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Predicting Location Probabilities of Drivers to Improve Dispatch Decisions of Transportation Network Companies based on Trajectory Data

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Abstract: The demand for peer-to-peer ridesharing services increased over the last years rapidly. To cost-efficiently dispatch orders and communicate accurate pick-up times is challenging as the current location of each available driver is not exactly known since observed locations can be outdated for several seconds. The developed trajectory visualization tool enables transportation network companies to analyze dispatch processes and determine the causes of unexpected delays. As dispatching algorithms are based on the accuracy of arrival time predictions, we account for factors like noise, sample rate, technical and economic limitations as well as the duration of the entire process as they have an impact on the accuracy of spatio-temporal data. To improve dispatching strategies, we propose a prediction approach that provides a probability distribution for a driver's future locations based on patterns observed in past trajectories. We demonstrate the capabilities of our prediction results to (i) avoid critical delays, (ii) to estimate waiting times with higher confidence, and (iii) to enable risk considerations in dispatching strategies.

1 INTRODUCTION

The usage of transport network companies (e.g., Careem, Lyft, or Uber) rapidly increased over the last years. These companies offer a peer-to-peer ridesharing service by connecting vehicle drivers with passengers to provide flexible and on-demand transportation (Masoud and Jayakrishnan, 2017). Based on incoming passenger requests, the ride-hailing service provider has to assign an order (request) to an appropriate driver from a pool of available drivers, which are constantly moving in a road network freely. For that reason, it is necessary to have exact location information of all drivers to i) optimize the order dispatching process and ii) communicate accurate waiting times to passengers.

The dispatching of orders focuses on reducing the overall travel time and waiting time of passengers, optimizing the utilization of available resources, and increasing the customer expectations (Xu et al., 2018). There is a wide spectrum of dispatching algorithms that determine the potential best candidate for an order on the basis of various aspects. Spatio-temporal cost functions, which are calculated based on the current location of drivers and passengers, are an integral part of these algorithms (Liao, 2003). Examples for such metrics are the distance to the pick-up location or the estimated time to reach the pick-up location.

Due to the evaluation of trajectory data of available drivers, a detailed analysis of dispatch decisions is possible. It enables transportation network companies to identify limitations of dispatching policies and allows the comparison of different strategies and configurations. By inspecting the dispatching process of bookings, the causes for unexpected critical delays can be investigated and an understanding of potentially risky scenarios can be developed.

As one cause for delayed pick-up times and suboptimal dispatch decisions, we identified the inaccuracy and uncertainty of the driver's exact location, which is used for the travel time estimation and the order dispatching. Surrounding urban effects cause signals to be noisy and lead to deviations of the recorded GPS location and the real one of a driver (Wang et al., 2011). Additionally, the technical limitations of the GPS system and economical considerations constrain the emission of signals. To reduce bandwidth and storage costs, drivers' GPS locations are recorded and sent in specific intervals respecting a defined sampling rate. Furthermore, the entire dispatch process, including the acceptance confirmation by the driver, consumes several seconds, in which the driver is changing the position.

Based on these observations, it is necessary to analyze and optimize the used locations of drives to improve the accuracy of arrival time predictions and optimize order dispatch algorithms.

The contributions in this work are the following:

- We implemented a trajectory visualization tool, which enables transportation network companies to analyze their dispatch processes and determine the causes of unexpected critical delays.
- We propose a location prediction approach, which determines a distribution of potential future locations of drivers based on patterns observed in past trajectories.
- Compared to common dispatching algorithms that rely on outdated driver positions only, we are able to avoid critical delays by assigning drivers based on their estimated current potential position accounting for their individual driving behavior (speed, turn probabilities, etc.).
- We demonstrate that the prediction results allow to forecast potential waiting times with higher confidence which, in turn, effectively helps to decrease customers' cancellation rates.

This paper is organized as follows. In Section 2 we describe the problem domain. Afterward, we present the developed application to analyze dispatch processes (Section 3). In Section 4, we present the limitations of dispatch decisions based on the last observed location of drivers. In Section 5, we describe our probabilistic location prediction approach. In Section 6, we present related work. Conclusions are given in the last section.

2 BACKGROUND

In the following section, we define all relevant information entities that are part of the problem domain and necessary to understand the visualization concepts as well as the proposed algorithm to avoid risky dispatches.

A road network is a directed multigraph that represents real-world traffic infrastructure of a specified area along with the corresponding metadata (Ben Ticha et al., 2018). In the graph, each node represents an intersection between at least two road segments, which are represented by edges. These road network maps are created and maintained by humans or automatically updated by trajectory-based algorithms (He et al., 2018). The meta-information includes, for example, the length and speed limit of a road segment as well as the exact geographic locations for all intersections and road segments (Ben Ticha et al., 2018).

Definition 2.1. *Road Network: A road network is a multigraph R represented by a 4-tuple $R = (I, E, \Sigma_I, \Sigma_E)$. I is a set of nodes representing intersections. Σ_I and Σ_E contain the node and edge labels, respectively. $E \subseteq V \times V \times \Sigma_E$ is the set of edges encoding road segments between intersections. The node labels Σ_I are composed of an intersection's GPS location, whereas the edge labels Σ_E consist of a road segment's geographic extent, length, and speed limit.*

Definition 2.2. *Road Segment: A road segment r is a directed edge that is confined by a source $r.source$ and target $r.target$ intersection. It is associated with a list of intermediate GPS points describing the segment's geography. Each road segment contains a length and a speed limit. A set of connecting road segment composes a road.*

In this work, a trajectory is a chronologically ordered sequence of map-matched and timestamped observed locations of a driver, which represents a continuous driving session. For that reason, we use a segmentation algorithm to split the raw positional data of a single moving object into separate trajectories. The start and end of driving sessions are defined by events like changes of the occupancy state or inactive time intervals of drivers.

