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Personalized Routing using Crowdsourced Connected Vehicle Data

Anuj Tiwari, Karl Berntorp, Stefano Di Cairano, and Marcel Menner

Abstract— **This paper develops an algorithm for personalized route recommendations in traffic networks, using crowdsourced connected vehicle data. Current policies usually consider minimal travel and/or minimum energy paths for planning a route between a given origin-destination pair in a road network. However, individual driving preferences may involve a combination, in varying proportions, of the time and energy aspects while choosing a route, and may also depend on additional features such as the type of vehicle, amount of expected speed variations along the routes, turns, etc. These additional factors need to be considered to provide individualized route recommendations for different drivers. This paper uses individual driving histories to, i) create a generalized probabilistic model of the driver-specific features given certain macroscopic traffic conditions for each road segment between a chosen origin-destination pair, and, ii) learn a personal cost function based on the predicted features. The algorithm for recommending routes for different drivers is validated using Simulation of Urban MObility (SUMO)-based simulation of an urban road network.**

I. Introduction

Connected and automated vehicles (CAVs) have been proposed for future transportation systems as a solution to improve traffic flow, efficiency, and safety, and there is a rich history of research literature in this direction [1]–[3]. More recently, the use of connected vehicles as mobile sensing platforms for Crowdsourced Vehicular Sensing (CVS) [4], [5] has been proposed, which can be used for modeling urban traffic networks [6], for instance to predict individual driver behavior using location-specific crowdsourced data [7].

This paper proposes using the crowdsourced vehicular data about traffic conditions in urban traffic networks for optimum route prediction for individual drivers. Previous work on route choice models have focused on minimum travel and fuel consumption paths [8]–[12]. However, individual route preferences can depend on additional factors, in addition to the travel time and fuel consumption, such as route familiarity, type of roads, such as urban streets or highways, etc. This paper proposes using personalized driving histories of individual drivers to predict optimum paths based on personal preferences. The personal preference over route choices can be modeled as the cost of choosing one route over another based on past driving patterns. However, it is not trivial to find a mathematical formulation of the personalized cost associated with route choices.

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The approach proposed in this paper is to use driving histories to learn the route choice models of individual drivers by extracting a surrogate cost function from such data. The availability of sophisticated onboard sensing in connected vehicles enables CAVs to relay microscopic vehicle-specific data, which may include the ego vehicle's speed, acceleration, and energy consumption, corresponding to the surrounding traffic conditions, described through the macroscopic features consisting of averaged surrounding traffic speed, acceleration, etc. Such microscopic vehicle-specific data are expected to be different for the same macroscopic traffic conditions, depending on different driving behaviors. For instance, conservative drivers can have slower speeds in the same free-flow traffic conditions, as compared to aggressive drivers. The main contribution of this paper is to develop an algorithm for learning a personal cost function for route choices of drivers, by statistically modeling the relationship between micro-macro traffic features from individual driving histories, and predicting personalized optimal routes for trips between a given origin-destination pair. Specifically, first the driving history is represented as feature vectors, with microscopic and macroscopic features, for an individual driver, and then the implicit cost function of the ego vehicle is modeled as a joint probability using a Gaussian Mixture Model (GMM). The GMM of the feature vectors models the correlation between microscopic and macroscopic features that captures the past driving behaviors of individual drivers for different traffic conditions. Second, given the macroscopic features provided by the crowdsourced connected vehicle data, which depict the traffic conditions, the most likely ego vehicle behavior is predicted using the GMM from driving history. Third, the cost for choosing a given route is estimated based on the likelihood of the feature vectors along the route in the driving history, where the feature vectors consist of the microscopic predicted features from the GMM and the macroscopic features from the crowdsourced data. Finally, the paper presents the implementation of the proposed data-based algorithm through a simulation example in Simulation of Urban MObility (SUMO) [13], [14], where connected vehicle data and individual ego vehicle driving histories are created for a realistic urban traffic road network.

