How to eliminate detour behaviors in E-hailing: On-line detection and Pricing regulation

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With the fast development of information and communication technology (ICT), taxi business becomes a typical electronic commerce mode. However, one traditional problem still exists in taxi service, that greedy taxi drivers may deliberately take unnecessary detours to overcharge passengers. The detection of these fraudulent behaviors is essential to ensure high-quality taxi service. In this paper, we propose a novel framework for detecting and analyzing the detour misbehaviors both in off-line database and among on-line trips. Applying our framework to real-world taxi data, a remarkable performance \((\textit{AUC} > 0.98, 100\% \text{ of detour trajectories can be detected at less than 10\% false alarm rate})\) has been achieved in off-line phases, meanwhile, an excellent precision \((\textit{AUC} > 0.9)\) also has arrived in on-line detection. In additional, some constructive suggestions upon pricing regulation are also provided to control the happening of detours. Finally, some commercial value-added applications in DiDi benefited from our method have yielded good results to improve the map service.

Index Terms—Taxi trajectory, GPS data, Behavior analysis, Detour detection.

I. INTRODUCTION

In recent years, the advances in sensing, communication, storage and computing have changed our life in various aspects. One representative is the widely used online ride-hailing platforms, such as Uber, Lyft and DiDi, which redefine the industry of taxi service. The scale and richness of different digital trajectories collected by these platforms provide us with opportunities to understand social behaviors and community dynamics in different contexts, showing great potential to revolutionize the services in various areas ranging from public safety, urban planning to transportation management [1].

In modern cities, taxi service is a typical electronic commerce mode which is supervised by Global Positioning Systems (GPS) and online ride-hailing systems. According to the 2018 statistics, there are over 100,000 taxis running every day in Beijing, and about 70,000 in Shanghai. Therefore, gathering and analyzing these large-scale taxis trajectories have provided us with a great opportunity to reveal the hidden facts about city dynamics and human behaviors [2]. Moreover, lots of value-added applications, such as transportation management, city planning, and personalized services, could benefit from big data analysis over taxis GPS data sets.

For a long time, taxi service has been facing a typical challenge that greedy taxi drivers who overcharge passengers may deliberately take unnecessary detours, especially when passengers travel in unfamiliar cities. Currently, experienced staff are responsible for detecting taxi driving frauds via manually checking the corresponding taxis trajectories based on feedbacks from passengers. However, it is extremely difficult for these staff to supervise the suspicious taxis trajectories based on feedbacks from passengers. However, it is extremely difficult for these staff to supervise the suspicious taxis trajectories based on feedbacks from passengers. Moreover, lots of value-added applications, such as transportation management, city planning, and personalized services, could benefit from big data analysis over taxis GPS data sets.

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After reviewing existing studies on anomalous trajectory detection, it is not difficult to find that all these previous studies focus on detecting anomalous behaviors on trip-based level. When considering how to control and eliminate these detected anomalies, we find that all these methods are discussing how to discover the problems rather than how to restrain the happening of anomaly. Moreover, the majority of these studies concentrate on providing a global evaluation of given trajectory, however, new questions have arisen for trajectory mining technique, e.g. Which parts of the trajectory are responsible for the anomalies? Why do the drivers take an anomalous trace, subjectively or unintentionally? To gain a more comprehensive understanding of these cases, more-refined detection, especially studying the anomalous behaviors of drivers in each segment, needs to be conducted to discover more details. Note that more-refined detection will be much beneficial for distinguishing the trajectory outliers caused by road network changes or drivers purposes. In addition, the most studies of taxi trajectory detection focus on certain...
OD pattern, which means the anomalous trajectories will be detected given the origin and destination \(5, 6, 11\). While applying detection technique to on-line framework, the distribution of trips OD in real-world is extremely flexible and some unfinished trips destination may be changed in the future. To utilize a finitely known information to achieve an accurately monitoring, a real-time framework should be elaborately established to integrate a variety of information.

In view of these challenges, we propose a framework to discover the anomaly both in off-line database and among online trips. According to our frameworks, two mechanisms including real-time warning and price policy has been introduce in the following phases to eliminate the detour behaviors. In summary, the major contributions of our paper are showed below:

1. By extracting the distanced-based feature and time-based feature in off-line phases, the proposed method naturally falls into the category of supervised learning. Implementing the logistic regression model, the proposed method has proved achieving a remarkable performance by using millions of real-world taxi data.

2. Based on aforementioned off-line model, we further employ the estimated parameter to conduct an on-line detection and propose a real-time warning mechanism. Applying these technique to the on-line experiments, our proposed method ultimately arrives at an excellent precision for giving a warning to the anomalous drivers.

3. In order to eliminate the detour behaviors in a long-term, we also conduct a comprehensive discussion upon pricing mechanism in E-hailing platforms. After extensive experiments, several suggestions upon pricing regulation also have been given to motivate drivers to avoid detours.

