DoppelDriver: Counterfactual Actual Travel Times for Alternative Routes

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Abstract—“What would have happened, had I taken the alternative route?” This is a question that many drivers often ponder, hoping that their chosen route is the best. This paper proposes DoppelDriver, a system that attempts to answer such questions on non-chosen alternative routes to a given destination by determining actual times of arrival (ATAs) from participatory users on the non-chosen routes. DoppelDriver offers a direct, actual travel time comparison among route choices. With DoppelDriver’s collection of actual travel time comparisons, users will be able to make strategic decisions on, and self-assessments of, their route choices. Also, we describe the potential usage and benefits of ex-post feedback (i.e. travel time on non-chosen routes) and how snapshots of travel time comparisons can be used to support strategic decision making on the choice of a route. Using real taxi GPS data, we investigate whether aggregating ATAs for road segments from other users mimics the ATA for the intended origin-to-destination route. Finally, we present our system design for a prototype implemented on the Android platform.

Keywords—vehicular computing; navigation systems; route choice; travel time; participatory sensing; crowdsourcing

I. INTRODUCTION

With the ever-expanding number of automobiles throughout the world, traffic congestion is a pervasive problem. Countless solutions exist to alleviate traffic congestion by using on-ramp flow meters, traffic cameras, optimized traffic signals, and more. In addition, as ubiquitous computing and real-time traffic flow information becomes pervasive in cars, another increasingly popular solution in Intelligent Transportation Systems (ITS) is destination-driven navigation systems. Most drivers rely on GPS navigation, be it through their cars or their smartphones where a rapidly growing market far from its ceiling is speaking volumes to the ubiquitous presence of navigation services.

One of the most empowering aspects of advanced navigation systems is their ability to predict the estimated time of arrival (ETA) taking real-time traffic flow into account and to provide estimated travel time route comparisons to generate a set of route choices to support the driver in the decision-making. However, when compared to the actual time of arrival (ATA), the ETA can easily be under- or overestimated due to, for example, dynamic traffic conditions or the use of simple and/or faulty algorithms. For instance, at the end of or during a trip a curious driver can discover that the ETA given by the online navigator, which he based his initial route selection on, can be far off from the ATA and wonder what would have happened on the other recommend routes that were not taken.

To the best of our knowledge, up till now, research into predicting accurate ETA based on historic GPS traces or real-time speed and location information from individual drivers have focused only on pre-trip and en route information, while overlooking ex-post information about foregone route alternatives (i.e. actual travel times concerning non-chosen routes). The difference between pre-trip/en route and ex-post information is that the former uses estimated travel times while the latter utilizes actual travel times. Enlightened by the studies in the transportation route-choice behavioral literature [4, 9, 10, 11, 12, 17] that highlight the potential use of ex-post information, this neglect is surprising.

The pervasiveness, efficiency, and market potential of ITS and map service providers strictly depend on users’ compliance with the systems and the information they offer. Despite efforts to support decision-making, travelers tend to disregard the suggestions these types of systems offer [5, 13]. In fact, [3] show that only about 13.5% of commuting trips match the fastest route. There are several explanations for user compliance with real-time information (i.e. the decision to follow the recommended route supplied through real-time information). From the transportation literature, we list a few limitations in current route recommendation systems as a means to alter drivers’ route choice behavior to make smarter decisions, which mainly rely on real-time ETA information.

Reliability: The quality of real-time information influences the users’ compliance with route choice, and as ETA is used as a decision-making tool for route choice, the impact of uncertain, inaccurate, and variable travel times can render it useless [13]. Similarly, differences in ETA and/or best routes offered by various map providers can also contribute to the uncertainty in route choice, and this uncertainty can make it challenging for users to choose the true optimal route.

Rationality: In situations of uncertainty, most people may simply decide on routes they have experienced previously because they have no time or method for rational assessment [11]. We observe this quite often as commuters routinely take the same route to and from work [16]. To some extent, this may be seen as rational; however, in the long run, the decision may cost the driver a significant amount of travel time, thus resulting in irrational decision-making [1].

