Understanding Passenger Reaction to Dynamic Prices in Ride-on-demand Service

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***Abstract*—In recent years emerging ride-on-demand services (eg., Uber or Didi) are penetrating into the market of traditional taxi service. In these new services mobile devices are a key enabler: they serve as the intermediary between passengers/drivers and the service provider, tracking the locations and behavior of both passengers and drivers. On the other hand, the use of mobile devices also help us to capture huge amount of data for analysis. Through collaboration with a leading service provider in China, we collect vast amount of accurate data and analyze, in this paper, passenger reaction to dynamic prices in such a service. We consider the analysis as an important step towards making the service more efficient and more attractive to the passengers. We present the patterns of passengers' reaction, and discuss if it is useful to estimate the trip fare for multiple times in order to get a lower price. Our findings pave the way for future study on system optimization and policy considerations.**

I. Introduction

Ride-sharing services like Uber [1] have drawn increasing attention. As a supplement or substitute of the traditional taxi services, it attracts customers by convenience, cleanness and (sometimes) low prices, and attracts drivers who want to make money using their own cars without applying for taxi licenses.

In fact, ride-sharing service is only one of the three categories of ride-on-demand (**RoD**) services, which is an analogy to the "video-on-demand" that we are familiar with: users request for personal rides as they wish. *The 1st category* is the traditional taxi service: cars are owned by the company and the supply is fixed; request is made by hailing, calling, etc.; trip fare consists of a fixed starting & unit price. *The 2nd* is ride-sharing service: cars are owned by drivers and the supply is dynamic; request is made from mobile apps; trip fare consists of both dynamic starting & unit price (e.g., the surge pricing of Uber fluctuates based on a function of supply and demand) and the dynamic pricing is embodied by a multiplier (e.g., a multiplier of 2x means that the starting and unit price are twice the normal values). *The last category* goes in between: cars are owned by the company and the supply is largely fixed; request is made from mobile apps; trip fare is dynamic. We call this category as CFDP (Company-owned-fleet, dynamic-pricing) RoD. This category is a response to people's concerns of ride-sharing service's safety and manageability issue, and meanwhile it retains the flexibility brought by dynamic pricing.

Mobile devices are a key enabler of emerging RoD services (i.e., the last two categories). Firstly, passengers use mobile phones to locate both themselves and drivers in requesting for rides. Their locations, behavior (e.g., estimating trip fares, finding nearby drivers, creating orders, using particular features, etc.) and relevant information are recorded by the service provider. Secondly, drivers have their locations uploaded periodically by the on-car mobile GPS devices, notifying both the passengers and the service provider their locations. In short, the use of mobile devices (including mobile phones and GPS devices) enables not only the tracking of locations and behavior of drivers & passengers, but also an in-depth study of such a service from different perspectives.

Compared to taxi, dynamic pricing is also a differentiating feature of the 2nd and 3rd category, and this reflects the effort to manipulate the supply (i.e., the number of cars) and demand (i.e., the number of passengers): a higher multiplier (e.g., 1.5x) reduces demand and increases supply in a busy area, and a lower multiplier (e.g., 0.9x) does the opposite in a not-busy area. More specifically, in ride-sharing service dynamic pricing aims to bring more supply onto the roads when necessary; whereas in CFDP RoD it motivates surplus supply to flow from low-demand to high-demand areas.

The adoption of dynamic pricing sometimes makes passengers hesitate. One would use the mobile app to estimate the trip fare before requesting for a ride. If he/she is unsure about the price, or feels the price is too expensive, the passenger may hesitate, and keep estimating the trip fare multiple times before requesting for a ride. This sort of passengers' reaction does not exist in traditional taxi service as it uses fixed prices. Hence, passengers' reaction (i.e., hesitation before requesting for a ride) is an important and unique indicator of their satisfaction and tolerance of the dynamic prices.

In this paper we present some detailed analysis based on accurate data from a CFDP RoD service provider, which is unique both in terms of the topic and the subject of study (i.e., the CFDP RoD service). The use of mobile devices facilitates data collection. The data could help us understand a service not studied in details before, and the results could also be generalized to other similar RoD services like ride-sharing. Specifically, we inspect passengers' reaction to dynamic prices (in different areas or during different time periods), focusing on two problems: "*what's the pattern of passengers' reaction?*" and "*is it useful to estimate the trip fare multiple times to get a lower price?*".

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II. Related Work

Taxi Service. As a traditional service, it has already been studied extensively, on scheduling [2], pricing [3], driver behavior [4], etc. There are also studies based on a network model [5] and on real trip data [6].

Ride-sharing Service. Fewer efforts have been put on this. For example, the authors in [7] try to evaluate Uber's surge pricing mechanism based on the data they obtain in a black-box way. [8] uses a case study to evaluate the effects of Uber's surge pricing. [9] uses a queueing-theoretic approach to compare the effects of dynamic and static pricing.

