Social Mobilization to Reposition Indiscriminately Parked Shareable Bikes

Extended Abstract

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ABSTRACT

With rapid growth of shareable bikes comes the problem of indiscriminately parked bikes blocking traffic. We propose a centralized pricing based dynamic incentive mechanism to mobilize the participants via crowdsourcing with regarding to reposition the indiscriminately parked bikes. We formalize the key component of the proposed incentive mechanism into two decision-making model: individual decision-making model Cost-refundable, Multiple Resources Constrained Multiple Armed Bandit (CRMR-MAB) and overall decision-making model multi-dimensional and multiple choice Knapsack problem (MMKP). We proposed a comprehensive decision algorithm GA-WSLS which combines the two. Realistic simulation based on real-world dataset from Singapore demonstrated significant advantages of the proposed approach over 7 existing approaches.

KEYWORDS

Crowdsourcing; Multi-Armed Bandit; Multi-dimensional Multiple Choice Knapsack Problem

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1 INTRODUCTION

In recent years, the shareable transportation is standing in the spotlight both in business and academia. Shareable bikes is the most developed service. Millions of bikes are pouring in to urban cities, people gradually find out the convenience of the comes with trouble. There are indiscriminately parked bikes blocking the walkway and bikes parked in inaccessible areas, which leads to lowering utilization [5]. To tackle this problem, Singapore regulation dictates that all shareable bikes must parked in designated zones [4].

Each indiscriminately parked bike can be regarded as a geo-spatial task to be solved. The system selects a specific time to push the offer of the task to the participants, choose one participant from all who accept the offer, and confirms the return of the bike by positioning the GPS chip built in the bike or the participants' mobile devices. Tasks can be set to multiple levels (categories) according to the distance of the task itinerary. The system itself has a limited budget. At the same time, in order to ensure that users are not disturbed by uninterested task requests and that users have a good experience, the system needs another virtual limited resource "total number of queries" to trade off between efficiency and user experience [10].

We abstract the above problem into a general crowdsourcing system and propose a suitable incentive mechanism for such a system. As an incentive mechanism, we need to consider participants' interest/cost in accepting an offer. Participants' costs vary independently and fluctuate over time. So we set some fixed prices to choose for every task. Therefore, the key component of the incentive mechanism is decision making, which price for a task and what time to present the offer. Moreover, in order not to spam participant with undesirable offers, we also make decision of virtual resources PT as how many participants an offer can be maximally presented to before expired.

2 PROBLEM FORMULATION

The core of this incentive mechanism is decision-making, for each task i calculating an offer o_i (with a price p_i, a scheduled presenting time h_i and query time pt_i), in order to maximize the total number of repositioned bikes under constrains budget B and total query times PT. We formulate the problem as Cost-refundable, Multiple Resources Constrained Multiple Armed Bandit (CRMR-MAB) for individual decision-making. CRMR-MAB can be regarded as a variant of Budgeted MAB [9]. The difference is CRMR-MAB has multiple

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resource constrains(budget B and PT) instead of one, budget. Also, the cost of "pulling an arm" only occurs when an reward is returned from the bandit. The arms are indexed by (l, h, p) with regarding to difficulty level/label of tasks, time of the day and price. And the cost of pulling $arm(l, h, p)$ is set as two dimension: 1)number of participants to be presented in PT and 2)p in B only when some accepts the offer. The reward is set to 1 as offer accepted. The probability of each arm return an reward r is the overall acceptance probability of an offer under the circumstance stated by the arm's index (l, h, p) as part of system knowledge $F\{r_{l,h,p}\}$.

We further formulate the problem as Multi-dimensional and Multiple-Choice Knapsack Problem (MMKP) [6] for overall decision-making model. A knapsack with two dimensional capacities B and PT. Every task is a set of items and the items are the available "arms" in CRMR-MAB. Each item j has an value 1 as offer being accepted and two dimensional weight price p_j in B and least expected number of participants needed pt_j(can be derived from system knowledge F) in PT. The item can also be indexed by (l, h, p) indicating circumstance. The constrain of traditional MMKP is relaxed to "choosing no more than one item from each set".

