Ethically Aligned Mobilization of Community Effort to Reposition Shared Bikes

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Abstract

We consider the problem of mobilizing community effort to reposition indiscriminantly parked shared bikes in urban environments through crowdsourcing. We propose an ethically aligned incentive optimization approach *WSLS* which maximizes the rate of success for bike repositioning while minimizing cost and prioritizing users' wellbeing. Realistic simulations based on a dataset from Singapore demonstrate that WSLS significantly outperforms existing approaches.

Introduction

Today's biking sharing systems (e.g. ofo) allow users to pick up and drop off bikes at any location, not limited to parking zones (Figure 1(a)). This flexibility has led to many cases of indiscriminant parking (Figure 1(b)) despite appeals to users to park shared bikes at designated parking zones (Figure 1(c)). This has resulted inconvenience to other road users. Existing approaches incentivizing users to change their travel plans to park bikes into parking zones (Singla et al. 2015) are not suitable for this problem.
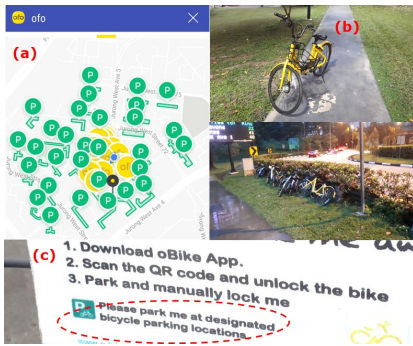

Figure 1: Examples of bike parking problems in Singapore.

To address this problem, we develop an incentive optimization approach to mobilize crowdsourcing users to reposition indiscriminately parked bikes into parking zones. We propose a revised multi-dimensional and multiple choice Knapsack formalization of this problem, and an efficient

solution to maximize the expected number of bikes repositioned while minimizing cost and number of queries.

Revised MMKP Problem Formulation

Assuming that within a bounded area, there are N_S shared bike parking zones. Let there be a total of N_B indiscriminately parked bikes $\{b_1, b_2, ..., b_{N_B}\}$. The objective is to maximize the number of bikes repositioned into parking zones while staying within the resource constraints.

At any given time, there can be N_U users, each having his own base price for repositioning a bike. A user's base price may vary at different time of a day and is related to the distance of travel needed to reposition a bike. Therefore, we divide each day into 12 time slots of 2 hours each $\{h_1, h_2, ..., h_{12}\}$, and consider moving distance d in multiples of a fixed unit distance d_{unit} (e.g. 50m). There are up to L levels of movement distance $\{d_1, d_2, ..., d_L\}$, and $d_l = l \cdot d_{\text{unit}}$. Distances longer than d_L are categorized as d_L. Denote user i's base price for a given distance d_l and time slot h_t as $c_i(d_l, h_t)$. We assume that the range of possible values for base prices is $c_i(d_l, h_t) \in [c_{\min}, c_{\max}]$, where $c_{\max} \geqslant c_{\min} \geqslant 0$. Each bikes is treated as a task, τ_j, which needs to be delegated to a user. Each τ_j contains information regarding bike id b, the destination parking zone z, and distance separating the two d_l, $\tau_j = \{b, z, d_l\}$. We aim to reposition each bike to its nearest available parking zone.

One obvious resource constraint is the total budget, B. In addition, we introduce another resource constraint - total number of queries, PT, for all tasks. One query equals to one offer presented to one user. The main reason to introduce PT is to prevent the algorithm from spamming users with lower price queries which negatively impacts user experience. By incorporating this constraint, we follow the ethically aligned design guidelines to prioritize users' wellbeing while attempting to achieve system objectives (Yu et al. 2018). We formulate our problem following the Multi-dimensional Multiple Choice Knapsack (MMKP) model (Hifi, Michrafy, and Sbihi 2004). We treat the decisions about each task τ_j as an item-set I_j which contains $|I_j|$ items formed by available choices of the posted-price offer $p \in [c_{\min}, c_{\max}]$, the time slot the task is scheduled for processing h, and expected number of queries to be sent to nearby users $pt = \lceil \frac{1}{F(d_l, h, p)} \rceil$, where $F(d_l, h, p)$ is the cumulative probability distribution function of how likely an

offer p will be accepted given d_l and h, which is to be learnt.