3. Last but not least, the statistical data generated by our method can be used to diagnose the changes of road network and evaluate the drivers behaviors, which proves our method can be used for innovative applications with wide commercial values.

The rest of paper is organized as follows. First, we give a preliminary knowledge and problem statement in Section 2. Then the Framework consisting of off-line classification, online detection and pricing regulation is elaborated in Section 3. Quantitative and qualitative experiments results are presented in Section 4 and two innovative applications are described in Section 5. Finally, we conclude our work in Section 6.

II. PROBLEM FORMULATION

In this section, notations used in this paper will be first introduced. A single-mode road network is represented by a directed graph \( G = (N, S) \), which includes a node set \( N \) and a link set segment \( S \). There are some important concepts defined as follows:

**Definition 1:** A segment segment, \( s \in S \) is a basic unit generated by intersected nodes in \( N \), and each segment in the road network will own a specific direction.

For a better understanding, Figure 1 presents the road network model near Beihang University, Beijing. The red points A and B stand for the intersections of streets, thus, the link between A and B is a standard segment in this paper.

**Definition 2:** A GPS point \( p \) is denoted by a triple \( \langle \text{lat}, \text{lng}, \text{timestamp} \rangle \), which stands for the latitude, longitude and the GPS generation time of \( p \).

**Definition 3:** A taxi trajectory \( tr \) is a series of GPS points which are generated by an occupied taxi and then ordered by timestamp,

\[
tr = \{p_1, p_2, ..., p_m\}
\]

Obviously, for this trip \( p_1 \) is the origin position and \( p_m \) is the destination position.

Because the GPS information is updated in a couple seconds, one taxi trajectory may contain hundreds (or even thousands) of records, which are mostly redundant in identifying the trip. To reduce the complexity of calculation, we match the taxi trajectory data with a successive segment series of the road network, namely, transforming \( tr = \{p_1, p_2, ..., p_m\} \) into a series of ordered segments. One of the most popular map matching algorithms is **Hidden Markov Model** which finds the most possible sequence of status given a sequence of observations \(12\). Adopting this method, we can transfer the taxi trajectory into abstract trajectories, which is defined below.

**Definition 4:** An abstract trajectory \( atr \) is a series of segments that are generated by the map matching process.

\[
 atr = \{s_1, ..., s_i, ..., s_n\}
\]

where \( s_i \) indicates the \( i \)-th segment unit in the trajectory.

To provide E-hailing drivers with real-time traffic guidance, the online ride-hailing platforms will automatically update the route plan at each part of trajectory to guide the taxi driver with dynamic shortest path \(19, 20\). For instance, in Figure 2 we can observe that the system will generate route plan with an ongoing trip. By monitoring the changes among each route plan, the managers of the platforms can get valid evidence on the behaviors of drivers. Thus, the route plan is defined below.

**Definition 5:** A one-off route plan \( r \) is a series of segments generated by the platforms.

\[
r = \{s_{r1}^1, ..., s_{rj}^j, ..., s_{rj}^v\}
\]

where \( s_{rj}^j \) indicates the \( j \)-th segment unit in the route plan \( r \).

**Definition 6:** Given \( atr = \{s_1, ..., s_i, ..., s_n\} \), a route plan set \( R \) is a set of route recommendations provided for this trip.
In other words, each abstract trajectory \((atr)\) has a route plan set \((rp)\), which is sorted by created time.

\[
R = \{r_1, ..., r_i, ..., r_n\}
\]

where \(r_i\) is the corresponding route plan at \(s_i\), intuitively, \(s_i^1 = s_i\).

After assigning the GPS points to segments and introducing the route plans, we will handle with \(atr\) and \(rp\) in the rest of this paper. Our goal is to discover the anomalous segments in the trajectory and identify the detour behaviors among the trips. Formally, the problem is defined as below.

**Problem:** Given the trajectory \(atr = \{s_1, ..., s_i, ..., s_n\}\) and its corresponding route plans \(RP = \{r_1, ..., r_i, ..., r_n\}\), several problems in this paper will be solved includes:

- **Off-line classification:** This implies that the method should have a high detection accuracy and a low false alarm rate to classify the detour trips and normal trips via off-line data-set.
- **On-line detection:** With the real-time updating of trajectory and route plans, we should further to provide real-time indicator to monitor the on-going trajectory.
- **Long-term regulation:** From the perspective of long-term, we should discover the primary causes of detour behaviors and offer the platforms some suggestions to restrain the happening of detour.

Complete notations which will be used in the subsequent analysis are listed in Table I.