A. Related Work

Personalizing vehicle control: Related work often considers personalized vehicle control or data-based controller calibration, see e.g., [15]–[23]. The work in [15] calibrates a motion planner for personalizing the autonomous driving experience. In [16], an optimal controller is calibrated using driving data. The work in [17] uses a game-theoretic controller for vehicle interactions using various types of driver models, [18] calibrates an agent-based simulation to reproduce the individual/group traffic behaviors, [19] proposes risk-aware model predictive control and Gaussian processes to model the evolution of the environment using traffic data, and [20] uses a maximum likelihood method to learn a cost function for model predictive contouring control. In [21], a cost function is calibrated for multi-agent dynamic games. Similar to our approach, [22] also learns a non-parametric cost function, which is subsequently used for energy-optimal control of electric vehicles. However, few papers address vehicle route choice models based on personal driving preferences, which can be a function of many variables besides time of travel and energy efficiency.

Vehicle routing: Vehicle routing algorithms are a subset of combinatorial optimization problems which have been studied for applications such as freight distribution and collection, and transportation networks [24]. In the context of transportation networks, vehicle routing has been mainly studied for minimizing travel time and uncertainty, and fuel consumption, e.g., in [8] Support Vector Machine (SVM) is used to create non-parametric driver route choice models based on travel time, travel time fluctuations, and fuel costs as the route attributes. Similarly, energy-optimal route planning has been proposed in [12], which provides a fuel-optimal route in addition to optimal speed and gear profiles for a given origin-destination pair for heavy duty vehicles. However, in the case of personal vehicles, travel time, its reliability, and fuel consumption are not the only factors that affect the driver's route choices. There can be other attributes that may inform a driver's choices, e.g., familiarity of the route's surrounding area, type of roads, ease of driving, etc., which can potentially be inferred from driving history information as presented in this paper. Moreover, a driver's route choice may result from trading-off multiple different or conflicting objectives.

B. Outline

The rest of the paper is organized as follows. The algorithm for learning the route choice model is derived in Section II, its application to an example urban network is shown through SUMO simulations in Section III, and concluding remarks are given in Section IV.

II. Mathematical Formulation

This section presents the algorithm for modeling the personalized choice behavior from driving history, which is then used to predict the individual cost for traveling on routes.

The driving history of a vehicle on the road network is represented using feature vectors $X_i \in \mathbb{R}^n$, where i corresponds to a road edge $i \in \mathcal{N}_E$ in the network with $\mathcal{N}_E$ being the total number of segments in the network, and $n = n_V + n_E$ with n_V microscopic vehicle-specific features and n_E macroscopic traffic features, or conditions, of road edge i. Hence, a feature vector is composed of

$$X_i = \begin{bmatrix} x_{V,i} \\ x_{E,i} \end{bmatrix}$$

where $x_{V,i} \in \mathbb{R}^{n_V}$ are the microscopic vehicle features and $x_{E,i} \in \mathbb{R}^{n_E}$ the macroscopic edge features. It is assumed that each ego vehicle's driving history is stored as a set of feature vectors X_i.

Let $\mathcal{C}_V(X_i)$ be the unknown cost associated with a road segment i for an ego vehicle, where X is a state describing the vehicle behavior and features of the road. In general, the cost $\mathcal{C}_V(X)$ for the ego vehicle may be difficult to model using, e.g., a parametric model such as a quadratic cost function. Hence, in this paper we model $\mathcal{C}_V(X)$ using a probability density function (PDF), $P(X)$, with

$$\mathcal{C}_V(X) = -\log\left(P(X)\right). \tag{1}$$

Using the negative logarithmic likelihood is sensible as we model $P(X)$ being a distribution from the exponential family. As a result, we can model traffic/vehicle data measurements X_i as samples from $P(X)$,

$$X_i \sim P(X), \tag{2}$$

which, in turn, we can utilize to reason about $P(X)$ using measurements X_i. The reasoning for choosing a probabilistic model is that road conditions that have been observed more frequently for a specific driver are also more likely for future route choices. Hence, this paper

- develops an algorithm for learning a driver's cost function as in (1) for route choices using driving history given by samples (2) and
- uses such a driver-specific cost function to predict an optimal route for a given origin-destination pair using crowdsourced data depicting current traffic conditions on the road network.

A. Modeling driving behavior as joint PDF

The implicit cost function of an ego vehicle is modeled from its driving history as a joint probability as in (2) between the microscopic ego vehicle features $x_{V,i}$, such as vehicle speed, acceleration, energy consumption, etc., and macroscopic road features $x_{E,i}$, such as speed averaged over all the vehicles on the road, congestion, average energy consumption, etc. These are stored as the feature vectors X_i at different road edges $i \in \mathcal{N}_E$. Such a mapping between microscopic features models the ego vehicle's behavior in different traffic conditions, while also learning the more frequented, and hence preferable, road conditions from individual driving histories. Therefore, this approach leads to learning of driver's tendencies and preferences from driving histories, and provides a method to model the implicit cost function intrinsic to a driver for making route choices.