Perception: Arguably, people may think they are on the fastest route, even when their decision is wrong and do not follow the system’s recommended route [5, 13]. People often
experience these events in their ordinary commute, where they think they are better route planners than their navigation system, and persist in using “their” route [1, 13]. Consequently, their false beliefs result in poor decision-making if it turns out they were wrong. One behavioral factor that explains this is habit, which appears to have a strong influence on drivers’ behavior. Even when real-time traffic information is provided, and even after experiencing long delays, drivers are still willing to adhere to “their” route [13].

**Experience**: In many situations, drivers face dilemmas over their route-choice decision, especially when real-time information regarding the recommended alternatives does not coincide with previous driving experience [7, 13]. In addition, repeated cycles of accumulated experience on continuous commutes can be a better decision-making factor than route-choice systems [6] because real-time information cannot foretell whether traffic will get better or worse.

The plausible solution to overcome such limitations of route-choice systems, and to acquire a higher rate of user compliance, is to address the misperception, motivate drivers to think rationally, and combine “experience” with “real-time information”. In particular, ETA information alone as given by the online navigators may not be sufficient for drivers to make the optimal decision. In addition, this paper proposes the use of ex-post feedback on the actual travel times for the chosen (i.e. from their own experience) and non-chosen alternative routes (i.e. foregone experience). In fact, the findings in [9] emphasize the importance of post-trip feedback in attaining high compliance rates. They concluded that providing feedback built up the credibility of the information system and achieved high levels of compliance with the system.

Up till now, there has been no systematic way to compare and assess ex-post route choices and to learn from them in order to make more efficient and strategic decisions in the future. Hence, this paper proposes DoppelDriver, a system that provides comparisons of ATAs for alternative non-chosen routes. The system makes use of other participating users, who act as doppelgängers to provide ATAs for alternative routes of interest to the user. With such feedback, users will have the ability to assess their route choices and log them in a trip diary that can be used in the future for strategic decision-making when selecting a route. To the best of our knowledge, this is the first work that 1) exploits the use of actual travel times from other vehicles on non-chosen routes to be compared to that of the chosen route and 2) provides the ability to assess the route choice and use it as reference for future decision-making.

**II. PRELIMINARIES AND MOTIVATION**

As the proposed solution is novel, we particularly emphasize on the potential for ex-post feedback to assess non-chosen routes, which motivates our system’s practical usage.

**A. Potential of ex-post feedback for chosen/non-chosen routes**

Almost all studies in the information technology domain have focused on pre-trip and en route trip information, and because the proposed approach incorporates ex-post feedback on forgone alternatives, we stretched out to find related work in the transportation route-choice behavioral literature. Below, we summarize the findings that emphasize the potential use of ex-post feedback.

In light of the previous studies that highlight the potential use of ex-post feedback, Chen et al. [9] developed a model based on empirical studies to capture the effects of commuters’ compliance with real-time information by varying the information quality and providing post-trip feedback on actual foregone alternatives. In their experiment, they provided three levels of post-trip feedback: the chosen route (the driver’s own experience), the recommended route provided by the system, and the actual best route. They emphasized the importance of post-trip evaluation, where users can compare actual choices to the optimal route choice and assess the quality of their decisions. Their findings show that feedback builds credibility and higher compliance rates with the information system, and thus, they suggest that ITS systems provide such information to users. One of the interesting findings in [10] regarding the effects of feedback was that since users were able to compare their chosen routes with the true optimal choice they were encouraged to select more efficient routes.

Based on the joint relationships among real-time information, post-trip information, learning, and habit, Bogers et al. [11] experimented on three scenarios. For all three scenarios, drivers were given real-time traffic information. In scenario 1, ex-post information was based on only the chosen route; scenario 2 provided ex-post information for both chosen and best routes for the latest period; and scenario 3 provided ex-post information for both chosen and best routes for all past periods. Because travelers who receive information on foregone alternatives can also learn about the characteristics of the non-chosen routes, Bogers et al. drew the following conclusions. Drivers react primarily to the route queue length information, yet ex-post information helped them learn and improve performance. Also, under the scenario that provided all past travel times for both the chosen and best routes, travelers had significantly better scores versus the other scenarios.

