Passenger Saver based on Uber Surge Multiplier

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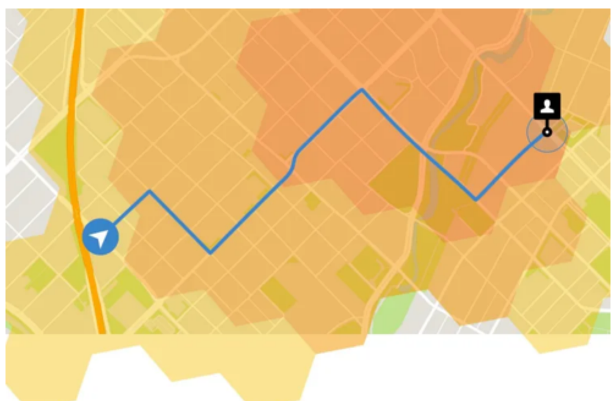

Fig. 1. Schematic Diagram of Distribution of Uber Surge Multiplier.(https://www.uber.com/us/en/drive/partner-app/how-surge-works/)

1 INTRODUCTION

Uber is a technology company that is famous for managing a ride-sharing platform. One of the most important characteristics of Uber is the flexibility of supply[4].Today, what we will focus on is Uber's dynamic pricing called "surge multiplier".Moreover,Uber will charge passengers based on two factors: time and distance. During times of high demand, Uber will use this to increase prices[3]. The surge multiplier will vary from region and time. **Fig. 1** quoted from

*All team members have contributed similar amount of effort.

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the Uber website illustrates how this works. The darker the color is, the higher the price is. To be honest, this method may increase the efficiency of ride-sharing. With the help of surge, it reduces some customers out of the market, for example, many young students may give up calling a Uber when the price is relatively high. Besides, a higher price is able to attract more drivers to drive during the high-demand time or come to this region[3]. The surge multiplier will be updated every 5 minutes. It may sound reasonable, but this information is only visible for drivers. Passengers can be charged a higher price unconscious. Our purpose in this project is letting this information be accessible to passengers as well. For example,in **Fig. 1**, one person is on the edge of a high surge multiplier region. We will use data from the past to give him a guide to move to the nearest region with the lowest surge multiplier. To use more valid data, we decide to use the Uber data from San Francisco due to the largest number of Uber[5].

2 LITERATURE REVIEW

More and More researchers are interested in analyzing the spatial and temporal disparity of Uber demands[6, 7, 18], becuase Uber a representative of "sharing economy". Wang, et. al[18] studied the Uber accessibility by analyzing average wait time in different areas of Atlanta (**Fig. 2(a)**)[6, 7]. They tried to fit the data with models to figure out what factors (like wealth, race, public transportation etc.) influence the spatial disparity of Uber. Similar researches went on in New York City , which focused on analyzing number of pick-up data (**Fig. 2(b)**). Also, comparison between Uber and traditional taxi are made (**Fig. 3**), predicting that demands for Uber may exceeds that of taxi in the following years due to its convenience and relatively low price[6, 15]. Other reviewed papers are shown in the reference lists[9, 13].

Now that more and more users join the Uber ride, it's important for riders to know how the price of trip is calculated. As economist pointed out, truthfulness and information disclosure between riders and riding-sharing companies is vital to further development of ride sharing. Some researchers begin to pay attention on the surge mechanism of Uber[1, 3–5, 10, 14]. Chen, et. al tried to open a black box of surging price algorithms by applying a model to analyze Uber trip data based on cars supply, demand, wait times, locations, etc [3]. As they figured out, surge multiplier changes with areas and time (**Fig. 4**). It is refreshed every 5 minutes. Other researchers criticized the unfairness of surge, suggesting that surge price should be disclosed to public [3, 4]. Therefore, we want to make surge exposed to users while help them to choose a better place and occasion to book a Uber ride. In order to realize these functions, papers on map constructions are reviewed[2, 8, 11, 12, 16, 19] . Several studies are based on Google map API which is used to implement data visualization on maps [8, 12]. Brakatsoulas, et. al[2] studied algorithms that exploit the trajectory nature of the tracking data which is helpful to us in designing a path leading to an area with lower surge multiplier.