Definition 2.3. *Trajectory: A trajectory $T_d^{t_s,t_e}$ is a chronologically ordered sequence of map-matched and timestamped observed locations of a driver d in a given time interval $[t_s, t_e]$.*

Definition 2.4. *Ping: A ping p_d^t depicts a map-matched observed location of a driver d at time t. The state p_d^t is given by a 3-tuple (l, s, t), denoting that the driver d is located at location l with the occupancy state s at time t. The location l consists of the tuple (x, y) representing the map-matched GPS coordinates with longitude and latitude.*

As mentioned in the previous section, the accuracy of GPS locations is affected by various factors (e.g., noise) (Wang et al., 2011). For that reason, it is possible that the observed locations of a driver are off-road. Therefore, we use common map-matching algorithms to match the locations to a reference road network. For each observed location a map-matched location on a road segment is determined based on the trajectory of a driver.

3 VISUALIZATION OF DISPATCH PROCESSES

With the capabilities to display the trajectory data, our application enables transportation network companies (i) to analyze dispatch decisions, (ii) to evaluate and compare different dispatching algorithms, (iii) to determine the effect and accuracy of location prediction algorithms, and (iv) to label spatio-temporal data for comprehensive investigations or as foundation for machine learning approaches. Through the detailed analysis of past dispatches, it is possible to identify reasons for late pick-ups and determine characteristics of scenarios, in which the risk for a delay exists. Additionally, it provides the opportunity to identify general problems of dispatch strategies and to examine the behavior in edge cases.

3.1 Analyzing Dispatch Decisions

An overview of bookings enables transportation network companies to navigate through various dispatch processes to identify problematic dispatches efficiently (e.g., significant delays). The bookings can be filtered and sorted by different criteria (e.g., delay, manually assigned labels) to select specific dispatches to be analyzed in more detail (see Figure 1).

In the analysis view, the system visualizes the spatio-temporal data associated with the dispatch decision on a map. As shown in Figure 1, the trajectory of the assigned driver (colored dots), the position of the pick-up location (black marker), and the shortest route to the pick-up location (green line) are displayed. Additionally, the corresponding information (e.g., estimated time of arrival determined by the transportation network company and the Open Source Routing Machine (OSRM) [1]) are shown. The trajectory of the driver is divided into orange and blue dots, which represent the associated pings. The color change indicates the timestamp at which the driver acknowledged the transportation request, and the trip was assigned. Consequently, the orange points represent the free-time trajectory of the driver. In periods without passengers or passenger requests, the drivers drive freely around intending to get in an excellent position to be selected by the dispatch algorithm for the next booking request.

The blue dots of the trajectory represent the route of the driver after the assignment of the trip. Here, the driver has a particular target location and tries to reach the pick-up location on the shortest path. By comparing this trajectory with the shortest path determined by OSRM, the user has a good indicator of problematic dispatches. As displayed in the example (see Figure 1), the delay of the driver was caused by an initial detour. Furthermore, we can analyze the circumstances around the assignment of the trip and determine potential reasons for the detour (e.g., inaccurate positional information or a driver's position on a road segment, which makes it impossible for him to drive the shortest route). In Section 4, we discuss these issues in more detail.

To evaluate different prediction algorithms as well as our probabilistic approach (described in Section 5), the application visualizes the predicted locations along with the determined probabilities. The locations are displayed directly on the map to allow the user to compare the predicted positions (purple circles) with the last observed location and the trajectory of the driver after the dispatch process.

3.2 Determining the Estimated Fastest Pickup Routes

The application illustrates the fastest route between the last ping of the dispatched driver's free-time trajectory and pick-up location as a solid line. We use the OSRM, a tool of the OpenStreetMap community, to calculate a driver's fastest pick-up route. In contrast to routing services used by deployed dispatching algorithms of transportation network companies, the routing functionality of OSRM is not traffic-adjusted. Instead, it estimates the cost of a road segment, i.e., its traversal time, as its length divided by its speed limit. The traversal speed estimation via the speed limit is a significant simplification, as the scenario that a driver traverses the road network without any traffic and with traversal speed indicated by the speed limit is very unlikely.

However, this constraint is acceptable, as even if we use the same traffic-adjusted routing service as the deployed dispatching algorithm, the calculated pick-up route and its traversal time may differ from the route the dispatching algorithm has retrieved at the time of the dispatch from the same service. The reason is that routing services, such as Google Maps, incorporate traffic in real-time to keep estimates accurate and hence, the suggested fastest route for the same pair of GPS coordinates changes continuously with the underlying traffic. The fastest pick-up route that we retrieve from OSRM is not guaranteed to be identical to the pick-up route that was used by the dispatching algorithm. Hence, the estimated traversal time of the fastest pick-up route and the estimated traversal time calculated by the dispatching algorithm of the transportation network company are not comparable to each other.