In a recent behavioral model study, Chorus [4] explains that the importance of the acquisition of ex-post information, and the behavioral decision to acquire it, is fundamentally different to the traditional acquisition of pre-trip or en route travel information. Based on psychological theories, when a traveler decides whether to acquire ex-post information concerning repeated route choice, the traveler has to accept a tradeoff between wanting to ignore the potential regret associated with the already executed choice, and wanting to learn in order to minimize potential regret from future decisions. When travelers value the ex-post information it implies that the learning benefits that will reduce levels of regret for the next trip are likely to outweigh any regret associated with the current trip.

**B. Usage of ex-post feedback for chosen/non-chosen routes**

Because ETA serves to determine the travel time based on current traffic conditions, below is an explanation of the usage of ex-post information and how the proposed system provides it.

**Curiosity and Assessment**: After a decision has been made, the tendency people have is to think about how things would have turned out differently. The “What if?” thoughts that poke at a user given multiple choices is known in psychology parlance
as counterfactual thinking. An example of counterfactual thinking applied to route choice is, “What would have happened on the alternative non-chosen route?” which is the motivation for this work. Counterfactual thinking is anticipated with either regret or rejoice (i.e. the opposite of regret). For instance, drivers may be stuck in traffic and wonder where they would be, had they been travelling another route. Ex-post information can inform drivers that the other route was even more congested, confirming that the chosen route was actually better, causing rejoice. But regret theory suggests that when provided with ex-post information, drivers may want to ignore the information to avoid regret. In addition to [4] and [8], concerning the tradeoffs of balancing regret versus learning, [14] investigated whether curiosity about an unchosen alternative could overcome potential regret from learning about the unchosen outcome. Their findings show that when information was readily available, curiosity found to overcome regret aversion.

In this sense, there is active curiosity and a need for individual assessment on travel-time comparisons with secondary and tertiary routes, which presently remain unfulfilled and unavailable within any web-based or smartphone-based navigation applications or services. Providing real-time travel comparisons with actual travel times for both chosen and non-chosen routes via mobile participatory sensing addresses the inherent user concern activated by counterfactual thinking. DoppelDriver allows the user to definitively conclude which route was best, firmly answering the natural human tendency to constantly consider the merits of alternative routes that one could have chosen. Offering all users the chance to answer a nagging curiosity that is innately present, this research has relevance to almost any navigation system user.

**Learning:** Iterations of a repeated route choice can be viewed as a learning process. Due to cognitive limitations, people require numerous iterations to detect a pattern, and cannot remember all their choices and what the optimal choice was [11]. Thus, DoppelDriver provides a Trip Diary that logs user selected routes and the true best route, based on the alternative routes’ actual travel times. Also, since the trip diary logs all previous commutes that were of interest, this can expedite the learning rate, as shown in an experiment in [12].

DoppelDriver will prove especially useful to commuters or individuals who travel to the same destination more than once. Armed with the ability to see the actual travel times for both the chosen and non-chosen routes, the user is now empowered—he or she can legitimately identify the optimal route, especially when there are similar times for the ETA in the route choice set. For the next commute or trip, the user can make a smarter decision, and confirm that the selected route is truly the fastest each time he or she travels [16].

**Personalized Route Choice.** In [2], Shiflan et al. analyzed drivers’ route-choice behavior with real-time pre-trip and ex-post information. Main findings were that risk-seeking individuals tend to prefer a route characterized by a lower average, but greater variance, in travel time. On the other hand, risk-averse individuals preferred lower variance, but better averages. Depending on the route-choice behavior, drivers’ preferences can be roughly classified into risk-averse travelers, indecisive travelers, and expected-time minimizers [15]. ETA alone cannot provide users with a personalized choice. Thus, DoppelDriver provides a trip diary that gradually collects personal history of ex-post information with actual travel times on alternative routes from an origin to a destination of particular interest. The trip diary shows the average of, and variance in, the actual travel times, depending on departure time. Drivers can select routes based on their preferences through the actual average travel time and travel time variability for alternative routes.

