according to Stieltjes Integral, we rewrite the constraint as following

$$\begin{aligned}&\sum_{t=1}^{T}(\int_{c_t}^{M}xdF_t(x))\\ =&\sum_{t=1}^{T}(\int_{c_t}^{M}xf_i(x)dx+(1-F_i(M)M)\\ \leq&\sum_{t=1}^{T}\nabla f_t(\frac{2}{\lambda}\sqrt{\lambda M-\beta}+\frac{c_t}{\sqrt{\lambda c_t-\beta}}-\frac{2}{\lambda}\sqrt{\lambda c_t-\beta})\\ \leq& B\end{aligned}$$

The Stieltjes Integral here has its practical significance. Because we assume that the cost lies between $[0,M]$, in other word, the mechanism do not accept any price higher than M, thus for all posted price c that are higher than M, the mechanism will only pay M instead of c.

Now since we get the solution of the F_t, the remaining work is to determine the parameters λ and β, we go back to our initial optimizationproblem that minimize the regret bound. The Lagrangian is thus given as follows

$$\begin{aligned}L(\mu,\beta,\lambda)=\sum_t\Bigg(&\nabla f_t\Big(\sqrt{\lambda c_t-\beta}+\mu(\frac{2}{\lambda}\sqrt{\lambda M-\beta}\\ &+\frac{c_t}{\sqrt{\lambda c_t-\beta}}-\frac{2}{\lambda}\sqrt{\lambda c_t-\beta})\Big)\Bigg)-\mu B\end{aligned} \tag{21}$$

when β and λ get its optimal value, it must holds that ∂. According to the complementary relaxation condition, $\mu\neq 0$, which means that the constraint condition in **??** for the optimal solution is strict. To get the analytic solution of the optimal value of β and λ is infeasible , thus we use the numeric solution for the equation **??**.

C. Analysis of the result

There are many things we can learn from the parameter β and λ.

We first simply set the $\beta = 0$ for a special case. Through simple calculation, we can have an estimation of λ_0 as following

$$\lambda_0 = \frac{T}{B}(2\theta_0 - \theta) \tag{22}$$

where $\theta_0 = \frac{1}{T}\sum_t \nabla f_t \sqrt{M}$, $\theta = \frac{1}{T}\sum_t \nabla f_t \sqrt{c_t}$ Since that $\partial L/\partial\beta > 0$, $\partial L/\partial\lambda < 0$, we obtain that the optimal solution (β^*, λ^*) statisfy that $\beta^* > \beta^0$, $\lambda^* < \lambda_0$ Thus we have the estimate of the upper bound of the regret of RPM in theorem 4.

Theorem 4. *For a fixed β, the regret of RPM produced by the algorithm in* **??** *is bounded by*

$$Regret < O(\frac{T}{\sqrt{B}}(2\theta_0 - \theta)\sqrt{1 - \frac{\beta B^2}{T\theta^2}}) \tag{23}$$

Proof:

■

One problem in this situation is that we may not get enough prior knowledge to both c_t and ∇f_t. One way to solve the problem is that we initially set β to a fixed value and λ to a very small value, e.g. 0.0001. Then in each time t, we update the value of λ with

$$\theta_0^{(t)} = \sum_{i=1}^{t-1} \frac{\nabla f_t(h_t)}{t-1}\sqrt{M} \tag{24}$$

$$\lambda^{(t)} = \frac{T^2}{B^2 M}\theta_0^2 + \frac{\beta}{M} \tag{25}$$

VII. The budget minimization senario

In this senario, we consider the situation that the main purpose of the mechanism is to find a strategy that can achieve . According to most money-saving way to acquire the data inorder to achieve a satisfactory regret bound R. One can easily observe that ths problemThe objective function is in the form of a integral, which is not an easy problem of the classical optimization problem. Besides, to solve the very exact form of the budget do not make sense. Thus we use the aproximation of the budget B as following

$$\sum_t c_t q_t \le B \le \sum_t M q_t \tag{26}$$

Theorem 5.

$$\begin{aligned} &\min_{q_t} \sum_t c_t q_t \\ &s.t. \sum_t \frac{\nabla f_t^2}{q_t} \le R \\ &0 \le q_t \le 1 \end{aligned} \tag{27}$$

A. The optimal mechanism

We give our mechanism as the following theorem

Proof: Consider the convexity of the objective function, we give the Lagrangian

$$L = \sum_t c_t q_t - \lambda(-\sum_t \frac{\nabla f_t^2}{q_t} + R - \sum_t \mu_t(1 - q_t)) \tag{28}$$

The optimal K-T condition of the problem **??** is

$$\frac{\partial L}{\partial q_t} = c_t - \lambda[\frac{\nabla f_t^2}{q_t^2}] - \mu_i = 0 \tag{29}$$

when $q_t = 1$, we get $u_i \neq 0$, when $q_t \neq 1$, $\mu_i = 0$, thus we have

$$q_t = \min\{1, \sqrt{\frac{\lambda}{c_t}}\nabla f_t\} \tag{30}$$

According to our constraint condition

$$\sum_t \sqrt{\frac{c_t}{\lambda}}\nabla f_t \le R \tag{31}$$

we can get an approximation of the $\sqrt{\lambda}$ through simple calculation

$$\sqrt{\lambda} = \frac{T}{R}\theta \tag{32}$$

where we use θ to denote the term $\frac{1}{T}\sum_t \sqrt{c_t}\nabla f_t$. Since 30 holds for $\forall c_t$, and c_t is arbitrarily given.We may assume that the convoluted distribution function of the price mechanism is of the form

$$F_t(c) = 1 - \sqrt{\frac{\lambda}{c}}\nabla f_t \tag{33}$$

And the PDF is

$$f(c) = \frac{1}{2}\sqrt{\frac{\lambda}{c^3}}\nabla f_t \tag{34}$$

■

B. result analysis

Now we can make a relatively more precise estimate the budget B

$$E(B) = \sum_t \int_{c_t}^{M} c f(c) dc \tag{35}$$

$$= \frac{T^2}{R}\theta\varphi \tag{36}$$

where $\varphi = \sum_t \frac{1}{T}\nabla f_t(\sqrt{M} - \sqrt{c_t})$. Analogous to the **??**, in each round t, we set $\theta^{(t)}$ and $\phi^{(t)}$.

C. Example of

VIII. Experiments and Simulations

In this section, we conduct the experiments and simulations to validate the performance of our system model and data procurement mechanism. We use the data collected in FoxCom Shanghai,where we tested the RSS value of 10 AP in 13 different locations, the distribution of the location and AP points are shown in Figure**??**. Since that the workers collected our data did not ased for reward to us, we simply simulate the costs of the data through a normal distribution with mean value of 0.5 and variance of 1. We implement

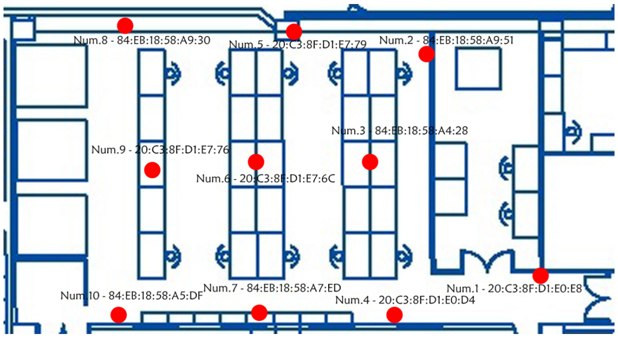

Fig. 2. Location Description.

IX. Conclusion and Future Work

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