### III. Methodology

Having defined the necessary notations and stated the problem, we present the detour detection method in this section. As shown in Figure 3, the method consists of four phases. The focus of the first phase is data preparation. The result of data pre-processing is helpful for detour trajectory detection which is investigated in the second phase. The second phase aims to conduct an off-line classification based on the previous processed data including addressing anomaly, qualifying abnormal parts, evaluating the trip and LR-based categorizing. After developing an off-line model to discover detour trips, we further propose an off-line detection mechanism and pricing regulation to eliminate the detour behaviors from the perspective of platforms.

#### A. Data preparation

With the large amount of taxi trajectories consisting of mass GPS points, valid taxi OD pairs can be extracted.

| Table I | NOTATIONS |
|---------|-----------|
| Variable | Explanation |
| \(s\)   | Road segment |
| \(p\)   | GPS point, \(p = \langle lat, lng, timestamp \rangle\) |
| \(tr\)  | Trajectory, \(tr = \{p_1, p_2, ..., p_m\}\) |
| \(atr\) | Abstract trajectory, \(atr = \{s_1, ..., s_i, ..., s_n\}\) |
| \(r\)   | One-off Route plan, \(r = \{s_1^r, s_2^r, ..., s_q^r\}\) |
| \(\epsilon\) | Destination changing probability |
| \(R\)   | Route plan of given trajectory \(atr\), \(R = \{r_1, ..., r_i, ..., r_n\}\) |
| \(\Omega\) | Set of anomalous segments, \(\Omega = \{s_i, \ldots\}\) |
| \(D\)   | Set of anomalous distance of given \(\Omega\), \(D = \{d_i, \ldots\}\) |
| \(T\)   | Set of anomalous segments of given \(\Omega\), \(T = \{t_i, \ldots\}\) |
| \(TR\)  | Set of historical trajectory, \(\forall tr \in TR\) |
| \(TR^*\) | Set of labeled detour trips |
| \(U\)   | Utility of E-hailing drivers |
| \(\Theta\) | Indicator of log-odds in categorizing model |
| \(\delta\) | Proportion of detours in a given trajectory set |
| \(f_0, d_0, t_0\) | Base fare, begin-charged distance and begin-charged time |
| \(K, K_0\) | Actual destination, initial destination of trajectory \(atr\) |
| \(\Delta d, \Delta t\) | Unit distance and unit time |
| \(\alpha_1, \alpha_2\) | Fare rate per unit distance and per unit time |
| \(\alpha_3, \alpha_4\) | Operating cost of unit distance, opportunity cost of unit time |
| \(K, K_0\) | Actual destination, initial destination of trajectory \(atr\) |
| \(X^{(1)}, X^{(2)}\) | Ratio of detour distance; Ratio of delay time |
| \(\beta_0, \beta_1, \beta_2\) | Coefficients to be estimated in categorizing model |
| \(\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2\) | Estimated coefficients from categorizing model |

**Fig. 3.** Overview of our method
These historical trajectories and corresponding route plans could provide platforms with a strong evidence for identifying drivers abnormal behaviors.

As shown in Figure 3, we firstly collect the dataset of GPS points for target cities. Secondly, applying the map matching method, we transform dataset of GPS points into a series of segments and obtain the set of atr. Then we extract the corresponding route plans route plan based on trajectory id from the database. Therefore, we can obtain a structured mapped indexing table $T_{trace}$ that contains three columns, atr identifier, the abstract trajectory atr and the route plans route plan. Hence, we define a function $query(\text{atr id})$, which could easily get a collection of atr and route plan from $T_{trace}$ when a certain trajectory identifier information is given. For instance, suppose there is an existing atr and $RP = \{r_1, ..., r_8\}$ as shown in Figure 2, we can obtain the $T_{trace}$ shown in Table II

### Table II

| atr id | atr | route plan |
|-------|-----|------------|
| 001   | $\{s_1, s_2, ..., s_8\}$ | $\{r_1, r_2, ..., r_8\}$ |

B. Off-line classification

In this part, we will discuss how to categorize off-line trajectory as normal trip or detour trip. According to the processed data, four phases including addressing anomaly, qualifying abnormal parts, evaluating the trip and categorizing will be conducted below.

1) Addressing anomalous segments

Before trying to detect the detour trajectory, we need to address the anomalous segments which cause deviations in the trajectory atr. It is obvious that an inconsistency between current segment and the next segment in previous route plan will result in a deviation. Therefore, we define the set $\Omega$ to pick out all of anomalous segments in given trajectory below:

**Definition 7:** Given the $T_{trace}$, $\Omega = \{s_i, \ldots\}$ is extracted as a set of anomalous segments. The $s_i$ filtered into $\Omega$ should satisfy the following constraint:

$$s_i \neq s_2^{r_i-1}, \forall i \in \{2, ..., n\}$$ (1)

Equation (1) indicates the current position $s_i$ deviates from the schedule $s_2^{r_i-1}$ at the previous step $s_{i-1}$. Take Figure 2 as an example, when the trip arrives at $s_3$, the driver choose a different route rather than original plan, in other words, $s_3 \neq s_2^2$.