This paper uses a data-based approach, where (2) is approximated using a GMM and fitted to the ego vehicle's feature vectors from driving history, to obtain the joint probability between the microscopic ego vehicle features $x_{V,i}$, and macroscopic road edge features $x_{E,i}$. Let K be the number of Gaussian distributions in the GMM. Then, the GMM is

$$P(X) = P\left(\begin{bmatrix} x_V \\ x_E \end{bmatrix}\right) = \sum_{k=1}^{K} \pi_k \mathcal{N}\left(\begin{bmatrix} x_V \\ x_E \end{bmatrix} \middle| \mu_k, \Sigma_k\right)$$
$$= \sum_{k=1}^{K} \pi_k \, p_k\left(\begin{bmatrix} x_V \\ x_E \end{bmatrix}\right), \tag{3}$$

where π_k is the mixing coefficient, μ_k and Σ_k are the mean vector and covariance matrix, respectively, of the k^{th} Gaussian distribution $p_k(X)$ in the GMM (3), and,

$$\mathcal{N}(X|\mu,\Sigma) = \frac{1}{\sqrt{(2\pi)|\Sigma|}} \exp\left(-\frac{1}{2}(X-\mu)^T\Sigma^{-1}(X-\mu)\right).$$

The mean $\mu_k \in \mathbb{R}^n$ and covariance $\Sigma_k \in \mathbb{R}^{n\times n}$ of the k^{th} Gaussian component in the GMM (3) can be segmented into their microscopic and macroscopic features as follows,

$$\mu_k = \begin{bmatrix} \mu_{k_V} \\ \mu_{k_E} \end{bmatrix}, \quad \Sigma_k = \begin{bmatrix} \Sigma_{k_{VV}} & \Sigma_{k_{VE}} \\ \Sigma_{k_{EV}} & \Sigma_{k_{EE}} \end{bmatrix}, \tag{4}$$

where $\mu_{k_V} \in \mathbb{R}^{n_V}$ and $\mu_{k_E} \in \mathbb{R}^{n_E}$ are the mean vectors of the k^{th} Gaussian for the microscopic and macroscopic features respectively, and $\Sigma_{k_{VV}} \in \mathbb{R}^{n_V\times n_V}$ and $\Sigma_{k_{EE}} \in \mathbb{R}^{n_E\times n_E}$ are the covariance matrices of the microscopic and macroscopic features respectively, and $\Sigma_{k_{VE}} = \Sigma_{k_{EV}}^T$ is the cross-covariance matrix.

B. Predicting ego vehicle behavior given macroscopic conditions

The Gaussian mixture distribution of the joint probability of feature vectors in (3) can be used to predict an individual's driving behavior on a road edge i, i.e., $x_{V,i}$, from the crowdsourced macroscopic traffic conditions, $x_{E,i}$, on the road edge i.

First, the joint probability distribution (3) is formulated as

$$P\left(\begin{bmatrix} x_{V,i} \\ x_{E,i} \end{bmatrix}\right) = \sum_{k=1}^{K} \pi_k \, p_k\left(\begin{bmatrix} x_{V,i} \\ x_{E,i} \end{bmatrix}\right)$$
$$= \sum_{k=1}^{K} \pi_k p_k(x_{E,i}) \, p_k(x_{V,i}|x_{E,i})$$
$$= \sum_{k=1}^{K} c_k p_k(x_{V,i}|x_{E,i}), \tag{5}$$

where $p_k(x_{E,i})$ is the marginal probability distribution of macroscopic features $x_{E,i}$ on road edge i, $p_k(x_{V,i}|x_{E,i})$ is conditional probability distribution of the microscopic vehicle features $x_{V,i}$ given the macroscopic traffic conditions $x_{E,i}$ on road edge i, and $c_k = \pi_k p_k(x_{E,i})$ is the contributing factor of individual conditional probabilities $p_k(x_{V,i}|x_{E,i})$.

