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A Campus-Scale Mobile Crowd-Tasking Platform

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Abstract
By effectively utilizing smartphones to reach out and engage a large population of mobile users, mobile crowdsourcing can become a game-changer for many urban operations, such as last mile logistics and municipal monitoring. To overcome the uncertainties and risks associated with a purely best-effort, opportunistic model of such crowdsourcing, we advocate a more centrally-coordinated approach, that (a) takes into account the predicted movement paths of workers and (b) factors in typical human behavioral responses to various incentives and deadlines. To experimentally tackle these challenges, we design, develop and experiment with a real-world mobile crowd-tasking platform on an urban campus in Singapore. In this paper, we first introduce *TA$Ker* and then demonstrate the effectiveness of different behavioral experiments, such as bundling and differential task pricing methods.

Author Keywords
mobile; crowdsourcing; context-aware; bundles; incentives; cheating; smart-campus; social-ties; collaboration.

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

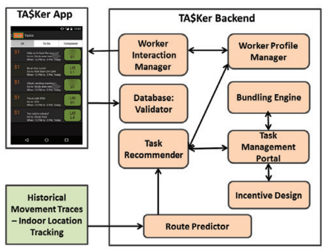

Figure 1: *TA$Ker* framework - architecture.

Introduction

Mobile crowd-sourcing, where a decentralized pool of voluntary workers use mobile devices to accept and perform location-specific tasks that match their natural daily movement patterns, has generated considerable excitement and interest recently. In densely-crowded cities such as Singapore, such a participatory model of task execution can significantly reduce both operational cost and response latency, across domains such as last-mile logistics (e-commerce package delivery), retail marketing compliance (checking in-store product placement and stock levels) and municipal monitoring (obtaining feedback on problems related to garbage, potholes, broken streetlights, etc.).

In spite of such promise, mobile crowd-sourcing continues to suffer from problems such as unpredictable and unfair task completion rates and worker churn (e.g., existence of super-agents [3]). We believe that such deficiencies can only be rectified via a **centrally-coordinated crowd-sourcing** approach, where (a) tasks are recommended (*pushed*) to people based on their predicted movement trajectories, and (b) aspects such as task pricing and cheating detection incorporate the *behavioral dynamics* of workers. However, most research on mobile crowd-sourcing is based on *synthetic* models of worker preference and behavior—e.g., game-theoretic models of task pricing that assume perfectly rational agents.

To obtain behavioral insights and harness them for centrally-coordinated, trajectory-aware mobile crowd-sourcing, we have built and operationalized a mobile-crowdtasking platform, called *TA$Ker*, on our university campus. *TA$Ker* is both (a) **real**–i.e., it crowd-sources reports on the status of various real-world conditions on the campus and pays out real monetary rewards, and (b) **experimental**–it explicitly supports testing the impact of changes to crowd-sourcing parameters, such as task pricing, task bundling and centralized (push) vs. decentralized (pull) task selection mechanisms. All tasks in *TA$Ker* presently involve some form of *reporting of physical, on-campus state*, such as "length of queue in the food court", "availability of a soda brand in a particular vending machine" and "cleanliness level of a specific toilet". In prior work [2], we described an initial, proof-of-concept study (80 student participants performing around 1000 tasks over a 4 week trial period) of an early, limited version of *TA$Ker*. The more detailed study is available in [1].

Overview of *TA$Ker*

As detailed in [2], in addition to the mobile App, the *TA$Ker* backend system includes the following key components (refer Fig. 1): (a) *Route Predictor*, that predicts an individual user's movement trajectory based on user's historical movement traces; (b) *Task Recommender*, that suggests tasks (from the overall pool of available tasks) which best match (i.e., minimize the additional detour overhead) the predicted trajectory of an individual worker; (c) *Task Management Portal*, that allows *TA$Ker* administrators to create, modify and monitor the set of available tasks, (d) *Bundle Engine*, which combines multiple tasks that lie in close proximity to each other into a bundle, and (e) *Incentive Engine*, that decides the right reward values of the tasks based on the factors such as how crowded the task location is?