[1] http://project-osrm.org

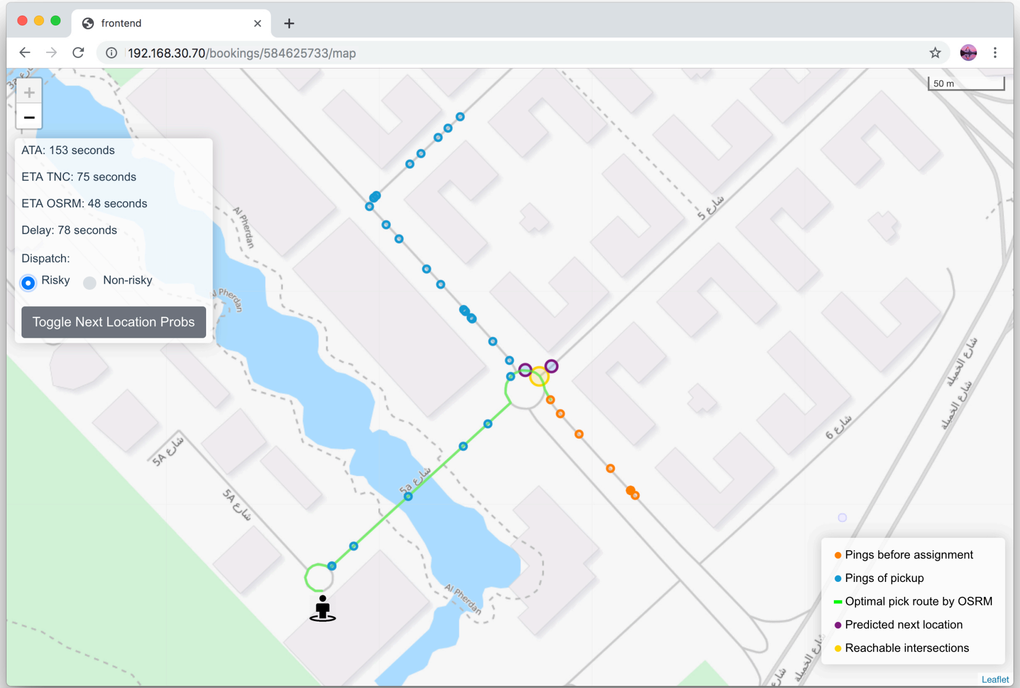


Figure 1: A screenshot of the application, displaying the trajectory of the driver (orange and blue dots), the fastest route (green line), and the predicted next locations via purple circles.

4 IMPROVING DISPATCH DECISION BY LOCATION PREDICTION ALGORITHMS

As already mentioned, it is necessary to provide exact location information of all available drivers to communicate accurate pick-up times to passengers and to efficiently assign passengers to drivers. The assignment of available drivers to requesting passengers in the context of transportation network companies is a dynamic vehicle routing problem or dial a ride problem.

The vehicle routing problem is characterized as dynamic, if requests are received and updated concurrently with the determination of routes, see Psaraftis et al. (Psaraftis, 1995). In the setup of transportation network companies, new passenger requests have to be continuously assigned to available drivers considering further information, such as the current traffic situation or the availability of drivers, which are unknown in advance. For that reason, companies are applying different policies typically intending to optimize specific objective functions (e.g., to minimize the overall waiting time of passengers or route costs) (Psaraftis et al., 2016).

Correspondingly, the applied policy to select a driver from a set of available drivers is based on a cost function (e.g., minimum costs, minimum distance, minimum travel time, maximum number of passengers). Most of these functions use the location of the passengers and the location of the available drivers as inputs. A common example is the nearest vehicle dispatch, which assigns the passenger request to the driver with the shortest travel time to the pick-up location (Jung et al., 2013). Based on the locations, the travel time is determined by using services that offer traffic-adjusted routing services (e.g., Google Maps).

For that reason, accurate calculations require precise and up-to-date location information about all available drivers. However, there are different factors like noise or technical limitations of GPS system (Wang et al., 2011).

Additionally, the given sampling rate, data transfer problems, and the time consumed by the entire process affects the accuracy of the spatio-temporal information. Consequently, the actual position of a driver at the time of the order assignment can deviate significantly from the last observed location, which is currently used as input to calculate the estimated travel time or distance.

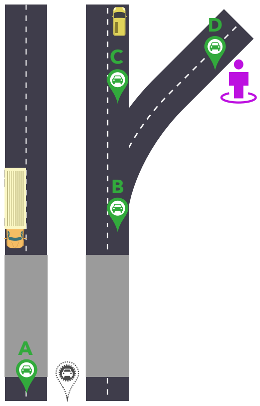


Figure 2: An example highlighting the implications of the driver's current location's inaccuracy and uncertainty. The dotted location marker between the two highway lanes depicts the last recorded location. The other markers indicate a driver's possible current locations on the two roads.

4.1 Limitations of Status - Quo Dispatch Decisions

To demonstrate the limitations of dispatch decisions based on the last observed location, we use the dispatching example depicted in Figure 2 to exemplify the implications of the inaccuracy and uncertainty of a driver's current location at the time of dispatch. The example shows a dispatching scenario on a highway, where the upper-right user pin represents the passenger's pick-up location and the car pins represent a single driver's GPS locations. While the dotted marker represents the driver's last recorded location (which the dispatching algorithm uses), the solid markers represent the driver's possible locations at the time of dispatch. The driver's last recorded position in the example is affected by noise so that the recorded location resides between the two highway lanes. Depending on its implementation, the dispatching algorithm may now assume that the driver is on the right lane, however, if the driver's correct location is A, the actual travel time can be much higher than its estimated counterpart, as turns on highways are impossible and the next exit may be far away.