Second, the conditional probability is leveraged to predict the vehicle features. In this paper, we choose the Gaussian distribution with the highest contributing factor c_k,

$$k^* = \underset{k}{\text{argmax}} \; c_k = \underset{k}{\text{argmax}} \; \pi_k p_k(x_{E,i}), \tag{6}$$

to obtain the predicted microscopic vehicle features $\hat{x}_{V,i}$ on road edge i as

$$\hat{x}_{V,i} = \mu_{k^*_{V,i}} + \Sigma_{k^*_{VE,i}} \Sigma^{-1}_{k^*_{EE,i}} \left(x_{E,i} - \mu_{k^*_{E,i}}\right). \tag{7}$$

Remark 1: If the different modes of driving, defined by each Gaussian in the GMM, are well separated, the simplified choice of k^* in (6) for predicting the ego vehicle behavior is fairly accurate. However, other choices are possible. For instance, in the case of not well-separated Gaussians in the GMM, we can use the overall joint probability distribution in (5), rather than a single Gaussian as in (7), which could be done by using particle filtering for obtaining the conditional probability distribution [25].

C. Edge cost based on driving history

The cost of choosing a road edge i on a trip is quantified using it's macroscopic traffic conditions $x_{E,i}$ and the corresponding predicted microscopic vehicle features $\hat{x}_{V,i}$, which leads to the predicted feature vector on road edge i as

$$\hat{X}_i = \begin{bmatrix} \hat{x}_{V,i} \\ x_{E,i} \end{bmatrix}.$$

The cost $\mathcal{C}_{V,i}$ of choosing edge i is the negative log-likelihood of the predicted feature vector, $\hat{X}_i$,

$$\mathcal{C}_{V,i} = -\log\left(P\left(\begin{bmatrix} \hat{x}_{V,i} \\ x_{E,i} \end{bmatrix}\right)\right), \tag{8}$$

which quantifies the likelihood of the predicted feature vector based on the joint distribution $P([\hat{x}_{V,i}, \; x_{E,i}]^T)$ obtained from the driving history of the ego vehicle. Hence, for a given origin-destination pair on a road network, the crowdsourced data from connected vehicles on the road edges are used to first predict an ego vehicle's microscopic features, and then a personalized cost based on driving history is computed on the road edges of the network. Finally, the minimum cost path is chosen for personalized routing for the origin-destination pair using Dijkstra's algorithm [26]. Note that other routing algorithm can also be applied, using the assigned cost of route edge i in (8).

III. Simulation Results

In this section, SUMO is used for collecting traffic data over a realistic road network, and the GMMs are used for predicting the cost of individual route choices using macroscopic road and microscopic driver features.

A. SUMO simulation setup

The example road network for the simulation study is constructed from a section of the Cambridge, MA city, see Fig. 1, using OpenStreetMap. OpenStreetMap is an open-source collaborative mapping initiative, which can be imported in SUMO leading to a graph as shown in Fig. 2. Traffic data are generated by populating the road network with heterogeneous vehicles of different vehicle types and driver behavior, see the SUMO documentation [13], [14]. Passenger vehicles, taxis, delivery vehicles, trucks and trailers vehicle types in SUMO are used to create heterogeneity

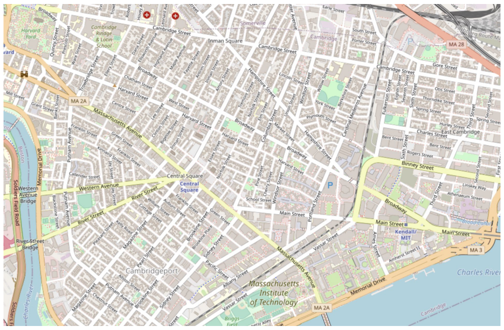

Fig. 1. The urban road network example of Cambridge, MA used for the simulation study.

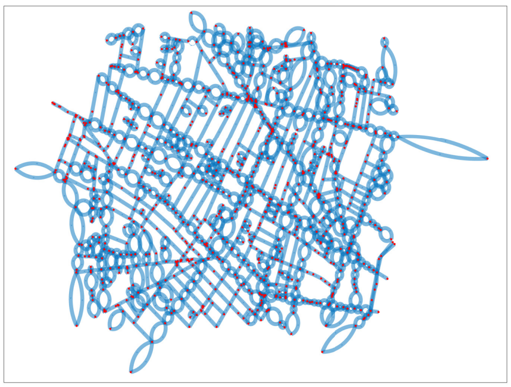

Fig. 2. The exported underlying graph structure of the example urban road network in Fig. 1, as a set of nodes in red and directed edges in blue.