**III. Determining Counterfactual Route Travel Time**

Our algorithm is based on how ordinary people obtain actual travel times on a non-chosen route. If a driver travels from an origin to a destination (O→D) and would like to compare one's travel time to that of the unchosen route in order to assess the route choice, the ordinary way would be to ask someone who started at the same time and origin how long it took to travel to their mutual destination. For example, as shown in Figure 1, John normally commutes from O to D at 9 am and has two alternative routes, r₁ and r₂. Routes r₁ and r₂ are represented as A→C→E→F and A→B→D→F, respectively. John cannot simultaneously travel both routes at the same time, so he would not be able to compare and assess his choice. However, if Mary, John’s neighbor, traveled on route r₂ while John traveled on route r₁ to the same destination, they would be able to collaborate to figure out what the best route turned out to be by alternatively driving each route in their daily commute.

Realistically, people would not be willing to go through such a hassle, and it is nearly impossible to find someone who has the same start time along with the same origin–destination pair. This paper provides a solution to this problem by combining portions of three trips: Mr. Red, who passes through road segments A→B from 9 to 9:05 am; Mr. Blue who passes through road segments B→D at 9:04 to 9:10 am, and Mr. Green who passes through road segments D→F from 9:12 to 9:18 am. The aggregation of the actual travel time of Mr. Red, Blue and Green can represent Mary’s route r₂. Thus, it is possible to use the aggregation times of road segments traveled by different users to calculate the actual trip time for the alternative route. John can eventually compare the route he took to the alternative route he is interested in. However, selecting the best-fitted participants to provide the actual travel times and whether combining those travel times to represent the actual end-to-end trip is not obvious and thus, this paper explores further into the feasibility of the proposed solution.
IV. DoppleDriver Overview

A. Preliminary

We call our system DoppleDriver, because other participating users act as dopplegängers who are simultaneously “driving” on alternative routes that you are not traveling on. Also, we denote the alternative routes that are of interest (but not taken) as counterfactual route(s). Below are some preliminaries introducing terms that are used throughout the paper.

A waypoint is a latitude and longitude coordinate set denoted as \( wp = (lat, long) \). A GPS point is denoted as \( p = (u, wp, ts, o) \) where \( u \) is user \( u \in U \), \( wp \) is the waypoint, \( ts \) is the timestamp and \( o \in \{0, 1\} \) is the state of passenger occupancy. A road segment is an edge of a road network that does not share a junction. Terminal waypoints, defined as either road segment’s start or end of each road segment, are denoted as \( rs_i \). Travelling two terminal waypoints of a road segment is denoted as \( rs_i \rightarrow rs_j \). Dot notation is used to refer to an element. So, the travel time for \( rs_{ij} \) is \( t.rs_{ij} \) and the start time and end time when traversing from waypoint \( rs_i \) to \( rs_j \) are \( st.rs_{ij} \) and \( et.rs_{ij} \), respectively. A route \( r \) is a set of consecutive road segments, \( r \equiv rs_1 \rightarrow rs_2 \rightarrow \cdots \rightarrow rs_n \). The origin and destination point of the route can be represented as \( rs_1 \) and \( rs_n \), respectively. A trip \( tr \) is the trajectory of a sequence of GPS points, i.e., \( tr \equiv p_1 \rightarrow p_2 \rightarrow \cdots \rightarrow p_n \).

B. Algorithm

This subsection explains the DoppleDriver algorithm in detail, along with an example to illustrate it. Figure 2 is a simplified form of the counterfactual route \( cr: rs_O \rightarrow rs_1 \rightarrow rs_D \), to explain the algorithm. First is an explanation of how to elect the best-fitting sharing user for each road segment, and how the end-to-end route travel time is calculated.

Selection algorithm. Referring to Figure 2, the algorithm first checks the initial start time of the querying user at origin \( rs_O \). A sharing user is in the candidate user set \( CU \subseteq U \) if \( \{ u_m \in U \mid st(u_m).rs_{0,1} - st(u_m).rs_{0,1} < \tau \} \). This is interpreted as finding all sharing users who are in the corresponding road segment and nominating those to candidate users if the difference in the initial start time of the querying user and the sharing user falls within a given window time frame, \( \tau \). Then, among the candidate users, one is selected as the elected user whose difference between the initial start time of the querying user and the start time of candidate user is at a minimum, which can be expressed as \( \{ cu_m \in U \mid \min[st(rs_{0,1}) - st(cu_m).rs_{0,1}] \} \). To summarize, the selection algorithm can be explained such that it is seeking to elect one sharing user out of many to represent the travel time on the corresponding road segment. The selection algorithm is reiterated until all road segments are covered.