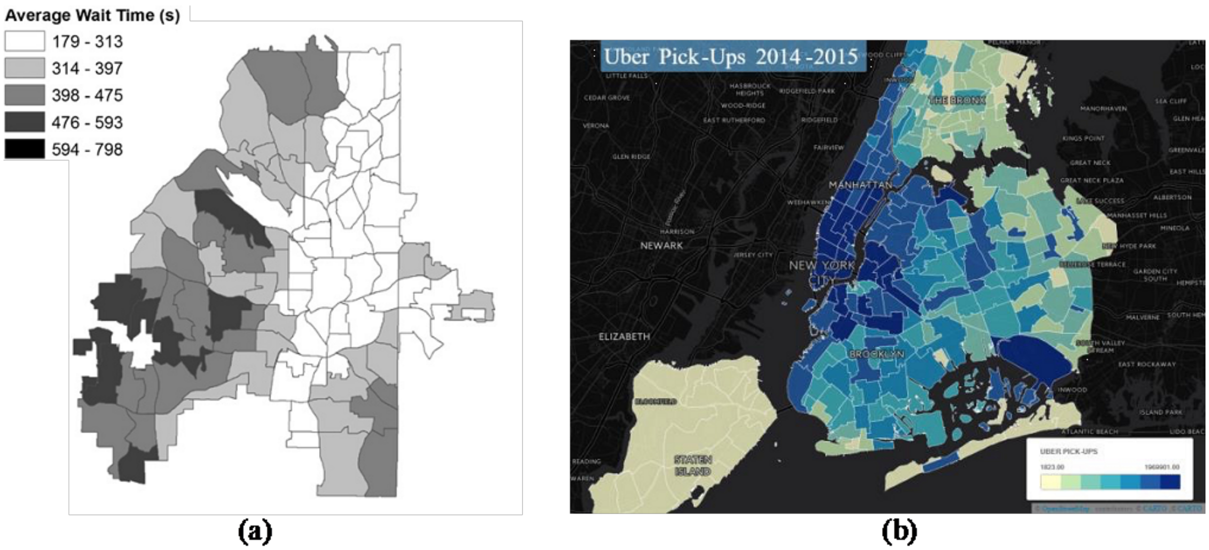


Fig. 2. (a) Estimated wait time of Uber in Atlanta in 2016 (reprinted from Wang, et. al, 2018) (b) Uber demands in New York city in 2014-2015 (reprinted from Correa, et. al, 2017)

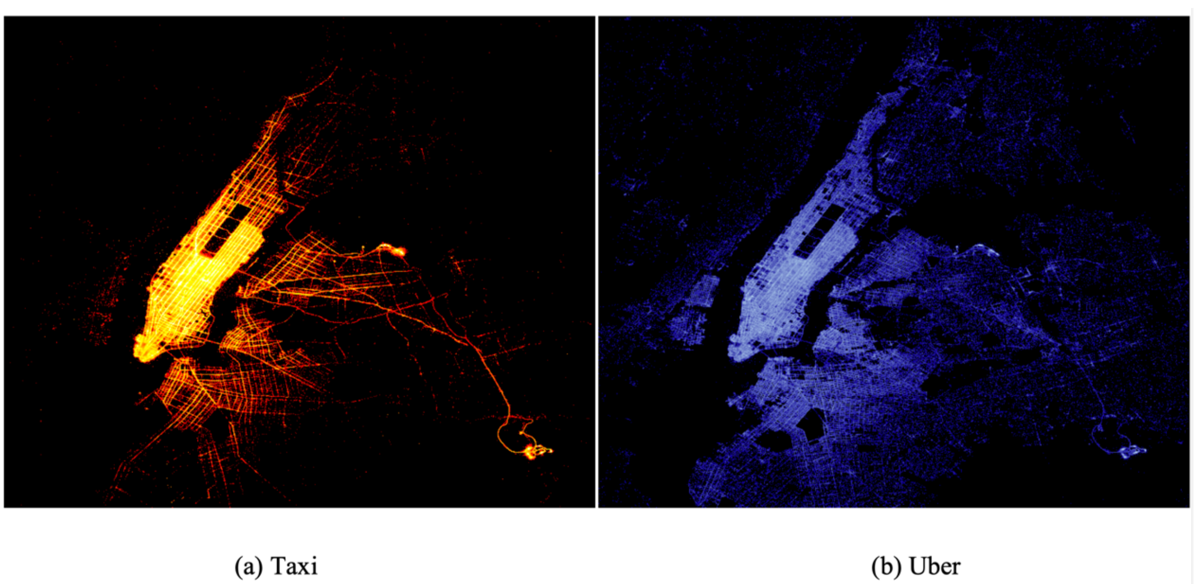
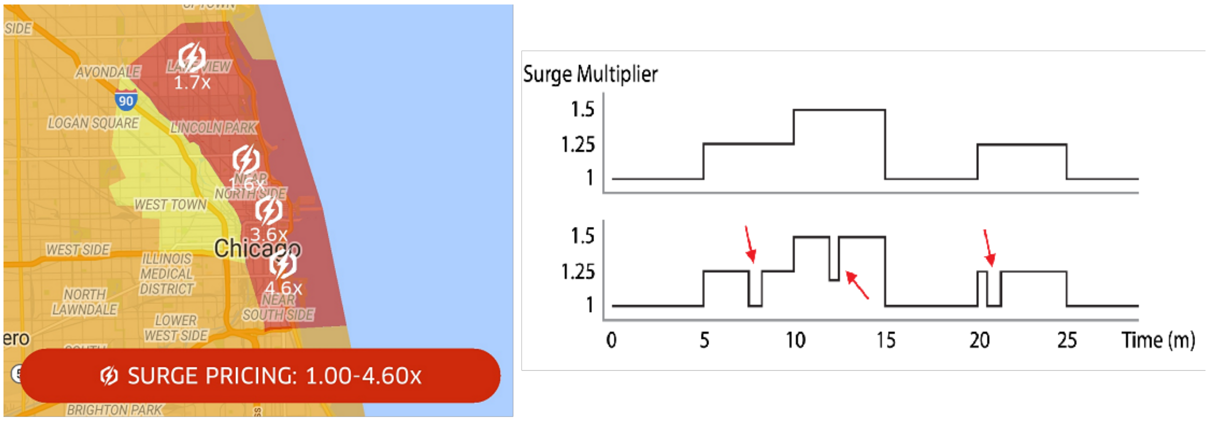