Even when on the right side of the street, the driver's location at the time of dispatch relative to the necessary highway exit is unknown: the driver may have or may not have taken the exit (location D and C), or the driver may not have reached the exit (location B). The actual travel time varies significantly with locations $B-D$, as missed exists on highways are costly in terms of time. Consequently, there is a high risk of delay. Additionally, the driver's last recorded location may be older than indicated by the sampling rate or urban effects, such as tunnels, prevent the emission of GPS signals. Also, the entire process of assigning a driver and the acknowledgment of the drive takes several seconds, where the position of the driver is continuously changing.

As shown by the example, an inaccuracy and uncertainty of the drivers' locations at the time of dispatch can significantly influence the determined value of the cost function (e.g., travel time). Therefore, the dispatching algorithm has to decide based on incorrect information, for which reason it may not assign the optimal driver to a requesting passenger and also the driver could arrive delayed at the pick-up location. For that reason, we introduce the concept of Detoured Dispatches and Risky Dispatches, see below.

Definition 4.1. *Detoured Dispatch: A dispatch is classified as a detoured dispatch if the assigned driver's arrival at the pick-up location is delayed due to an initial detour of the driver.*

Definition 4.2. *Risky Dispatch: A dispatch is said to be risky if the dispatched driver's arrival at the pick-up location is likely to be delayed due to uncertainty about the current position of a driver, which may lead to an initial detour or a sub-optimal route.*

After the selection of a driver, the exact current position is also necessary to calculate the estimated waiting time, which is communicated to the customer. The waiting time has to be accurate as the cancellation rate strongly increases with the displayed waiting time. High cancellation rates reflect unsatisfied passengers leading to a drop in passenger retention rate, as the industry of ride-hailing is characterized by fierce competition. Ultimately, high cancellation rates reduce the revenue of a transportation network company. The communicated waiting time has to be accurate, i.e., the actual travel time cannot be much longer than the calculated travel time. Otherwise, the passenger has to wait longer than initially communicated, leading to an increase in the cancellation rate. We observed that passengers do not tolerate delays, as more than 50% of all delay-related cancellations happen within the first two minutes of a delay.

To evaluate the share of delays caused by detoured dispatches, we analyzed a sample of 500 dispatch decisions with our application manually. The dispatch processes were randomly selected from a real-world dataset of a transportation network company, which includes the bookings and the spatio-temporal data of Dubai, spanning from November 2018 to February 2019. Further, we limited the analysis to dispatch processes where the driver arrived at the pick-up location between one and five minutes delayed. We classified a dispatch as detoured if the driver performed an initial detour after the confirmation of the trip and returned

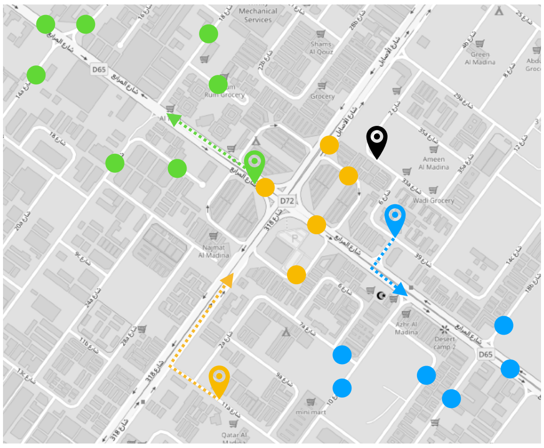


Figure 3: Predicting potential current locations of candidate drivers to be assigned to a waiting customer (black marker): Example of three different drivers (green, blue, orange marker). The dots represent predicted potential next locations of each driver based on their driving behavior.

to the determined fastest route afterward. Based on the random sample, we identified that in about 20 percent of the delayed arrivals, the driver performed an initial detour.

4.2 Probabilistic Location Predictions and Implications for Dispatch Decisions

An example of how probabilistic location predication can influence the dispatch decisions is shown in Figure 3. The black marker represents the pick-up location and the blue, green, and orange markers the last observed map-matched location of three available drivers. A traditional dispatching algorithm that uses a specific cost function (e.g., shortest distance or shortest travel time) would assign the booking request to the blue driver based on the last observed locations. By analyzing the predicted potential positions of the drivers, we can see that the blue and green drivers are likely to move away from the location of the passenger. In contrast, the orange driver is directly driving in the direction of the passenger. For that reason, it is highly likely that the orange driver would be the best option for the algorithm.

In this example, we demonstrate that by including the driving behavior and direction of drivers, the result of the dispatch algorithm can change. Additionally, we can immediately detect whether the estimated time of arrival of a certain driver (e.g., the blue driver in Figure 4) would be too optimistic and detours and, in turn, critical delays are likely.

In the second example (see Figure 4), we demonstrate the impact of the probabilities calculated based on observed patterns in past drives. The size of the dots represents the probability of the corresponding location. The larger a dot is, the higher is the probability of the location. Similar to the first example (see Figure 4), the blue driver has the shortest distance and seemingly the shortest travel time to the pick-up location. But the big dot in the left-bottom corner indicates that there is a high chance that the blue driver misses the exit. For that reason, it may be preferable to assign the trip to another driver.