III. Dataset

A. Shenzhou UCar

Our datasets are collected from Shenzhou UCar [10]. The CFDP RoD co-exists with ride-sharing service in China, as a complement to tackle its safety and manageability issues. Shenzhou UCar is one of the largest and earliest providers of CFDP RoD service in China, covering more than 50 cities with a fleet of more than 30,000 cars, offering about 300,000 trips per day by the end of 2015 [11].

B. The Event-log Dataset

We collect the event-log dataset to study passengers' reaction to dynamic prices, by writing a proxy in the passengers' app. Usually, a passenger first uses the app on his/her mobile phone to estimate the fare of the intended trip from a particular location *A* to location *B*, triggering an *EstimateFee* event. The estimation could be performed for once or multiple times, until finally he/she creates an order when satisfied with the estimated fare, or gives up if the current dynamic price is too high to accept. A *CreateOrder* event is triggered if the passenger creates an order; and no event is triggered if the passengers gives up. There are many other events corresponding to different passenger behavior, but in our paper we only collect these two for the study of passengers' reaction.

Each entry in this dataset corresponds to a single event and includes the time it happens, the event code (i.e., *EstimateFee* or *CreateOrder*), the IMEI of the passenger's device, location information, the estimated trip fare from *EstimateFee*, etc. This dataset contains about 8.14 million entries during from Nov. 2015 to Mar. 2016 for Beijing alone. Entries are properly anonymized for privacy concern.

C. The Functional Areas

To make our study accurate and representative, we choose Beijing to analyze. It is a large city with many potential passengers, guaranteeing large enough volume of data to study. Also, as a large city, it has a clear partitioning of functional areas. We focus on three categories of functional areas:

- **business area**: the place for working. Different industries (e.g., financial or IT industry) may have different areas.
- **residential area**: the place for living. In China, some large residential areas accommodate $\geq$10,000 residents.
- **transportation area**: Typical transportation areas include the airport terminals, railway stations for inter-city trains.

We choose some representative functional areas from our knowledge, as shown in Fig. 1. For example, for transportation area, we choose the airport and an inter-city train station. We have also mined these areas based on other data, but we omit the data mining methodology because of limited space.

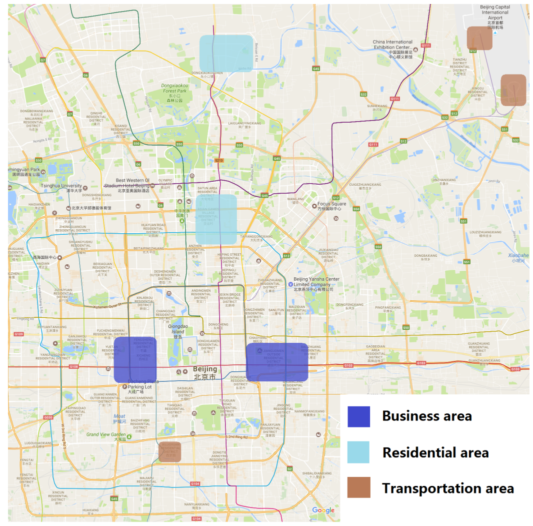

Fig. 1. Selected functional areas in Beijing.

IV. Analysis of Passengers' Reaction

Passengers' reaction is an important and unique indicator of their satisfaction and tolerance of the dynamic prices they experience. In this section, we try to answer two questions: "*what's the pattern of passengers' reaction?*" and "*is it useful to estimate the trip fare multiple times to get a lower price?*".

A. Patterns of Passengers' Reaction

As mentioned in $III-B, we record two events: *EstimateFee* and *CreateOrder*. A passenger's reaction to the dynamic price he/she encounters can be described by a combination of these two events. For example:

- **Scenario 1**: One opens the app and types in the boarding and arriving location of the intended trip, and asks the app to estimate a corresponding trip fare. The estimated trip fare returned by the app is a dynamic value based on the current supply & demand condition. If the passenger is satisfied with the estimation, he/she then creates an order and finds a driver nearby to pick him/her up. In this case, the passenger's reaction to the price could be described as an *EstimateFee* event followed by a *CreateOrder* event.
- **Scenario 2**: The passenger is not satisfied with the fare estimation returned by the app, and chooses to wait for several minutes before estimating the fare again, as he/she is in no hurry. Then after the second estimation, he/she gets a lower fare that is acceptable, and then creates an order. In this case, the passenger's reaction is a *CreateOrder* event following two *EstimateFee* events.
- **Scenario 3**: Similar to scenario 2, the passenger performs three rounds of trip fare estimation. But this time he/she still considers the price too high and decides to switch to

other means of transportation (e.g., bus, metro, etc.). So he/she leaves without any further estimation. In this case, his/her reaction consists only three *EstimateFee* events.