Fig. 3. Heatmaps of taxi and Uber pick-ups in New York City (reprinted from Correa, et. al, 2017)



(a) **(b)**

Fig. 4. (a) Surge multiplier changes with different areas (b) Surge multiplier changes with time (reprinted from Chen, et. al, 2015)

3 PROJECT PLANS AND APPROACHES

For this project, the duration is roughly two months. During preparing for proposals and presentations, everyone joined in discussion, prepared slides, reviewed some papers and concluded them. Xipeng, Jinli, Haomin, Yanjun, Peng,Yuntian worked on introduction, literature review, approaches, plans, integration, presentation respectively. Next, our plan can be divided into four parts: data collection (Peng and Jinli), program design(Yuntian and Yanjun), interface design(Haomin) and program refine (All members). We'll firstly get the data and build our database, then use certain algorithms to analyze the data, and finally put the data into visualization. So finishing data analysis will be our "midterm" and the final exam is running our system to get plans to avoid high surge multiplier. During this project, the cost can be the fund we need for some particular database and it may cost a lot in many other computing tasks if we want to build a real-time system. With success, it can help people avoid unnecessary high payment for a ride and ease the pressure of traffic. We plan to run some experiments to see if it works. And the risk is perhaps we will turn out to find that most high surge rides are inevitable. But if it goes smoothly, the payoff can be a launched application. For plans,we will group the collected data by time, area and date. We use them as keys because rush areas tend to change with these three conditions. After that, we will establish a model based on Markov chain to predict the normal price at a specific place and a specific time. Comparing the normal price with the current price, users will know whether they are in a surge area and to what extent it is surging. Also, using the grouped data we will show users the border of the surging area and how long it is expected to last. If users are in the center of an surging area, unluckily they have to wait until the crowd disperse, or they can just spend the extra money. If users are close to the border, they can choose to walk a couple of minutes to an uncrowded place and take a Uber for a lower price. The next step is to visualize the areas with different surge multipliers. We choose to use Google Map API[8], which can offer us accurate data of certain areas[12]. Our plan is to spot our points of interest and mark the boundaries of certain areas. After that, we will also color certain areas, so that it can clearly alert[17] the user about the price difference if he stays in current area. Then we will offer him the time he needs to wait or the best route[2] he needs to walk to get lower price based on users' preference.

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All team members have contributed similar amount of effort.

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