We use a significantly larger study (involving 900 undergrad students who performed 30,000+ tasks over a 2 month period) to study four key new aspects of crowd-sourcing operation: (a) Bundling–this refers to a group of tasks, where users complete all tasks in the group to get payment. This study helps us to understand the worker reaction to the aggregated vs. unit pricing of tasks, (b) Differential pricing–whereby the prices of tasks at different locations are de-

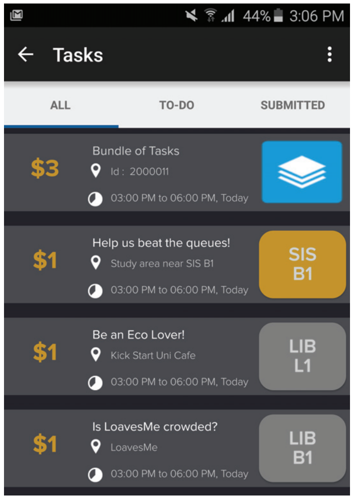

Figure 2: List of Bundles and Individual Tasks

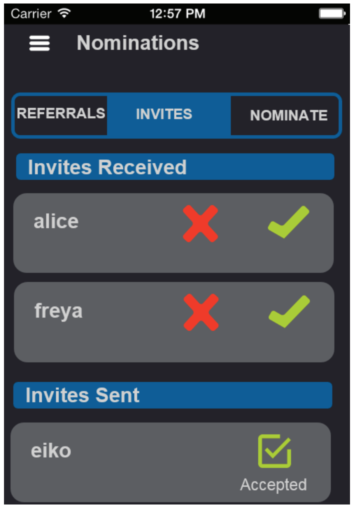

Figure 3: List of friend invites sent and received.

termined based on different strategies. This allows us to understand how differential pricing can counteract spatial skews in completed tasks, (c) Cheating–the act of reporting results without being at the specified task location. Our study demonstrates how the tendency to cheat is influenced by both intrinsic (individual personality based) and contextual (based on properties of the tasks) factors, and (d) Task referral–this refers to dynamic collaboration among peer crowd-workers. This investigates whether and how such feature can help to improve the overall task completion rate.

Screenshots for the Android App are shown in Fig. 2 & 3.

Key Insights

- **Task Bundling:** We show that workers prefer bundled tasks (set of tasks that must all be performed to earn the payment specified for the task bundle). Task bundling improves worker productivity compared to individual tasks. More quantitatively (see Fig. 4), task bundling improves worker productivity, with a worker earning 77% ($0.20) more per minute of additional detour, compared to individual tasks.
- **Differential Pricing:** We demonstrate that an inverse density based pricing strategy, where task rewards were defined to be inversely proportional to the popularity (number of occupants) of different university locations, not only effectively counters such spatial skews in task completion rate but also significantly increases the fair sharing of rewards among workers. Our analysis shows that a popularity based differential pricing mechanism significantly reduces (5-fold) the variation in spatial skewness of task completion rate (we depicted this in Fig. 5).
- **Cheating Characteristics:** We empirically demonstrate that the tendency to cheat has both intrinsic (individual personality-based) and contextual (based on properties of the tasks) factors. In particular, (a) we find that when the users perform the first two tasks of a bundle, the majority of the responses received were within 2 minutes distance from the task location and the latter part of the bundle tasks are executed while being 6 minutes away, depicted in Fig. 6, (b) tighter time windows for tasks lead to disproportionately more cheating (80% of the cheating occurred on tasks with the execution window less than 90 minutes)).
- **Dynamic Collaboration among peer crowd-workers:** By incorporating task referral feature, we demonstrate its popularity and effectiveness. This feature increased the task completion rate by 14%. We then show that a user's intrinsic preferences for selecting tasks can be learnt and modeled, using various crowd-sourcing related features such as (i) detour overhead, (ii) popularity of the task location, (iii) the task's incentive (with the last two factors having a dominant effect on worker preferences). Finally we show that incorporating social factors in a per-user based task preference model results in a significant improvement, increasing the prediction accuracy by 31%.