3 PROPOSED APPROACH

An comprehensive decision-making algorithm GA-WSLS is proposed, which combines 1) a Thompson Sampling [2] based greedy algorithm GA for CRMR-MAB and 2)a heuristic algorithm WSLS for the MMKP. At each round, GA uses Thompson Sampling to extract expected reward of arms available for current task. The expected reward r is extract based on the history of the offer acceptance, circumstance represented by the index (h, p) of each arm. The pulling strategy is based on all available arms' expected reward $\tilde{r}_{l,h,p}$ and remaining resources (B_e, PT_e), choose arm (h, p) according to:

$$(h, p) = \arg\max_{(h,p)} \left\{ \min \left[\frac{B_e}{p}, PT_e(\lceil 1/\tilde{r}_{l,h,p} \rceil)^{-1} \right] \right\}. \quad (1)$$

After obtaining a practical system knowledge $F\{r_{l,h,p}\}$, we switch the decision making from individually to an overall approach WSLS, for better resource management to achieve higher result. After modeling MMKP with remaining resources and tasks, we applied item dominance [7] in each set to eliminate useless items to improve efficiency. Also, we add zero items to each set to guarantee a feasible solution for any resources and tasks remaining situation. The initial choice in each itemset is the non-zero item with the least combined sum of capacity occupancy ratio of all dimensions. Then, it uses a swapping strategy to switch item-elect within and among itemsets. The algorithm then selects the item that can free the more resources in terms of ratio with regard to the remaining resources B and PT. When obtain a solution from WSLS for MMKP, we translate the solution into offers and put the offers into waiting queues matching their scheduled time h. We iterate WSLS with the remaining resources and tasks after finishing the execution of the previous solution, until not enough resources remain or all tasks are solved.

4 EXPERIMENTAL EVALUATION

To evaluate the effectiveness of proposed GA-WSLS. We designed a simulation with real dataset from Singapore [3] with real designated parking zone information. We choose 4 classic MAB approaches [1] (Random, ϵ-greedy, Upper Confidence Bound and Thompson Sampling) and 3 state-of-the-art Budgeted MAB approaches (f-KUBE [8], m-UCB [9], c-UCB [9]). Moreover, we use GA as another baseline. WSLS-h and WSLS-H are set as Oracle with different size time window knowing the ground truth of system knowledge F. In the beginning of the simulation, We set total 10,000 bikes and 5,000 participants in the area. Each task set the difficulty level by moving distance, total levels $L = 10$. Also, total time slot of the day $H = 12$ and prices set $P = 10$ range from [5,50]. Each participant's base cost are independently sampled $e_{u,l_i,h} \sim N(\mu = p_l, \sigma^2 = 6.0)$ and varies for different situation (l, h).

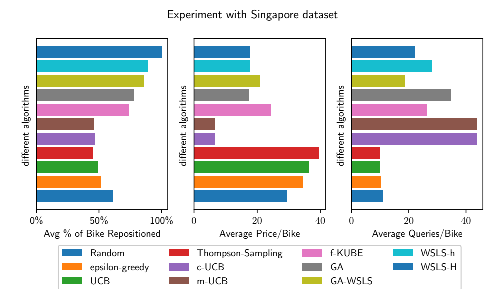

Figure 1: Experiments results

Figure 1 shows all approaches comparison under the follow metrics: 1) average percentage of bikes repositioned, 2) average price per bikes and 3) average queries per bike. As shown in figure, GA-WSLS achieves most repositioned bikes comparing to other algorithms except the two oracles. Besides f-KUBE and GA, all other baselines only achieves half the tasks. The oracle WSLS-H, with total time window, nearly finishes all tasks, slightly better than WSLS-h and GA-WSLS. It can be observed that, the average resources consumption of GA-WSLS and two oracles are maintaining ranking in the middle, which means they balance the consumption between different resources and realize reasonable resources allocation. Budgeted-MAB approaches tends to consume highest amount of query resource PT which leads to lowest price per bike. On the other hand, the classics trade lower query times with higher prices. However, the tendency of these baselines focusing too much on one-sided resources makes the total number of tasks they ultimately accomplish worse than that of GA-WSLS.

5 CONCLUSIONS

In this paper, we address the problem of indiscriminately parked shareable bikes. The problem is generalized as a crowdsourcing problem scenario with complex and large number of tasks, limited resources, non-dedicated participants and time-varying participation enthusiasm. We proposed an centralized pricing based dynamic incentive mechanism, GA-WSLS. It is shown our proposed approach can rationally utilize resources, ensure participants' enthusiasm and improve the completion rate of tasks.

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