in the traffic conditions. Both periodic and random trips are generated for these vehicles to populate the road network during the SUMO simulation, which runs for a duration of two 2 hours to simulate both recurring traffic along major roads, and random trips between nodes in the road network. The vehicles over the duration of the simulation, and the congestion keeps on increasing, making the first hour of simulation to have more free flow conditions over the road network, while congestion appearing in the second hour of the simulation depicting rush hour conditions. Additionally, six ego vehicles, as shown in Table I, are defined to generate individual driving histories. Vehicles 1 to 3 have smaller max acceleration, and smaller gains for maintaining desired time headways in the Adaptive Cruise Control (ACC) car following model in SUMO. On the other hand, Vehicles 4 to 6 have higher max acceleration, and higher gains in the ACC car following model to simulate more aggressive behavior. Random trips on the road network to create driving histories for the ego vehicles are generated during the simulation.

B. Design choices

Microscopic and macroscopic features: The vehicle specific microscopic features over the edge i, $x_{V,i}$, considered in the example study are mean vehicle speed, mean vehicle acceleration, mean energy consumption, mean vehicle noise, and travel time. Mean vehicle noise relates to speed variations indicating the level of accelerations and decelerations.

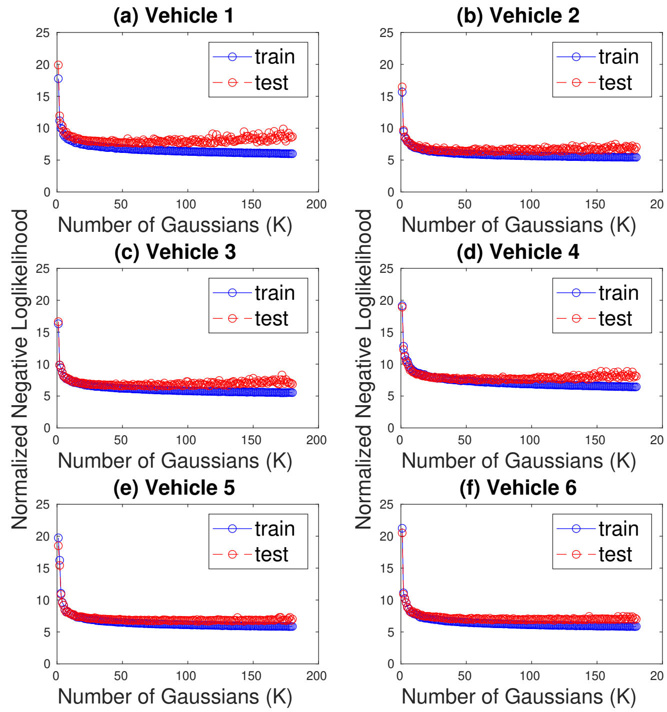

Fig. 3. The training error in blue and validation error in red of the the GMMs for the six ego vehicles defined in Table I.

TABLE I

SIX DIFFERENT EGO VEHICLES IN SUMO

Ego Vehicle	Max Acc.	Max Decel.	Vehicle Type	Car-Following Model
1	$2 m/s^2$	$2.2 m/s^2$	HDV	ACC (conservative)
2	$2 m/s^2$	$2.2 m/s^2$	PC	ACC (conservative)
3	$2 m/s^2$	$2.2 m/s^2$	EV	ACC (conservative)
4	$4 m/s^2$	$2.2 m/s^2$	HDV	ACC (aggressive)
5	$4 m/s^2$	$2.2 m/s^2$	PC	ACC (aggressive)
6	$4 m/s^2$	$2.2 m/s^2$	EV	ACC (aggressive)

The macroscopic traffic conditions on edge i $x_{E,i}$ are the mean speed, mean acceleration, mean energy consumption averaged over all the vehicles on the road edge, and edge occupancy and vehicle density on the road edge.