An example is illustrated in Figure 2, where if we assume the initial elected user at the origin is \( u_1 \), we now find the next elected user at location \( rs_2 \). Users \( u_2 \) and \( u_4 \) fall within the window time frame, and, thus, are nominated as candidate users. Among the candidate users, the difference between \( u_2 \)’s start time and \( u_4 \)’s end time is minimal, and thus, \( u_2 \) becomes the elected user whose travel time on road segment, \( e.rs_{1,2} \), is used. The end-to-end travel time for the entire counterfactual route can be computed as \( \sum_{eu \in C} et(eu).rs_{i,j} - st(eu).rs_{i,j+1} \), which can be explained as the sum of each elected user’s road segment traverse times.

V. Feasibility Study

This section presents a feasibility study on real taxi GPS data to study whether the aggregated travel times of road segments can be represented as the total travel time of a complete trip. The methodology, test data settings, and results are described in the subsections below.

A. Methodology

A simple illustration of the methodology for the feasibility study is shown in Figure 3, which compares the travel time of a complete taxi trip as shown with the black solid line, to the sum of the travel times of the other taxi trips shown in solid blue, red, and green lines in each corresponding road segment. The travel time of a taxi corresponding to a road segment is estimated as the portion of the road segment that the taxi traversed. Also, note that GPS trace intervals that exceed 5 mins were filtered out to reduce noise.

B. Test Data

An empirical feasibility study was carried out using large-scale taxi GPS point sets from Beijing on January 6, 2009, from 1 pm to 2 pm and 5 pm to 6 pm, which are denoted as non-rush hour and rush hour, respectively. We employ a set of methods to preprocess the GPS data set, such as data cleansing, map...
matching, identifying trajectory and travel time estimations. Due to space limitations, the details of the preprocessing techniques are omitted. A summary of the taxi data set and the descriptive statistics for both rush hour and non-rush hour periods are shown in Table 1.

### Table I. Taxi Data Set

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Non-rush</th>
<th>Rush</th>
</tr>
</thead>
<tbody>
<tr>
<td># of taxis</td>
<td>7,288</td>
<td>8,093</td>
</tr>
<tr>
<td># of trips</td>
<td>2,049</td>
<td>2,797</td>
</tr>
<tr>
<td># of road segments traversed</td>
<td>60,551</td>
<td>71,209</td>
</tr>
<tr>
<td># of GPS points traversed</td>
<td>128,826</td>
<td>147,008</td>
</tr>
<tr>
<td>mean road segments traversed</td>
<td>29.55</td>
<td>25.46</td>
</tr>
<tr>
<td>standard deviation of road segments traversed</td>
<td>15.30</td>
<td>15.47</td>
</tr>
</tbody>
</table>

*Taxi data set accounts for approximately 7% of the total traffic

### C. Analysis

Comparison of the aggregated road segment travel times was analyzed with respect to the actual trip time, i.e. counterpart trip travel time versus the actual trip travel time. We first determined the distribution, if any, of the travel times and then based on the distribution, we decided what statistical inference to apply.

For each AT time, we obtained the corresponding CT time. If there were at least a single road segment that could not be acquired for the complete CT, it was acknowledged as failure to get a CT time. For a window size set at 600 sec, the success rate was 77.9% and 77.4%, and for a window size set at 300 sec, the success rate was 63.7% and 63.5% for non-rush and rush hour traffic, respectively. As seen in Figure 4, as the window size decreases, the success rate also decreases. The taxi data set accounts for approximately 7% of the total traffic. Even with such a low volume of taxis, the results are somewhat satisfying, and the success rate will probably increase dramatically as more users participate.