After extracting the anomalous set $\Omega$, now we have an efficient mechanism to look for the anomalous segments in the trajectory. The main purpose of the following stage is to provide a score quantifying the anomalous degree of the segments in the $\Omega$.

2) Qualifying anomalous segments

In practice, there will exist a significant difference between the previous and current route plans located at anomalous segment. Both two scenarios in Figure 4 depict that a driver takes a new route rather than following the previous route plan, while after a lap of inconsistent segments, the current route plan usually coincides with the previous deviated route plan because the destination is unchanged. In detail, Figure 4 A reflects a long detour occurs, while Figure 4 B depicts that the driver take a shortcut compared to previous route plan.

In order to characterize the anomaly degree of each anomalous segment in $\Omega$, we need to take both the route distance and travel time occurred at each segment into account, and the principal idea of this method is to comparing the difference between the current $r_i$ and the previous $r_{i-1}/\{s_{i-1}\}$ in terms of distance level and time level. Therefore,

**Definition 8:** Given the $\Omega = \{s_i, \ldots\}$, $D = \{d_i, \ldots\}$ is the set of anomalous distance and $T = \{t_i, \ldots\}$ is the set of anomalous time occurring at each anomalous segment in $\Omega$, respectively. Here, $d_i$ and $t_i$ can be denoted as follows:

$$d_i = Dist(r_i) - Dist(r_{i-1}) + Dist(s_{i-1})$$ (2)

$$t_i = Et(r_i) - Et(r_{i-1}) + Et(s_{i-1})$$ (3)

where $Dist(\cdot)$ indicates the function calculating the sum of network (topology) distance, and $Et(\cdot)$ represents the function calculating the estimated travel time. In practice, we just simply assume that we have sufficient taxi trajectories to estimate the travel time among the specific segment sections, and then we employ the Wide-Deep-Recurrent (WDR) learning model [14] to solve it.

Intuitively, Equation (2) imposes that $d_i$ is the difference between the remaining distance $Dist(r_i)$ and the previous distance $Dist(r_{i-1}) - Dist(s_{i-1})$. Equation (3) computes the $t_i$ which is the estimated travel time difference between $r_i$ and $r_{i-1}/\{s_{i-1}\}$ during the current time. The advantage of using this measurement is that it contributes to exactly identifying the deviation behaviors such as avoiding congestion, experienced choices and so on. Hence, we can easily observe three kinds of scenarios of $d_i$ and $t_i$ as follows:

- If $d_i > 0$ and $t_i > 0$, we can observe the deviation occurring in $s_i$ leads to a worse condition, which means more travel distance and more time-consuming.
- If $d_i > 0$ or $t_i > 0$, the deviation occurring in $s_i$ results in complex situations and needs further discussions.

a) The driver chooses another longer route to avoid the traffic jam compared to the initial route plan ($d_i > 0$ and $t_i < 0$).
b) The driver thinks he takes a shortcut compared to the original plan, but unfortunately, he cuts off in traffic ($d_i < 0$ and $t_i > 0$).

- if $d_i < 0$ and $t_i < 0$, it’s obvious the driver takes a better route.

3) Evaluating the trip

Upon the previous stages, we have updated the anomalous segments set $\Omega$ and obtained the deviation distance and travel time on each segment in $\Omega$. After $atr$ has finished, we need further to provide a holistic evaluation by summarizing both $D$ and $T$ of the given trajectory.

In reality, however, we should note that some deviations occurring at the tail of the trajectory probably construct a strong noise to misjudge the driver’s purpose. As shown in Figure 5, A-D, the driver heads for an actual destination $K$ in Figure 5 D compared to initial setting $K_0$ without advance reports to the system. In this case, the purposes of drivers deviations can be fallen into several kinds: changing to a totally different destination, choosing an accessible place to drop off, etc. As a consequence, it’s meaningless to pay attention to these anomalous segments (i.e. in Figure 5 B and D) at the tail due to the inaccurate destination.

Further employ Tail filtering algorithm to cut off the noises at the tail of $atr$ and update $\Omega$.

Given the way the ongoing score $D$ and $T$ is computed, once the trip has finished and $\Omega$ has been modified, the distance-based feature $X^{(1)}$ and the time-based feature $X^{(2)}$ of the given trajectory $atr$ can be defined as:

$$X^{(1)} = \begin{cases} 0 & \text{if } \Omega = \emptyset \text{ or } \epsilon < \bar{\epsilon} \\ \frac{\sum_i d_i}{\text{Dis}(atr)} & \text{Otherwise} \end{cases}$$

$$X^{(2)} = \begin{cases} 0 & \text{if } \Omega = \emptyset \text{ or } \epsilon < \bar{\epsilon} \\ \frac{\sum_i t_i}{\text{At}(atr)} & \text{Otherwise} \end{cases}$$

where $\text{At}(atr)$ represents the actual travel time of $atr$.