For the ease of representation, we give a letter to each event: **E** for *EstimateFee* and **C** for *CreateOrder*. Then scenario 1, 2 and 3 correspond to **(EC)**, **(EEC)** and **(EEE)**, respectively.

We define a single attempt for a trip as a passenger's reaction from opening the app to finally creating an order, or giving up. And, the *pattern* of an attempt is the series of events in the attempt: **(EC)**, **(EEC)** and **(EEE)** all are *pattern*s.

The pattern of an attempt reveals the extent to which supply is matched with the demand. If a passenger estimates the fare for many times, the fare may be too high to accept, meaning that the demand may be severely high on this location; if a passenger estimates the fare for many times and finally gives up, the trip fare may be even higher. Or, equivalently, the more **E**s in front of a **C**, the higher multiplier a passenger may experience; having an all-**E** pattern like **(EEE)** means that the passenger may receive higher multipliers than having a pattern like **(EEC)**.

In our analysis, we calculate the frequencies and average multiplier range of top patterns, both in the whole city or in selected business/residential areas (shown in Fig. 1). The multiplier "range" is defined on each attempt, and is the ratio of the highest to the lowest estimated trip fare. It could be regarded as the relative dynamic pricing multiplier. The "average range" of a pattern is the average range of all attempts having this pattern. Table. I and II show the top patterns with corresponding frequencies and average ranges, in selected areas and the whole city, respectively.

We also plot the relationship between frequency and ranking for top patterns in business and residential area, and use a power-law function $y = f(x) = ax^b + c$ to fit the relationship, with x being integers representing the ranking and y being the percentage representing the frequency, shown in Fig. 2 & 3:

- Business area: $a = 54.7, b = -1.15, c = -5.646$.
- Residential area: $a = 66.4, b = -0.4842, c = -26.28$.

The fact that the relationship between frequency and ranking for top patterns in business and residential area follows power-law function shows that, on one hand, few patterns occur very frequently. In both cases, only the patterns **(EC)** and **(E)** have high frequencies. On the other hand, the relationship is long-tailed, which means that there are a lot of patterns having much lower frequencies.

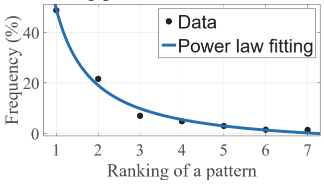

Fig. 2. Business area: frequency v.s ranking.

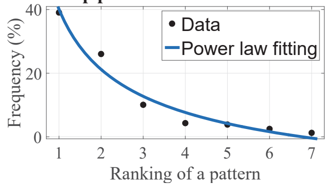

Fig. 3. Residential area: frequency v.s ranking.

The insights are:

TABLE I
TOP PATTERNS IN BUSINESS AND RESIDENTIAL AREAS.

business area			residential area		
pattern	**freq (%)**	**avg range**	**pattern**	**freq (%)**	**avg range**
(EC)	48.70	1.0	(EC)	39.06	1.0
(E)	21.55	1.0	(E)	26.03	1.0
(EE)	6.96	1.13	(EE)	10.07	1.14
(EEC)	4.82	1.18	(EEE)	4.31	1.32
(EEE)	2.94	1.28	(EEC)	3.86	1.19
(EEEE)	1.46	1.53	(EEEE)	2.50	1.44
(EEEC)	1.37	1.72	(EEEEE)	1.26	1.69

TABLE II
TOP PATTERNS IN THE WHOLE CITY.

pattern	freq (%)	avg range
(EC)	39.77	1.0
(E)	25.44	1.0
(EE)	7.89	1.22
(EEC)	4.20	1.19
(EEE)	3.80	1.43
(EEEE)	2.16	1.62
(EEEEE)	1.18	1.79
(EEEC)	1.17	1.47
(EEEEEE)	0.65	1.95

- The percentage of attempts that finally lead to the creation of orders (i.e., having an **C** at the end of the pattern) is 52.33%, 62.52% and 49.28% for the whole city, selected business and residential area, respetively.
- The above insight shows that, in general, in about half of the attempts passengers indeed accept the dynamic prices and create orders. Also, passengers in business areas have a significantly larger probability of accepting trip fares – they are less price-sensitive and more time-sensitive.
- **On average, how long passengers hesitate before creating orders?** For those attempts leading to the creation of orders, the weighted average number of times of fare-estimation is 1.14, 1.14 and 1.09 in the whole city, selected business and residential areas, respectively.
- **On average, how long passengers lose patience and give up?** For those attempts in which finally the passengers give up, the weighted average number of times of fare-estimations before giving up is 1.73, 1.52 and 1.71 in the whole city, selected business and residential areas, respectively. This, again, shows that passengers in business areas are time-sensitive and would not estimate trip fares for many times.
- The relationship between the frequency and ranking of top patterns can be described using a power-law function. There are only a few patterns (in particular, **(EC)** and **(E)**) having high frequencies, and a great many patterns having much lower frequencies.

