A Driver Guidance System for Taxis in Singapore

Demonstration

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ABSTRACT

Traditional taxi fleet operators world-over have been facing intense competitions from various ride-hailing services such as Uber and Grab. Based on our studies on the taxi industry in Singapore, we see that the emergence of Uber and Grab in the ride-hailing market has greatly impacted the taxi industry: the average daily taxi ridership for the past two years has been falling continuously, by close to 20% in total. In this work, we discuss how efficient real-time data analytics and large-scale multiagent optimization technology could help taxi drivers compete against more technologically advanced service platforms. Our system has been in field trial with close to 400 drivers, and our initial results show that by following our recommendations, drivers on average save 21.5% on roaming time.

KEYWORDS

taxi driver guidance; multiagent optimization; mobility-on-demand

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1 INTRODUCTION

In many big cities, taxis can be considered as a transportation mode that is closest to owning private cars. In some Asian cities, taxis are even considered to be part of the public transportation system. For example, as per the government statistics for the year 2016 in Singapore, the daily average ridership of taxis was more than 11% among all the public transportation modes [2]. From the traffic planner's perspective, it is therefore very important to make taxis reliable, responsive and cost-effective. One of the challenges faced by the taxi drivers is to position themselves in the vicinity of areas with stochastic passenger demands. Added to the challenge is the lack of knowledge on the number of available taxis in the area surrounding them. It is thus not surprising to see that taxis on average spent over 50% of their operation time roaming vacant.

To address the aforementioned challenges faces by taxi drivers, we design and implement the Driver Guidance System (DGS) to balance the taxi demand and supply in real-time by providing guidance to the taxi drivers in Singapore. The DGS uses the real-time information of movements of all the taxis in Singapore for predicting the expected demand and supply within a time horizon. The next step of providing individual guidance to the taxi drivers is generated by a multiagent optimization engine which matches each taxi driver with an expected demand such that the overall revenue is maximized. The DGS has been fully developed and deployed for field trials since September 2017. As of January 2018, about 400 taxi drivers have volunteered to use and test DGS on the streets of Singapore. The data gathered from the field trial shows a reduction in the average roaming time of the taxi drivers with the use of DGS. This essentially means that by following the guidance provided by the DGS, the taxi drivers spend less time cruising through the streets to get their next passengers.

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2 THE DRIVER GUIDANCE SYSTEM (DGS)

The DGS is designed to be modular, including the following four major components: 1) data stream handler, 2) demand and supply prediction engine, 3) multiagent recommendation engine, and 4) mobile application. A brief description is provided for each component. For detailed description, we refer interested readers to [3].

2.1 Data Stream Handler

We receive the real-time GPS coordinates and states of all currently active taxis in Singapore via a private API from Land Transport Authority of Singapore. This incoming stream of data is usually marred with GPS and communication errors. Hence, the first component of the DGS handles this noisy input data stream in order to cleanse the data for further use. Another important step performed in this component is to associate each GPS log with a corresponding street in Singapore through a *map matching* process. This step allows us to sense the movement of taxis on each street for generating real-time predictions. The map matching process uses a Hidden-Markov-Model based algorithm [5] and establishes the continuous trajectory of the movements of each individual taxi in a rolling horizon manner.