In summary, we have so far merged the anomalous distance $d_i$ and anomalous travel $t_i$ to get the holistic distance-based feature $X^{(1)}$ and time-based feature $X^{(2)}$. Given a trajectory, $X^{(1)}$ can be treated as the ratio of detour distance and $X^{(2)}$ can be treated as ratio of delay time.

4) Logistic regression based categorizing

Logistic regression (also known as logit model) is widely used to model the outcomes of a categorical dependent variable [16]. Logistic regression measures the relationship between the categorical dependent variable and one or more independent variables by estimating probabilities using a logistic function, which is the cumulative logistic distribution. And in this paper, we have discussed how to compute a distance-based feature $X^{(1)}$ and a time-based feature $X^{(2)}$, hence we further apply the logistic regression model to categorizing the detour and non-detour trips.

Provide that the detour indicator is a discrete variable $Y_j$ ($Y_j = 1$ represents a detour trip) with factors $X_j = (X_j^{(1)}, X_j^{(2)})$ as independent variables, an logistic model can be written in terms of cumulative probability of a specific detour indicator for a given set of factors $X_j$:

$$P(Y_j = 1|X_j) = \frac{1}{1 + e^{\beta_0 + \beta_1 X_j^{(1)} + \beta_2 X_j^{(2)}}}$$

Apply logit transformation to the cumulative probability we have:

$$\ln \frac{P(Y_j = 1|X_j)}{1 - P(Y_j = 1|X_j)} = \beta_0 + \beta_1 X_j^{(1)} + \beta_2 X_j^{(2)}$$

where $P(Y_j = 1|X_j)$ is called the odds, which represents the ratio of the probability of detour to the probability of non-detour. Similarly, $\ln \frac{P(Y_j = 1|X_j)}{1 - P(Y_j = 1|X_j)}$ is a log-odds, which is denoted as $\Theta_j$. In the rest of paper. Having transformed the probability into a log-odds, the logit function linearizes the association between the probability and independent variables. In this context, the model is a generalized linear model.

Though as a generalized linear model, simple linear regression estimation methods like least-squares estimation are not applicable. The maximum likelihood estimation (MLE) is applied instead. The log-transformation is widely used to deal with the likelihood function in practice. Therefore, if we set

$$\bar{\epsilon} = 1 - \frac{\text{Euc}(K, K_0)}{\text{Dis}(atr)}$$

where $\text{Euc}(A, B)$ represents the function acquiring the Euclidean distance between $A$ and $B$.

In this paper, the probability threshold $\bar{\epsilon}$ is empirically introduced, which aims to identify the purposes of drivers’ deviations. If $\epsilon < \bar{\epsilon}$, we think the driver wants to go to an entirely different destination $K$, so we dont research these special cases in this paper. Nevertheless, if $\bar{\epsilon} \leq \epsilon \leq 1$, we consider difference between $K$ and $K_0$ is caused by accessibility (parking, traffic rules and so on) of the destination $D$ rather than changing destinations. Under this circumstance, we further estimate $\beta_1$ and $\beta_2$ using logistic regression model.
\( P(Y_j = 1 | X_j) = h(X_j) \), then we have a log-likelihood function:
\[
L(\beta) = \sum_{n=1}^{N} [Y_j \times \ln(h(X_j)) + (1 - Y_j) \times \ln(1 - h(X_j))] \quad (9)
\]

The MLE method is thus deduced as:
\[
\hat{\beta} = \text{argmax} \quad L(\beta) \quad (10)
\]

Common optimization techniques are used in order to solve the MLE method involve Gradient Descent Algorithm and Quasi-Newton Methods. In this paper, for brevity, optimization algorithm is not provided. Alternatively, we can solve the above model by function LogisticRegression of Scikit-learn package from Python.

C. On-line detection

In this part, we will further discuss how to monitor the anomalous behavior in real time. Along with the movement of the trajectory, the sets \( \Omega, D, T \) will be updated according to all known information at every timestamp. Therefore, given the \( atr \) = \{s₁, ..., s₄\} at timestamp on \( s₁ \), the latest \( X_i^{(1)} \) and \( X_i^{(2)} \) at \( s₁ \) can be calculated below:
\[
X_i^{(1)} = \frac{\sum_D d_i}{\text{Dis}(atr)} + \text{Dis}(ri) \quad (11)
\]
\[
X_i^{(2)} = \frac{\sum_T t_i}{\text{At}(atr)} + \text{Et}(ri) \quad (12)
\]

We should note that \( \text{Dis}(atr) \) in Equation 5 will be replaced by \( \text{Dis}(atr) + \text{Dis}(ri) \) since the trip is unfinished. Also, \( \text{At}(atr) \) will be switched to \( \text{At}(atr) + \text{Et}(ri) \) to estimate the overall travel time. After then, we can calculate log-odds \( \Theta_i \) at current segment \( s₁ \):
\[
\Theta_i = \hat{\beta}_0 + \hat{\beta}_1 \times X_i^{(1)} + \hat{\beta}_2 \times X_i^{(2)} \quad (13)
\]
where \( \hat{\beta}_0, \hat{\beta}_1 \) and \( \hat{\beta}_2 \) can be estimated from off-line categorizing model from equation 10.