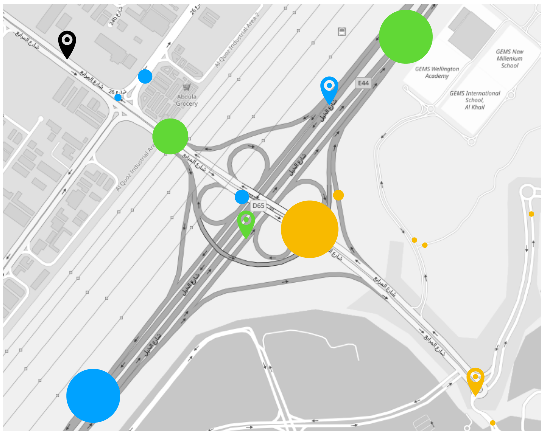


Figure 4: Improving dispatch decisions using probability distributions for the current locations of potential drivers: Comparing the likelihood of a driver to reach the customer (black marker) without critical delays. Example of three different drivers (green, blue, orange marker). The dots represent the predicted next locations of each driver (the larger the dot is, the higher is the probability of the location).

The green driver has a higher probability of being on the shortest route to the pick-up location, but also there is a not negligible probability that the driver stays on the highway and needs to perform a costly detour to reach the location of the passenger.

Based on the last observed location, the orange driver has the longest distance to the pick-up location, but the predicted probabilities show that she is highly likely driving the direction of the pick-up location. Consequently, to assign the order to the orange driver is potentially not the optimal decision, but the one with the lower risk of delays.

Our proposed approach enables transportation network companies to apply dispatching strategies that take risk considerations into account. Whether to optimize expected arrival times, worst-case scenarios, or other risk-aware criteria can be strategically determined by the companies. Our approach, however, is a key for such risk-aware dispatching strategies.

5 PROBABILISTIC LOCATION PREDICTION FOR RISK-AWARE DISPATCHING

To minimize detoured dispatches and enable risk-aware decisions, we propose a model to predict probabilities of future driver positions based on patterns observed in past trajectories. We suggest the algorithm to be used to predict the possible locations of dispatching candidates at the time of assignment of the trip. The dispatching algorithm calculates the estimated travel time from a combination of travel times considering the set of possible locations. By mining historic drives and predicting possible locations allows for a more precise estimation of pick-up times leading to shorter waits, in spite of the inherent uncertainty and inaccuracy of a driver's current position.

5.1 Description of the Probabilistic Location Prediction Algorithm

The goal of this approach is to observe repeating driving patterns from all drivers that can be generalized so that we can apply them to forecast upcoming driving behaviors. The generalization requires the analysis of past driving behavior that is representative of future behavior. As we forecast a driver's next locations around the time of dispatch, we constrain the analysis' dataset to free-time trajectories. In free-time trajectories, drivers are generally not influenced by external factors and thus can drive freely around.

At the time of dispatch, drivers are unaware of a request until it is communicated to them, which is after the dispatch process. Consequently, at the time of dispatch drivers drive freely around, and hence, their decisions are similar to the ones taken before in past free-time trajectories. The analysis of trajectories also allows us to extract information on the dynamic characteristics of the road network, such as traffic. Traffic affects drivers' traversal times on road segments and hence we need to incorporate this into the location prediction to ensure accuracy. Traffic repeats itself (Treiber and Kesting, 2013), we can use historical traffic patterns to forecast future traversal times on road segments consequently.

Remark 5.1. *The prediction algorithm consists of the five parts (i) data preprocessing, (ii) map matching, (iii) road segment candidates determination, (iv) turn probability calculation, and (v) location prediction. Most importantly, the final prediction of a driver's probabilistic location takes not more than 30 milliseconds, and hence, is applicable in real-life settings. Note, part (i), (ii), and (iv) of the algorithm can be processed offline and updated from time to time.*

5.1.1 Data Preprocessing

During the data preprocessing, we segment the trajectories in sub-trajectories that represent distinct driving sessions and extract the sub-trajectories with the occupancy state free. Afterward, we map-match the observed locations to retrieve their actual location on a road segment in the road network. Based on the map-matched pings, we interpolate the route between subsequent pings if their road segments are discontiguous.

Depending on the occupancy state, the driving behavior of a driver changes significantly. If the driver is transporting passengers or is on the way to pick-up passengers, she is driving the shortest route based on the current position, the destination, and the current traffic situation. These routes are often suggested by routing services.

In contrast, drivers with the occupancy state *free* are freely driving around with the goal of getting incoming bookings. Their routes are depending on personal experience and individual preferences as well as external circumstances. For that reason, we have to distinguish trajectories based on the occupancy state for our use case.

Definition 5.1. *Occupancy State of Trajectory: The occupancy state of a trajectory $T_d^{t_s,t_e}$ is defined by the state of all pings of the trajectory. For that reason, all pings of a trajectory must have the same occupancy state. We distinguish between the two states available and occupied.*

We define a route as an ordered sequence of connected road segments, which are determined by the trajectory and defines a semantic compression of the trajectory consequently. Multiple consecutive pings on a road segment are combined. Additionally, if the resulting road segments are not connected, the corresponding road segments to connect the segments by the shortest path are added to the route.