The original objective of MMKP is to pick exactly one item from each item-set to maximize the overall value of picked items. Since there may not always be enough resources left to pick one item from each item-set, we relax this constraint in our formulation to *picking at most one item from each item-set*.

The WSLS Approach

As described in our revised MMKP model, the joint decision about each task τ_j is an item in the item-set I_j with $|I_j|$ items. The $|I_j|$ items can be viewed as the arms in an $|I_j|$-armed bandit. Based on the framework in (Hifi, Michrafy, and Sbihi 2004), we propose a Weight Sensitive Local Search (WSLS) approach. It firstly ranks all tasks in ascending order of their d_l value. We set the time window $tw = 2$, meaning that a task can be processed in either the current time slot h_t, or the next h_{t+1}. Then, for each task, WSLS pulls the arms in the bandit to determine the joint decision tuple $\langle p, h, pt \rangle$.

Since all successfully repositioned bikes yield the same utility, WSLS focuses on finding items consuming less resources. It contains three steps: 1) finding an initial solution selecting items which result in the minimal sum of resource consumption ratios under both B and PT (i.e. $\underset{\langle p,h,pt \rangle \in I_j}{\operatorname{argmin}} \left\{ \left(\frac{p}{B} + \frac{pt}{PT} \right) | h \right\}$ for every task τ_j); 2) adjusting the choices of items based on resource violations to find a feasible solution (some selected item tuples may need to set to $\langle 0, 0, 0 \rangle$); and 3) swapping items through local search by eliminating items 'dominated' by others (Kellerer, Pferschy, and Pisinger 2004) to improve solution optimality.

Experimental Evaluation

In order to evaluate the proposed WSLS approach, we built a simulator based on a real-world dataset from Singapore containing location information of designated parking zones (https://data.gov.sg/dataset/lta-parking-standards-zone). The simulator also generates the locations of the bikes and the start locations for the user agents to create an evaluation environment.

We select four approaches as baselines for comparison with WSLS in the experiments: 1) Random, which randomly adjusts offer prices to query nearby users until someone accepts the task; 2) Greedy, which follows the greedy approach in (Auer, Cesa-Bianchi, and Fischer 2002) to adjust the offer prices; 3) Upper Confidence Bound (UCB), which follows the UCB approach in (Auer, Cesa-Bianchi, and Fischer 2002) to adjust the offer prices; and 4) Knapsack-based upper confidence bound exploration and exploitation (KUBE), which follows the approach in (Tran-Thanh et al. 2012) to adjust the offer prices. We set $N_B = 10,000$ and vary N_U from 5,000 to 15,000. Under each configuration, the simulation was run for 10,000 epochs. Prices are represented in the form of points in the simulation, and a user agent only accepts an offer if it is equal to or higher than its base price.

Figure 2 shows the results. The average percentage of bikes repositioned is averaged over all configurations and epoches, whereas the other two metrics are averaged over all configurations, epoches and bikes. It can be observed that WSLS achieves the highest percentage of bikes repositioned, beating the best performing baseline approach, KUBE, by 34%. It achieves the second lowest average offer price among all approaches, 17% higher than that of Greedy. However, WSLS only needs to query half as many users as Greedy does. Overall, WSLS achieves the most desirable trade-off among the three evaluation metrics.
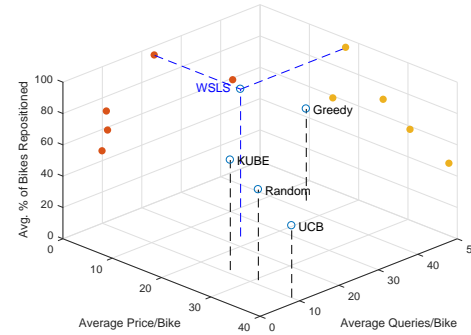

Figure 2: Experimental Results.

Conclusions and Future Work

In this paper, we proposed WSLS which jointly optimizes the offer price, the scheduled execution time, and the task query rounds in order to efficiently mobile community effort to reposition indiscriminantly parked shared bikes through crowdsourcing. We are developing a mobile app based on this approach, and working with community organizations in order to study how such a platform can be used to engage senior citizens to participate for the purpose of productive aging while achieving our original objective.

Acknowledgements

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