As a consequence, the latest log-odds \( \Theta_i \) should be treated as a significant indicator to detect the driver’s behavior:

- If \( \Theta_i > 0 \), it’s obvious that the on-going trip has fall into the category of detour. Therefore, in our on-line detection setting, a warning will be triggered as a form of sending message when \( \Theta \) has exceeded 0.
- Otherwise, the on-going trip will be treated as a normal case, and it should note that If there exists any warning message generated at the previous section, as a consequence, the platform will cancel the warning and inform the driver.

As cases depicted in Figure 6, the driver refused the initial route plan \( r₃ \) at \( s₄ \), afterwards he will receive a warning because the log odds of \( s₁ \) had exceeded the base line \( \Theta = 0 \). Nevertheless, the driver deviated from \( r₆ \) as well, after that the log odds were back to normal level and the warning would be cancelled.

In E-hailing companies, the analysis of taxi driver behavior based on our online detection method could provide an efficient evaluation of the drivers performance. Meanwhile, our online detection method could help E-hailing companies build a good service environment with fine, self-disciplined taxi drivers.

D. Long-term pricing regulation

From perspective of long-term, it is necessary to note that pursuing higher income might be the primary cause of detour trips. Therefore, rather than on-line detection, regulating proper fare rate will exert a significant influence on the drivers’ income level, further eliminate the number of detours happening in a long-term. In order to detect these deliberate misbehaviors related to drivers’ income, we may discuss the pricing mechanism in E-hailing platform at first, a price-wise linear fare structure has been widely used in taxi industries as below:
\[
f(atr) = f₀ + α₁ \times H(Dist(atr) - d₀) \times [Dist(atr) - d₀] + α₂ \times H(At(atr) - t₀) \times [At(atr) - t₀] \quad (14)
\]
where \( f₀ \) denotes the base fare if the total distance and the overall travel time do not exceed \( d₀ \) and \( t₀ \), respectively. Moreover, \( α₁ \) and \( α₂ \) represent the fare rate per unit distance and per unit time, respectively. And we introduce the Heaviside function \( H(\cdot) \) to identify whether the distance or the travel time reach the charging standards.

To conduct a deep analysis upon anomaly related to income, we define a utility function \( U \) of a driver gain some basic understanding of the detour behaviors:
\[
U = α₁ \times Δd + α₂ \times Δt - α₃ \times Δd - α₄(f₀) \times Δt \quad (15)
\]
where \( Δd \) and \( Δt \) are the unit of distance and time, respectively. \( α₃ \) represents the coefficient of operating costs per unit distance, and \( α₄ \) indicates the loss of opportunity cost per unit time, which depends on the base fare \( f₀ \).

By introducing a utility function \( U \), we can have a quantified indicator of a detour behavior in term of its monetary revenue. If the driver takes a detour (increase of \( Δd \) and \( Δt \)), he will receive a monetary income \( α₁ \times Δd + α₂ \times Δt \), while pay for a fuel cost \( α₃ \times Δd \) and opportunity cost \( α₄(f₀) \times Δt \). As a consequence, the changes of detour utility will have a significant influence on driver’s intention upon detour or not.

IV. RESULTS AND EXPERIMENTS

A. Data collection

In this study, we randomly select December 1th to 31th, 2018 and then choose floating-car datasets of these days from
TABLE III
STATISTICS OF OFFLINE DATASET

| City    | Beijing | Shanghai | Guangzhou | Shenzhen |
|---------|---------|----------|-----------|----------|
| | [TR] (million) | > 1 | > 0.5 | > 0.5 | > 0.5 |
| Driver (ten thousand) | > 3 | > 3 | > 3 | > 3 |
| [TR] | 41227 | 27236 | 17747 | 21281 |
| Period | 2018/12/01-2018/12/31 |  |  |  |
| Training(%) | 40 |  |  |  |
| Testing (%) | 60 |  |  |  |