Definition 5.2. *Route: A route $R_d^{t_s,t_e}$ of a driver d is a sequence of connected road segments, visited by driver d in the time interval $[t_s, t_e]$ ordered by the time of traversal.*

A booking represents a transportation request from a passenger. During dispatch, a potential driver is assigned to the booking. After the driver confirms the booking, her occupancy state changes from available to occupied. Accordingly, the state changes to available after the driver finished a booking.

5.1.2 Map Matching

The accuracy of GPS locations is affected by various factors (e.g., noise) (Wang et al., 2011), cf. Section 2. To match the locations to a reference road network, we use the established map-matching library *Barefoot*[2]. Additionally, we applied filters to remove physically implausible sequences of map-matched location caused by the breaks in the Hidden Markov Model used by this approach. Newson and Krumm (Newson and Krumm, 2009), also suggest filter and cleansing approaches for outliers (e.g., traversal speed and maximum acceleration thresholds).

5.1.3 Road Segment Candidates

To determine the relevant potential road segments on which the driver is estimated to be after the prediction frame based on the last observed location, we partially analyze the road network. Each road segment has an associated cost, which depicts its traversal time (i.e., the time a driver needs to traverse it completely). There are different approaches to determine the traversal time (e.g., speed limits, actual speed of the driver). We use an approach that mines the traversal speed from past trajectories.

The mined traversal speed is the average speed of all drivers on the road segment of past trajectories (e.g., of a given hour). Due to the fact that we consider all pings of a driver on a specific road segment, the mined traversal speed implicitly includes traffic effects like traffic light phases or traffic jams. Starting from the road segment of the last ping, we determine all possible paths of the driver by summing up the traversal times of the road segments until the prediction frame is exceeded. By definition, the algorithm expects drivers to reach the last road segment of a path and we add the last road segment to the list of candidates consequently. Instead of considering just all road segments in the neighbourhood, this approach allows to derive a set of road segments that includes all potential ones *and* is as small as possible, which in turn allows for faster predictions.

5.1.4 Calculation of Turn Probabilities

To determine the turning behavior at intersections, we can count the co-occurrences of road segment pairs (Krumm, 2016; Liu and Karimi, 2006) and calculated the corresponding probabilities. We model the turn probabilities by a Markov chain of n^{th}-order, as a driver's behavior at intersections can be represented by a sequence of events, in which the probability of each event, i.e., the decision at the current intersection, depends only on the state attained in the previous event, i.e., the decision at the previous intersection. Markov chains of a higher order allow us to represent the behavior of drivers better to drive around a specific area. This behavior is not uncommon for drivers of transportation network companies, due to the fact that specific regions are more profitable compared to others (Richly and Teusner, 2016).

[2]https://github.com/bmwcarit/barefoot

5.1.5 Final Location Prediction

At the last step, we extrapolate a driver's specific location on the determined road segments, as the estimated time to the passenger can vary based on the particular location on a road segment. During the short-term route prediction, we calculate a set of road segments candidates that a driver is expected to reach within the prediction frame f. We determine for each candidate road segment a driver's required traversal time $t_{path} \in \mathbb{R}_0^+$ to reach it. As the remaining time $t_{remaining}$ of each candidate road segment, i.e., $t_{remaining} = f - t_{path}$, is not large enough to traverse it completely, we expected the driver to be located on it. Given each candidates remaining and traversal time, we estimate the drivers detailed position via the fraction of the road segment the driver is expected to have traversed within the prediction frame.

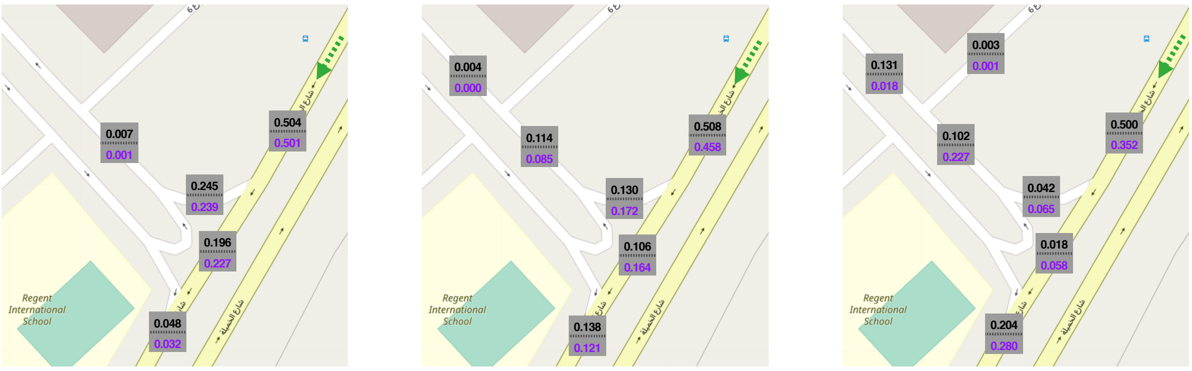
5.2 Numerical Evaluation

In this section, we evaluate the accuracy of our location prediction algorithm. We perform out-of-sample four-fold cross-validation for all experiments and report the average score over all four runs.

5.2.1 Experimental Setup

To evaluate our approach, we used a real-world trajectory dataset of a renowned transportation network company. The dataset includes observed locations of drivers and booking information in the city of Dubai, spanning from November 2018 to February 2019. Compared to publicly available datasets, it has a high sampling rate of 5 seconds. For the period, we have over 400 million observed locations.