With no defined window size, we first determined the distribution of window sizes. Figure 5 shows that the majority, i.e. approximately 97%, fall within a window size of 300 sec for both non-rush and rush periods. This plot shows the distribution of window size for non-rush and rush hour periods for periods where acquiring the travel times for the CT road segments was successful with respect to the AT. For the non-rush periods, the cumulative percentage for wnd<=300 was 97.9%, and for wnd<=600, it was 99.2%. For rush periods, the cumulative percentage for wnd<=300 was 97.4% and for wnd<=600, it was 99%. This shows that for both non-rush and rush periods, the majority of the window sizes fall under 300 sec.

For each trip where acquiring a CT failed, the number of road segments that were affected by the failure was determined. The distribution is shown in Figure 6. For non-rush periods with wnd=300, 46% of the total trips that failed to acquire a CT were due to a failure to obtain just one road segment, and a cumulative 90% were due to a failure to acquire up to five road segments. For wnd=600 in non-rush periods, 50% were due to failure to acquire one road segment’s travel time. For rush periods with wnd=300, 42.16% of CT failures were due to lack of one road segment, and similar with non-rush; a cumulative 90% were from failing to acquire up to five road segments. For rush periods with wnd=600, 50.24% of CT failures were due to lack of one road segment, and 93.5% were due to a failure to acquire up to five road segments. Recall from Table 1 that the mean number of road segments traversed was 29.55 and 25.46 for non-rush and rush periods, respectively. This can be interpreted as for an average of 30 road segments traversed, 50% of the CT failures were due to missing one road segment and 90% of CT failures were due to missing up to five road segments.

The data set was retrieved for AT times and CT times for those trips that successfully acquired a CT time. Then, kernel smoothing was applied to the distributions of both AT and CT times to visually inspect the distributions, which are shown in Figure 7. To determine if the AT and CT data sets were normally distributed, a few normality tests were conducted, such as the Kolmogorov-Smirnov test using R. The p-value for all tests on the data sets was < 0.02, and thus, the result was that the distribution is not normal. Also conducted were a log-normal test and a chi-squared test, and the results showed that the data set distributions did not fit (p-value<0.001). Such results are not unusual. Equivalent results are also shown in other previous work [3].

A paired equivalence test was applied, which was used to test whether two paired samples are nearly equivalent as to some outcome, such that any difference is insignificant. The paired difference of AT and CT time was computed, and distributions
are shown in Figure 8. All figures, i.e. non-rush and rush periods, show that the paired differences of ATs and CTs are concentrated near 0, meaning that the differences are trivial. Thus, also conducted were a non-parametric statistical hypothesis test and a Wilcoxon signed rank test, which assumed as the null hypothesis that the difference between AT and CT is within $\delta$ sec, and the alternative hypothesis is where the difference is greater than $\delta$ sec, as shown in (1).

$$H_0: |\mu_{AT} - \mu_{CT}| \leq \delta, \quad H_a: |\mu_{AT} - \mu_{CT}| > \delta$$  (1)

Confidence interval (CI), $\alpha$ was set to 95%, and $\delta$ was set to 30 sec, such that 30 sec represents a reasonable figure when saying AT and CT times are equivalent. The results are shown in Table II. It is clear that for non-rush periods, the median difference between AT and CT for the same trip is -4 sec, where differences range between -10.5 and 2.5 sec. For rush periods, the median difference was 16.5 sec for intervals between 8.0 and 25.0 sec. For the equivalence test, all accepted the null hypothesis, meaning that the differences between AT and CT are within 30 sec.

<table>
<thead>
<tr>
<th>TABLE II. SUMMARY RESULTS</th>
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<tbody>
<tr>
<td>Non-rush</td>
</tr>
<tr>
<td>wnd</td>
</tr>
<tr>
<td>$N$</td>
</tr>
<tr>
<td>est. median</td>
</tr>
<tr>
<td>CI</td>
</tr>
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<td>CI lower</td>
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<tr>
<td>CI upper</td>
</tr>
<tr>
<td>equivalence</td>
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<tr>
<td>p-value</td>
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</tbody>
</table>

* CI: Confidence Interval $\alpha = 95\%$

Based on the taxi data, the feasibility study showed that depending on the window size, the success rates to acquire a CT were approximately 80% and 65% for window sizes of 600 sec and 300 sec, respectively, whether they were non-rush or rush periods. Also, for trips that failed to acquire a CT time, approximately 40 to 50% were due to a failure to obtain just one road segment. The distributions of the differences between AT and CT were concentrated near 0 and, based on hypothesis testing, the difference was trivial. Therefore, we conclude that it is possible to aggregate travel time for a route by using segment travel times, and the aggregated travel time of road segments can be represented as the total travel time of a complete trip.