TABLE IV
OUTPUTS FOR THE LOGISTIC REGRESSION MODEL

| City    | Variable | Coefficient | Standard Error | Chi-Square | P-value |
|---------|----------|-------------|----------------|------------|---------|
| Beijing | Intercept | -8.5007 | 0.771 | -11.023 | 0.000 |
| | X^(1) | 36.9544 | 4.574 | 8.078 | 0.002 |
| | X^(2) | 33.0331 | 3.606 | 9.160 | 0.000 |
| Shanghai | Intercept | -8.2178 | 0.726 | -11.316 | 0.000 |
| | X^(1) | 35.4515 | 4.046 | 8.047 | 0.000 |
| | X^(2) | 32.0177 | 3.337 | 9.745 | < 0.001 |
| Guangzhou | Intercept | -9.3522 | 0.919 | -10.286 | 0.000 |
| | X^(1) | 43.2472 | 4.820 | 8.972 | 0.000 |
| | X^(2) | 36.2770 | 3.930 | 9.231 | 0.000 |
| Shenzhen | Intercept | -8.9822 | 0.871 | -10.313 | 0.000 |
| | X^(1) | 36.2151 | 4.362 | 8.302 | 0.000 |
| | X^(2) | 34.4427 | 4.132 | 9.309 | 0.000 |

four major cities (Beijing, Shanghai, Guangzhou, Shenzhen). After removing the abnormal cases with very short travel time (< 60s) or extremely high travel speed (> 120km/h), we obtain about millions of samples. Combining with passengers feedbacks and historical manual verification (customer response system in DiDi), all the trips can be labeled as detour or not. Table III lists the statistics of these four datasets. Meanwhile, the parameter τ is an empirical value set to 0.01 according to the recommendations of experienced experts from DiDi Chuxing.

B. Off-line model evaluation

The results of the logistic regression model are presented in Table IV. The results show that the coefficients of $X^{(1)}$ and $X^{(2)}$ differ across different cities, but signs of the coefficients remain positive, and the p-values show that both distance-based variable $X^{(1)}$ and time-based variable $X^{(2)}$ are significant. The aforementioned analysis is consistent with the reality. Moreover, the classifying boundaries of four cities are depicted in Figure 7.

The evaluation for the model in this paper is using the $AUC$ (Area Under ROC Curve). In practice, true positive rate $TPR$ (the fraction of anomalous data that is successfully detected) and false positive rate $FPR$ (the fraction of normal ones that is predicted to be anomalous) are two important measures to evaluate the performance of an anomaly detection method. Obviously, a good anomaly detection method should have both high $TPR$ and low $FPR$. The $ROC$ curve shows the $TPR$ (y-axis) against the $FPR$ (x-axis), and the $AUC$ value is defined as the area under the $ROC$ curve. Figure 8 depicts the $ROC$ curves of proposed method on four datasets in Table V. We can find that the proposed method is able to achieve high detection rate whilst keeping low false alarm rate. For all datasets, over 90% of detour trajectories can be detected at a 10% false alarm rate.

Without loss of generality, a typical comparison analysis is also conducted, we compare the $AUC$ value of LR with the iBAT method as shown in Table V, we can see that LR achieves quite high $AUC$ values (> 0.97 on all datasets) and the iBAT method achieves lower $AUC$ values (< 0.94 on all datasets), suggesting that the logistic method under our framework outperforms the iBAT method to detect the detour behaviors. This is due to the fact that iBAT suffers from the problem of data sparsity, if a trajectory is infrequent, its difficult to detect outlier based on the theory of similarity. While our method can overcome this obstacle to achieve a remarkable performance by combining the corresponding route plan information.
TABLE V
THE AUC VALUE OF LR AND iBAT METHOD

| City       | Beijing | Shanghai | Guangzhou | Shenzhen |
|------------|---------|----------|-----------|----------|
| LR         | 0.9747  | 0.9833   | 0.9825    | 0.9758   |
| iBAT       | 0.9327  | 0.9228   | 0.8935    | 0.9324   |

C. On-line detection performance

To evaluate the effectiveness of the on-line detection phase, we divided a trip into ten stages in terms of its completeness. Based on the statistics of warned trips quantity among each stage, we plot the AUC of each stage in the Figure 9. There are two interesting discoveries in the figures: Firstly, the warned trips quantity dramatically increase among the first 50% stages, in other words, the majority of detour behaviors may happen in the first half of the trip. Secondly, due to the limited information known in the first 50% stages, AUCs are not very high (less than 0.8) and there will exists lots of misjudged warnings. However, with going of the trip, the majority of misjudged warnings will be cancelled in our on-line mechanism and ultimately AUCs will achieve an excellent performance (AUC > 0.9) at the tail stages.