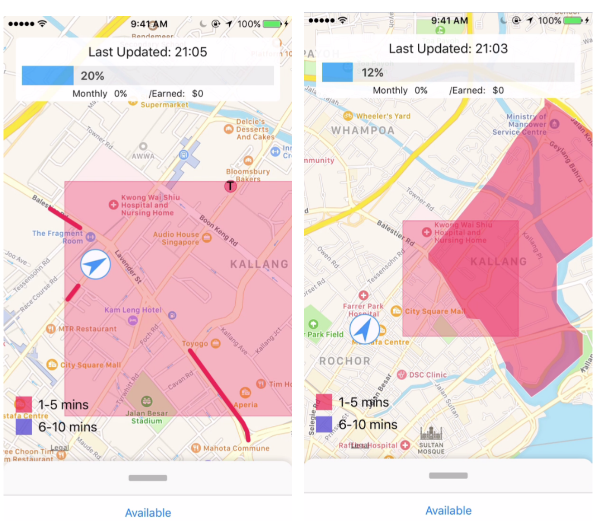
2.2 Demand and Supply Prediction Engine

The next important step is to predict the demand and supply distributions throughout Singapore. We use the supply information available from the real-time data stream to estimate the overall supply distribution in next few minutes. For predicting the taxi demand, we treat each free-cruising taxi as a *demand probe.* The demand prediction model generates the likelihood of getting a passenger on a street based on the amount of time elapsed since the last free taxi traversed that street [3]. The model also take into consideration the effects of the time of the day and the day of the week in order to make the predictions. Further, the aggregated demand predictions are continuously generated for a time horizon of 30 minutes. These information is then fed to the multi-agent recommendation engine in order to generate individual guidance of each taxi driver.

2.3 Multiagent Recommendation Engine

The multiagent recommendation engine has been designed to match each individual taxi driver (agents) with a demand such that the overall revenue of all the agents can be maximized. The agents are first segregated into a set of cells by dividing the whole Singapore into grids of size 1km x 1km. Further, the predicted demand information is also continuously updated for all the cells. The multiagent recommendation engine uses a multi-period, multi-driver stochastic model adopted from Lowalekar et al. [4].

To account for the movement of agents which may not follow the recommendations, the engine makes use of historical cruising patterns for simulating the behaviors of such agents across different grid cells. In addition, the portion of the predicted demand taken-up by the non-following agents are then deducted from the total predicted demand in each grid cell. With the remaining demand in each grid cell, the multi stage stochastic optimization formulation computes the best match at the current time step while considering multiple samples of agent movements and demand fulfillment in the future time steps within the given time horizon. The drivers are then assigned the best matching demand based on their locations and expected revenue. The formulation generates a system optimal solution with individual movement of taxis as the cost. The recommendations are calculated continuously in a rolling horizon manner in order to provide the same to the taxi drivers in real-time.



(a) Street-level (b) Region-level

Figure 1: Mobile App UI displaying different recommendation modes.

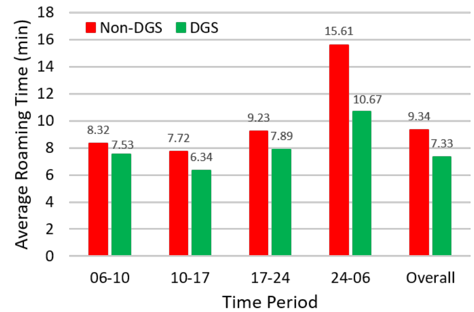


Figure 2: The average roaming time distribution for different periods of a day for DGS and Non-DGS trips.

2.4 Interfacing with Taxi Drivers

The recommendation for the taxi drivers are generated at two levels: 1) Region level (the 1km x 1km grid cells) and 2) Street level. To deliver the personalized recommendations to individual taxi drivers, the recommendations are displayed as an overlay over the map of Singapore using a mobile phone App (for both iOS and Android). The App switches between the two levels of the recommendations based on the current location of the taxi driver. The App automatically adjusts its zoom level, and shows different details. For the Street level, the streets having a high likelihood of passengers are recommended (see Figure 1(a)) whereas for the taxi drivers with no recommended streets in their vicinity, the App displays a recommended region that is in proximity of their current location (see Figure 1(b))[1].

3 THE FIELD TRIAL

Since September 2017, we have launched the field trial of DGS with volunteering taxi drivers. Using the mobile phone App, we track the amount of time the taxi drivers follow DGS recommendations. We then label a taxi trip as DGS-assisted if the driver spent more than certain percentage of roaming time following DGS guidances. In our analysis, we set this threshold to be 60%. The average roaming times for both DGS-assisted and non-DGS trips are plotted in Figure 2. From Figure 2 we can see that drivers benefit from the DGS across all time periods, leading to 21.5% drop in the average roaming time. The benefit of following DGS is particularly pronounced in the late night period, when the demands are usually sporadic and hard to predict. A further analysis of DGS effectiveness across regions and times also confirm this finding (see [1]).

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[1] A **video** demonstrating the motivations, objectives and expected outcome by the use of DGS can be accessed at : https://youtu.be/Hp3fOB6_Vf0

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