### VI. THE DOPPELDRIVER SYSTEM

Figure 9 illustrates the client/server architecture of the DoppelDriver system. The client-side interface interacts with the Maps API for route recommendations and information, which are passed to the server via the client, along with its location, as sensor data. Location and timestamp data are then used to calculate the travel time for each road segment on the counterfactual route. The following subsections discuss in detail the primary role of each entity.

#### 1) Client

As shown in Figure 9, a client user can be a sharing client, a querying client, or both. The client first inputs the desired destination, and the mobile device will send the origin and destination to the Maps API. The Maps API will then compute the route and recommend a list of route options to the client. Once the user chooses the selected and counterfactual route, route directions (i.e. waypoint and road segment information) for the routes are passed to the server. After arrival at the destination, the system displays to the querying client the requested counterfactual route’s total ATA.

#### 2) Maps API

The Maps API consists of three main functions. The first function is to provide map images and add overlays, such as markers or polylines to the map. The second is to provide geocoding to find the corresponding geographic coordinates from an inputted textual geographic location. Finally, the last function is to calculate and recommend a list of alternative routes for a given origin and destination, along with additional information such as ETA or distance.

#### 3) Server

Three processes are involved in the application server component. One is to handle follow requests for the counterfactual routes by searching and logging the sharing clients’ locations and travel times. Second, the follow module’s role is to elect users from among shared users to follow for each road segment along the selected route. Finally, the ATA calculation module’s role is to record the ATA when a sharing user traverses waypoints, to search for road segment ATAs, and to calculate the corresponding end-to-end selected route’s ATA.
VII. IMPLEMENTATION

The DoppelDriver prototype system was implemented where the client runs on an Android 4.1+ mobile platform. The Google Maps API, the Places API, and the Directions API were utilized for the Maps API. The Google Maps API is used for the base map, the Places API is used for specifying locations as latitude/longitude coordinates, and the Directions API is used to calculate and recommend a list of alternative routes, along with step information. The server side is a Dell Optiplex 780 machine equipped with a 3.16 GHz Intel Core2 Duo CPU, 4GB DDR3 1066 MHz RAM, and a WD 320GB 7200 RPM SATA II disk. Moreover, we have set up server-side scripts developed by PHP5 running on Apache 2 on Ubuntu 12.04.4 LTS, and the data on ATA is stored in a MySQL database. The field experiments were carried out on the aforementioned platform.

Figure 10 illustrates the initial implementation of the client prototype. When an origin and destination are introduced, a recommended list of alternatives is shown and sorted by shortest ETA. The user will then select which route to take and which counterfactual route to follow, as shown in Figure 10 (a). Then, the overall view of the selected route and counterfactual route is shown, as in Figure 10 (b). Upon arrival, when the selected route arrival time is more than the counterfactual arrival time, then both routes’ ATAs are shown, as seen in Figure 10 (c). On the other hand, if the selected route arrival time is shorter, the counterfactual route will show “Has not arrived” and a popup alert message will be shown upon arrival, notifying the ATA.

The Trip Log is shown in Figure 10 (d). Every trip can be saved so that users can utilize their previous experiences. The first column states the date and time of the trip. The second column shows the navigation system’s recommended best route (the recommended route that has the minimum ETA). The third column shows the route that turned out to have the minimum ATA (when counterfactual comparisons are available). The fourth column shows the route the user chose to drive. Finally, the last column represents whether the selected route was the true fastest route. The design of the trip log is modeled after the travel behavioral experiment with real-time traffic and ex-post information in [11]. The Trip Diary is shown in Figure 10 (e). Depending on one’s departure time, the Trip Diary uses the Trip Log data and past number of trips to calculate the averages and standard deviations of the actual travel times for that 15 min. time slot the departure time falls in (personalized route choice).