Fig. 9. The AUC of warned trips of online detection in four cities

D. Pricing policy

To describe the detour behaviors happening in each time interval, we define a detour proportion \( \delta \), which is the ratio of detour quantity and total quantity, as follow:

\[
\delta = \frac{|TR^*|}{|TR|}
\]

Figure 10 displays the changes of trip quantity and detour proportion \( \delta \) under different time interval in a day. As intuition suggests, all the trend of quantity in four cities show the evening-peak trend (among 17:00-19:00) and off-peak trend in early hours (among 3:00-5:00). While, as a sharp contrast, the detour proportion \( \delta \) climbs at the peak in early hours then gradually decreases and tends to some small fluctuations in the daytime.

To explain the changes of detour proportion \( \delta \), we further investigate the total income of drivers and on-duty drivers quantity in a day. As intuitively presented in Figure 11, the total income arrives at the high value during the morning-peak and the evening-peak. However, since a lower demand quantity and fewer drivers, it drops sharply in early hours (among 3:00-5:00). Therefore, we can figure out \( \alpha_4 \) as the average income per time unit of all drivers from aforementioned statistic.

![Fig. 10. Detour Distributions under different time interval in a day](image-url)

As we have mention above, each driver will have a detour utility from equation 15 so we can provide a statistic of
average utility in Figure 12. Meanwhile, to evaluate the gains of detour behaviors, the $\alpha_4$ has been also depicted in Figure 12 to give a comparison with detour utility. Consistent with a low detour proportion mentioned above, the detour utility approaches to $\alpha_4$ during daytime, in other words, taking a detour during daytime may have little effect on increasing monetary income. Contrast to our daytime, the detour utility is far beyond $\alpha_4$ during early hours and mid-night, which means that deliberate detour could bring much more profit than normal driving.

To give a intuitive suggestion, we introduce a piece-wise linear approximation to describe how detour proportion $\delta$ changes with detour utility $U$ among each time interval:

$$\delta = k \times U + b$$  \hspace{1cm} (17)

where $k, b$ are parameters to be estimated, and Figure 13 shows the approximated function in four cities, the statistic of estimated $k, b$ is listed in Table VII.

| city       | $k$  | $b$  | intercept of $U$ |
|------------|------|------|------------------|
| Beijing    | 6.06 | -1.76| 0.29             |
| Shanghai   | 6.99 | -2.15| 0.36             |
| Guangzhou  | 3.82 | 0.16 | -0.04            |
| Shenzhen   | 2.14 | 2.04 | -0.95            |

The first interesting observation is that the estimated bs of Guangzhou and Shenzhen are larger than 0, which means that there still exists some drivers to take detour although they are unable to receive more profit ($U = 0$). Not surprisingly, another points happening in Beijing and Shanghai are that there are no detours if $U$ less than a threshold, which equals to the intercept of $U$ axis depicted in Table VII. In above cases, the platform could increase $f_0$ in these cities to raise $alpha_4$ of all drivers, as a result, detour drivers will receive a less (even negative) utility compared to the previous condition. By this means, the platform can stimulate drivers in these cities to take a normal trip in order to maintain their income level.

V. APPLICATIONS

From the perspective of platforms, the method presented in this paper also has wide commercial value for optimize map services, such as identifying the changes of road network and recommending a better routes. To achieve this goal, we utilize the conditional probability of refusing route plan:

$$\lambda(\times | r) = \frac{\lambda(\times, r)}{\lambda(r)}$$  \hspace{1cm} (18)

where $\lambda(r)$ denotes the probability that system provides the route plan route plan, and $\lambda(\times, r)$ is the probability that driver takes a different route compared to given route plan. In reality,
\( \lambda(r) \) and \( \lambda(\times, r) \) can be estimated by using the historical trip data.

On the contrary, the road sections with low \( \lambda(\times|r) \) will indicate detour is more likely caused by drivers behaviors (taking a roundabout route or violating the rules) rather than road conditions. Having applied the above processes to evaluate the drivers performance on DiDi platform for a month, above 60% misbehaviors of drivers are reduced.

**VI. CONCLUSION**

In this paper, we have investigated the problem how to eliminate the detour behaviors in E-hailing platforms, which is motivated by the fact that anomalous trajectories can reveal many hidden facts about the city dynamics and human behaviors. To solve the problem, we propose a novel framework for detecting and analyzing the detour misbehaviors both in off-line database and among on-line trips. Applying our framework to real-world taxi data, a remarkable performance (\( AUC > 0.98 \), 100% of detour trajectories can be detected at less than 10% false alarm rate) has been achieved in off-line phases, meanwhile, an excellent precision (\( AUC > 0.9 \)) also has arrived in on-line detection. In additional, after conducting extensive experiments, some constructive suggestions upon pricing regulation are also provided to control the happening of detours. Finally, two commercial value-added applications in DiDi benefited from our method have yielded good results to improve the taxi service.

In the future, more real-world applications, such as road network changes mining and recommendation service correction, will be developed to validate our method. We believe that these value-added applications could benefit from our proposed method and significantly improve the level of taxi service.

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