B. *Is Multiple Estimation Useful?*

We have already analyzed some top patterns of passengers' reaction in the last subsection, and now we change our focus

TABLE III
MULTIPLE ESTIMATIONS FOR PATTERN **(EEC)**.

	on weekdays			on weekends		
area	$1^{st}>2^{nd}$	$1^{st}=2^{nd}$	$1^{st}<2^{nd}$	$1^{st}>2^{nd}$	$1^{st}=2^{nd}$	$1^{st}<2^{nd}$
B	24.8%	45.7%	29.5%	19.9%	46.0%	34.1%
R	25.1%	46.6%	28.3%	20.6%	45.4%	34.0%
T	23.6%	40.1%	36.3%	27.2%	34.4%	38.4%
W	26.9%	44.8%	28.3%	26.5%	43.8%	29.7%

TABLE IV
MULTIPLE ESTIMATIONS FOR PATTERN **(EEEC)**.

area	**1^{st}-lowest**	**2^{nd}-lowest**	**3^{rd}-lowest**	**all-equal**
on weekdays				
B	69.7%	15.1%	15.1%	17.0%
R	69.0%	13.2%	17.8%	20.9%
T	78.6%	11.0%	10.4%	22.0%
W	67.9%	15.7%	16.4%	18.9%
on weekends				
B	72.1%	19.1%	8.8%	19.1%
R	62.9%	14.3%	22.9%	17.1%
T	73.3%	8.9%	17.8%	26.7%
W	69.8%	15.1%	15.1%	18.8%

to go inside some patterns.

In the three example scenarios listed in the last subsection, we can see that sometimes passengers choose to estimate the trip fare for multiple times during a short period, in the hope that the price may go down and becomes acceptable. To be more precise, we regard events whose boarding (or arriving) locations are within 1km-distance as belonging to the same attempt. With this restriction, we find that 95% of event-to-event (belonging to the same attempt) time difference is smaller than 15.4 minutes. In other words, *passengers wait for less than 15.4 minutes before their next fare estimation for the same boarding and arriving location.*

The question we want to answer is "*is it useful to estimate the trip fare for multiple times?*". To simplify our discussion, we only focus on two representative patterns that have multiple fare estimations and meanwhile have non-negligible frequencies (see Table. I and II): **(EEC)** and **(EEEC)**.

In pattern **(EEC)**, we calculate the frequency of having the 1^{st}-estimation strictly higher/lower than (and equal to) the 2^{nd}-estimation. In pattern **(EEEC)**, we calculate the frequency of having the $1^{st}/2^{nd}/3^{rd}$-estimation as the lowest price, and the frequency of having all equal estimations. The results are shown in Table. III and IV. In these tables, we calculate the corresponding frequencies on both weekdays and weekends, in selected business (denoted by "B"), residential ("R") and transportation ("T") areas, and in the whole city ("W").

We have the following observations:

- Most importantly, **performing multiple fare estimations is, in general, not necessary,** no matter on weekdays or weekends, or in particular areas.
- To be more accurate, for the **(EEC)** pattern, only in about 20$\sim$28% attempts the 2^{nd}-estimation returns a lower price; for the **(EEEC)** pattern, only in about 8.8$\sim$22.9% attempts the 3^{rd}-estimation returns the lowest price. On the contrary, in about 28.3$\sim$38.4% attempts of pattern **(EEC)** the 2^{nd} estimation yields a higher price; and for the **(EEEC)** pattern, in about 62.9$\sim$78.6% attempts the 1^{st}-estimation already returns the best price.
- Compared to other areas, a passenger in the transportation area is most likely to get a best price when he/she estimates the fare only once. Equivalently, in the transportation area we always have a higher probability that the 1^{st}-estimation returns the lowest price.
- A passenger in the residential area has a higher probability to indeed get the lowest (or one of the equally lowest) price after multiple fare estimations than those in other areas. But it is still true that only estimating the fare once is already enough.

V. CONCLUSION & FUTURE WORK

Mobile devices are a key enabler in emerging RoD services like Uber: they help to locate and track the behavior of both passengers and drivers, and meanwhile generate huge amount of data. Therefore, we can leverage mobile devices to understand RoD services. We analyze the dataset from a CFDP RoD service provider and present our findings on passengers' reaction to dynamic prices they experience, hoping to provide clues to understand the service from a new and unique perspective. We explore the patterns of passengers' reaction and the dynamic price multipliers a passenger experience during multiple fare estimations, and find out that performing multiple fare estimations is in general not necessary.

The future work is centered on data-driven mechanism design, instead of solely based on a theoretic framework: designing better dynamic pricing algorithm to improve passenger experience & fairness perception.

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