Based on the time span between two observed locations, we segment the trajectory data of a driver in sub-trajectories representing continuous driving session. We classified the sub-trajectories based on the occupancy state and get 1.5 million free-time trajectories. The OpenStreetMap road network of Dubai has 139K road segments with average length of 115m.



(a) prediction frame: 5 s (b) prediction frame: 10 s (c) prediction frame: 20 s

Figure 5: Results of the next location prediction algorithm on a representative road segment. We run the experiment on 1 000 out-of-sample pings that share the same road segment indicated by the dashed green arrow. The upper value in the box denotes the relative frequency of drivers that are on the respective road segment after the prediction frame. In contrast, the value below depicts the probability we predict for drivers to be on that road segment after the prediction frame.

5.2.2 Evaluation of the Prediction Algorithm

We evaluate the overall quality of the next location prediction algorithm. We use 1 000 pings located on the same road segment, to predict the road segments their associated drivers could be on after the prediction frame, i.e., the road segment candidates, along with their respective probabilities. The drivers' correct road segment after the prediction frame serves as the ground truth.

We compare the discrete probability distribution of these predicted road segments with the discrete relative frequency distribution of the drivers' correct road segments of the ground truth. We model the turning behavior via 2^{nd}-order Markov chains. For the experiments, we set the prediction frame to 5, 10, and 20 seconds and evaluate the algorithm's performance for a representative example.

In Figure 5, we illustrate the results of our location prediction algorithm for drivers that are currently on a frequented road segment. The training dataset for the algorithm includes 21 751 traversal speed observations and 9 224 turn observations for the respective road segments. The predicted probability density over the set of road segment candidates is similar to the distribution of the relative frequencies of the individual road segments of the ground truth. The average absolute difference between the probability of a predicted road segment and its relative frequency in the ground truth for the prediction frames are small: 0.012 (5 seconds), 0.033 (10 seconds), and 0.075 (20 seconds). The result verifies the accuracy of our approach.

For a prediction frame of 5 seconds, the predicted probability deviates on average by 1.2% from the actual relative frequency. The difference proves that the location prediction algorithm is accurate for frequently observed road segments. As the prediction frame increases, the difference of the predicted probabilities of the road segments to their actual relative frequencies increases. The reason for this is that with increasing prediction frame, the impact of the estimated traversal speeds' inaccuracies increases. The imprecision of the estimation may be caused by temporary traffic conditions that the mined traversal speed estimations do not capture in full detail.

We conducted further location predictions for different examples. Naturally, we found that the results depend on the specific setting considered (road segment, time, individual driving behavior, etc.). However, overall, we obtained similar accuracy results as in the shown example, see Figure 6. Further, we observed that the most critical factor is the amount of data associated with a specific setting.

Moreover, we evaluated if the turning behavior at intersections changes with the time of the day (e.g., rush hour). For that reason, we construct one Markov chain that models the turning behavior of drivers during rush hour and one during the evening hours. We select these hours so that both Markov chains cover the same number of observations.

Further, to assess if the context-specific modeling boosts prediction accuracy, we assess if Markov chains of the same context have more similar turn probabilities than Markov chains of different contexts, considered as *Both*, cf. Figure 6. We measure the similarity via the average absolute difference of turn probabilities of the same Markov state. We constrain the comparison to intersections with at least 50 observations for each context. The restriction results in 2 485 intersections, for which we compare the turn probabilities.

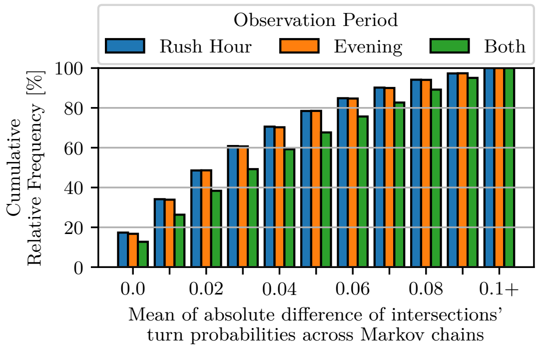


Figure 6: Sensitivity to context: The histogram shows the cumulative distribution of the mean absolute differences of intersections' turn probabilities of different times of the day.

The results, see Figure 6, show that the estimated turn probabilities are accurate for different contexts, i.e., rush hour and evening. For both contexts, around 80% of all Markov states' turn probabilities have at most an average absolute difference of 0.05. In contrast, the Markov chains differ across contexts more significantly. Only around 65% of the Markov states' turn probabilities have at most an average absolute difference of 0.05. In contrast to Krumm (Krumm, 2016), our results demonstrate that including context information can improve the accuracy of turn probabilities.

6 RELATED WORK

In the following section, we review the literature form the related research fields route prediction and turning behavior prediction.

6.1 Route Prediction

Route prediction algorithms can be separated into long-term and short-term route prediction algorithms. Long-term route prediction approaches forecast drivers' entire route to their final destination, whereas short-term route prediction algorithms predict only a fraction of the remaining route a driver can drive within a provided prediction time. Various long-term route prediction algorithms use Hidden Markov Models (HMM) that model a driver's intended route as a sequence of hidden states since drivers' intentions can only be observed indirectly by the driven routes (Simmons et al., 2006; Lassoued et al., 2017; Ye et al., 2015).