A. Field Experiment

A field study was carried out to validate the prototype by testing whether the ATAs on the counterfactual road segments were correctly shared and retrieved from the database, and to evaluate the search cost on different table sizes. Two drivers, one sharing and one querying client, simultaneously drove on two routes for the same origin and destination. The two routes were recommended from Google Maps where one route was via the highway with an average ETA of 15 mins (9.3 mi) consisting of 7 road segments while the other route was via local roads with an average ETA of 16 mins (7.3 mi) consisting of 13 road segments. A total of ten trips were carried out. Five trips were conducted, where at the origin, the querying client took the local route and requested the ATA on the highway route, i.e. the counterfactual route, where the sharing client was traveling on. The remaining five trips were conducted in reverse where the querying client took the highway route and the sharing client on the local road route. The database of our table that records the ATA was injected with random start and end travel times on random geo-points for start and end road segments. This process mimics how other drivers share their ATA. At the end of the trip, the retrieved ATA on the counterfactual route was compared to the sharing client’s travel time to validate that the sharing client’s travel time was correctly sent and retrieved from the database table. Also, the search time for the ATA on the counterfactual route was recorded on table sizes of 50K, 100K, 300K, 500K, 700K and 1,000K. Note that the taxi data set mentioned in the previous section was approximately 7% of the total traffic and covered the Beijing area where the table sizes were 309K for non-rush hour and 407K for rush hour.

![Fig. 11. Counterfactual Route ATA Search Time](image-url)
For all the ten trips, the retrieved counterfactual route’s ATAs coincided with the travel times of the sharing client. This shows that the sharing client’s travel times for all the road segments within the counterfactual route were correctly updated for each road segment that was traveled and the ATA values were properly calculated to provide the final ATA for the entire journey. Also, Figure 11 shows the average search time and the standard deviation in seconds per table size when the local road (7 road seg.) and the highway road (13 road seg.) were the counterfactual route. We can observe that the table size does not affect the search time whereas the number of road segments searched mainly affected the search time.

VIII. DISCUSSION AND FUTURE WORK

Deployment. A problem may arise if the system cannot find a driver on a certain road segment of the non-chosen route within a certain time interval in order to compute the actual travel time. Our current solution is to query the start point of such road segments and use the ETA (provided by online map providers) instead to contribute to the calculation of the entire counterfactual route travel time. Such information can be used where there is no actual arrival-time data so as to provide the entire counterfactual route travel time. The same approach can be taken during the initial deployment of DoppelDriver where there may not be enough users to collect actual travel times. The system could be bootstrapped by taking advantage of most recent ETAs for immediate next road segments.

Implementation. The choice of the threshold for the window size is of great importance as it reflects the computation of the actual travel time. As this paper worked on the hypothesis of window size of 300 and 600 sec, future work is left to study with varying window sizes on different GPS data sets in order to maximize ATA accuracy for each user.

Experiment. The main focus of this paper is to present the potential usage of ex-post feedback and to analyze the feasibility of the proposed algorithm on obtaining ATAs on the non-chosen routes. Although there has been literature on transportation behavior that discuss in-lab experiments on route choice behavior when provided with ex-post feedback, further work remains to study its impact of the proposed systems in real-world scenarios.

IX. CONCLUSION

This paper presents a rationale and a system for counterfactual thinking in route selection. We presented a method by which ATAs for alternative routes can be calculated by combining other travelers’ ATAs for segments that constitute the complete alternative route. A study based on taxi data shows that by selecting a suitable time window, it is possible to aggregate travel times for a route by using segment travel times.

This work presents the first crowd-participatory sharing service that collects data on actual arrival times. DoppelDriver empowers users with the ability to exercise strategic decision making and self-assessments of their route choices. Using data collected from participating users, DoppelDriver offers real-time comparison of alternative routes via real-time instantaneous position comparisons, as well as provision of ATAs in order to inform users in a novel way on how to better make routing decisions. We presented a design for, and prototype of, DoppelDriver where other user’s locations and arrival times were used to compare against the time of the selected route.

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REFERENCES