TA$Ker for Smart Campus

Besides providing insights into worker behavior, the *TA$Ker* deployment also helps us to target the partial development of a *smart campus*, where a volunteer student population is used to perform continuous sensing of campus resources. To illustrate these possibilities, we focus on two specific tasks–that report on the cleanliness of all the (a) restrooms and (b) rubbish bins. We show that the temporal pattern of these responses can help improve the operational efficiency of the campus cleaning staff. Also, for restroom and

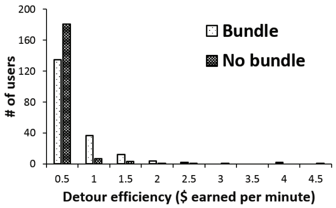

Figure 4: User detour efficiency when offering bundles vs. atomic tasks

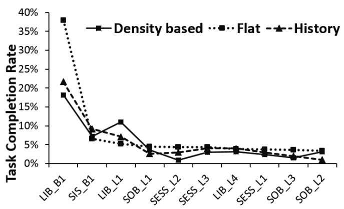

Figure 5: Task completion rate in more popular locations.

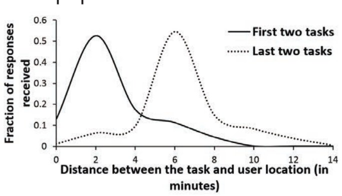

Figure 6: Sequence in bundling task impacts cheating

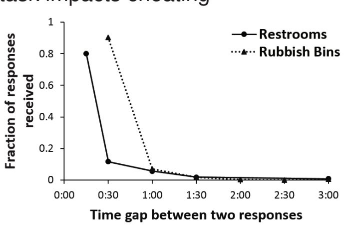

Figure 7: Inter-report gap distribution

rubbish bins, we generated tasks with execution deadlines such that we would ideally receive updates every 15 and 30 minutes, respectively. Fig. 7, which plots the distribution of the gap (latency) between two consecutive reports, shows that we can obtain reports on the restrooms 90% of the time with a latency of 30 mins or lower; for rubbish bins, we obtain almost 100% of the reports within a gap of 1 hour.

Demonstration

We demonstrate the feasibility of the campus-based mobile crowd-sourcing by using Android/iOS prototype. First, we will give an overview of how the tasks (and associated details) are being entered into the database via a Web interface. Then, the attendees will also be given the exposure to the end to end functionality of the App such as accepting and performing tasks, creating new tasks etc. Finally, we will show the *results analyzer* that is used to analyze the results of various experimental strategies, and thus deduce insights into the effectiveness of various task recommendation/incentivization strategies and their effects on individual/aggregated crowd-worker behaviors. This demo requires all the devices to be connected to the Internet. Attendees will be able to actively participate in the demonstration by using one of the demo devices.

Conclusion

TA$Ker was deployed to a pool of 900 student volunteers, who performed around 30000 total tasks over a deployment period of 8 weeks, who participated in 4 different experiments described earlier.

- Users prefer to choose bundled tasks over the atomic ones. We show that worker productivity significantly improves by 77% when they perform bundled tasks.
- We prove that a simple inverse density based pricing model can counteract such skews and uniformity.
- Our data demonstrates that the tendency to cheat can be either due to the intrinsic or contextual factors. We find that workers tend to cheat the latter tasks in the sequence of a bundle and tighter time windows for tasks lead to more cheating (80% of the cheating occurred on tasks with validity window less than 90 minutes).
- Dynamic peer referrals is very successful: its introduction increased the overall task completion rate by 14%.

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