Simmons et al. (Simmons et al., 2006) use an HMM that models the road segment, destination pairs as hidden states and the GPS data as observable states. While Simmons et al. (Simmons et al., 2006) do not require a separate map-matching step, Ye et al. (Ye et al., 2015) require one, as their HMM models the driven road segment as observable states, while clusters of route serve as hidden states. Other approaches use clustering techniques to group similar trajectories into clusters so that the deviations of the current trajectories to past trajectories are more tolerated (Lassoued et al., 2017; Froehlich and Krumm, 2008).

Lassoued et al. (Lassoued et al., 2017) hierarchically cluster trajectories via two different similarity metrics: same destination or route similarity metric. They define their route similarity metric as the fraction of shared road segment. Froehlich and Krumm (Froehlich and Krumm, 2008) predict the intended route by using an elaborate route similarity function to compare the current route to a representative combination of routes of each cluster. The similarity metric depicts the distance differences between the GPS recordings of trajectory without prerequiring a map-matching step. Further approaches use machine learning techniques, such as reinforcement learning (Ziebart et al., 2008a), neural networks (Mikluscák et al., 2012), and methods of social media analysis (Ye et al., 2015).

While long-term route prediction algorithms are helpful for the prediction of an entire route, their predictions are bound to previously observed routes. In our problem, however, the pick-up routes of individual drivers are rarely identical, as pick-up locations are not stationary, but various aspects can be used in short-term prediction.

Trasarti et al. (Trasarti et al., 2017) use clustering techniques to extract fractions the driver is expected to be able to drive within the provided prediction time. These approaches, however, still lack the support for new unseen routes.

Karimi et al. (Karimi and Liu, 2003) predict the most probable short-term route by mining the driver's turning behavior at intersections and using the trajectories' underlying road network. They traverse the road network in depth-first fashion to find the maximum reachable locations from the driver's current location. They determine the traversal time of road segments by using the corresponding speed limits. This approach was extended by Jeung et al. (Jeung et al., 2010) by mining the road segments' traversal time from trajectories. Both approaches require the trajectories to be map-matched, as the turn probabilities are calculated on the road segments level.

In contrast, Patterson et al. (Patterson et al., 2003) avoid map-matching by using particle filters that incorporate the error of all random variables into one model. Additionally, dynamic short-term route algorithms exist, that reconstruct their models on-the-fly on data changes. These approaches acknowledge the dynamic nature of traffic and moving objects, whose environment changes aperiodically. Zhou et al. (Zhou et al., 2013) continuously evict patterns from outdated observed trajectories so that the applied models only consider data from the most recent trajectories.

6.2 Turning Behavior Prediction

There are turning behavior predictions, which model drivers' turning behavior as a Markov process (Krumm, 2016; Ziebart et al., 2008b; Karimi and Liu, 2003; Liu and Karimi, 2006; Jeung et al., 2010; Patterson et al., 2003). These approaches are similar in the way they model the turning behavior at intersections as Markov chains, in which the states represent road segments, and drivers' decisions indicate their transitions at intersections. They differ, however, in the order of the Markov chain, i.e., the number of past road segments they consider.

While some consider only the last driven road segment to be an indicator for the next turn (Karimi and Liu, 2003; Liu and Karimi, 2006; Jeung et al., 2010; Patterson et al., 2003), Krumm (Krumm, 2016) proposes the usage of an n^{th}-order Markov chain, in which the next road segment is predicted by following the last n driven road segments as states in the Markov chain. They evaluate that the more past road segments the prediction considers, the more accurate is the prediction of the turning behavior.

However, with the increasing order of the Markov chain, fewer sequences of driven road segments are observed, as the Markov state space increases exponentially. Also, they experimented with inferring if the result's accuracy is sensitive to context information, such as time of day or day of the week. However, they did not find such sensitivity, as the fraction of matched road segment sequences of the given context was small due to the training dataset's size.

Ziebart et al. (Ziebart et al., 2008b) model the turning behavior of drivers via a Markov decision process whose cost weight of actions are learned via inverse reinforcement learning using context- and road-specific features. Further approaches analyze the speed and acceleration profiles of drivers to predict the turning behavior at an upcoming intersection.

Liebner et al. (Liebner et al., 2012) cluster speeding profiles using k-means to predict a driver's turning behavior at a single intersection. Phillips et al. (Phillips et al., 2017) and Zyner et al. (Zyner et al., 2017) use short-term memory neural networks to predict the turning behavior.

7 CONCLUSION

In this paper, we presented an application to visualize the trajectory data of drivers in the period of dispatch processes, which enables the identification of limitations of applied dispatching strategies. Furthermore, it supports transportation network companies to derive a deeper understanding of reasons for unexpected critical delays caused by inefficient dispatch decisions. By using the application, we identified inaccurate positional information as one aspect for the late arrivals of drivers at the pick-up location. These inaccuracies are produced by various circumstances (e.g., noise, technical limitations).

Further, we address this problem by proposing a location prediction approach that provides a probability distribution for a driver's future locations based on patterns observed in past trajectories. More specifically, we are able to quantify with which probability a driver has moved in which direction since the last ping under consideration of personalized and time-dependent driving characteristics. That enables us to support risk-aware dispatch decisions in contrast to common strategies, which use the last observed position of a driver only.

Finally, our prediction approach directly allows improving current dispatch strategies by avoiding critical delays and announcing waiting times with higher confidence. In future research we will further evaluate the proposed approach and study the impact of risk-aware dispatch decisions.

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