Number of Gaussians in the joint PDF model: The Gaussian mixture distribution of the joint probability of feature vectors, relating the microscopic ego vehicle features $x_{V,i}$ to the macroscopic road edge features $x_{E,i}$, modeling the driver behavior using driving history data, requires the tuning of the hyper-parameter K in (5), where K is the number of Gaussians in the GMM. The number of Gaussians K in the probability distribution $P(X)$ based driving history is selected through the hyperparameter tuning shown in Fig. 3. The feature vectors from the driving history of each of the ego vehicles are split into training (80%) and test data (20%), and the negative log-likelihood of the training and test data given the fitted GMM model are shown in Fig. 3, for increasing number of Gaussians K. The training error on the training data with the GMM keeps decreasing with

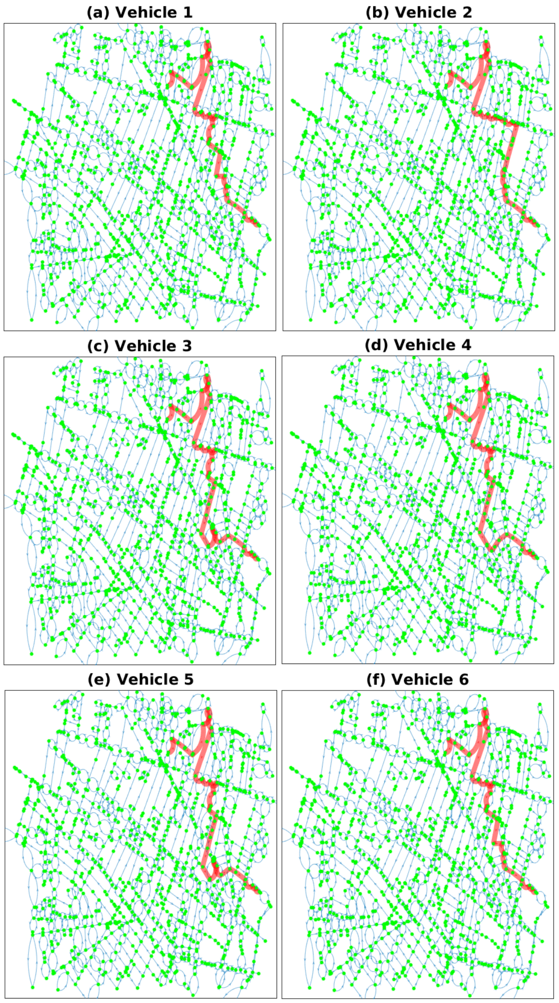

Fig. 4. Qualitative illustration of the personalized route prediction for the different ego vehicles in Table I using crowdsourced-vehicle data at a particular time instant, and individual driving histories based GMMs, between a given origin-destination pair on the example road network in Fig. 1 and 2.

increasing number of Gaussians K in the model. However, the validation error with the test data increases with GMM for large K due to overfitting. In the current example simulations, the number of Gaussians is selected as $K = 40$, so that the fitted GMM is not too complex, while also keeping the error small for both training and test data.

C. Qualitative illustration of different route choices

The personalized route prediction for the six ego vehicles on the example urban road network in Fig. 1 are presented in Fig. 4 for a given origin-destination pair of nodes on the road network, at a specific time instant during the SUMO simulation. The prediction algorithm provides four distinct paths for the Vehicles 1, 2, 3, and 4 as optimum based on their driving history for the same origin-destination pair. As shown in Fig. 4, Vehicles 5 and 6 have the same predicted optimum route as Vehicles 3 and 1, respectively. This specific example qualitatively presents the algorithm's ability to predict different optimum paths for different vehicles based

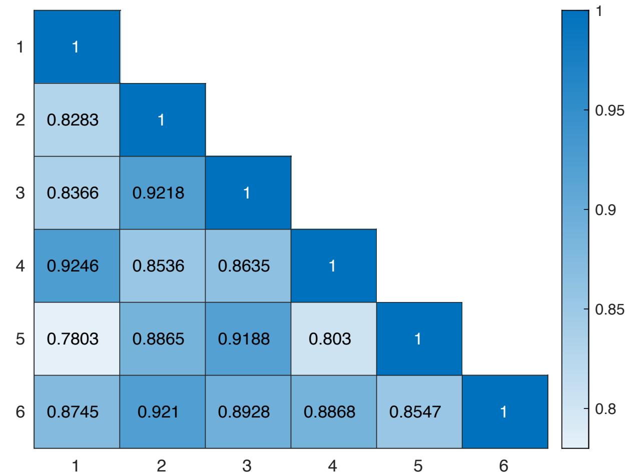

Fig. 5. Quantitative analysis of the overlap between predicted routes for the different ego vehicles in Table Iaveraged over 10 time instants and seven randomly selected origin-destination pairs in the example road network in Fig. 2 when the traffic is non-congested.

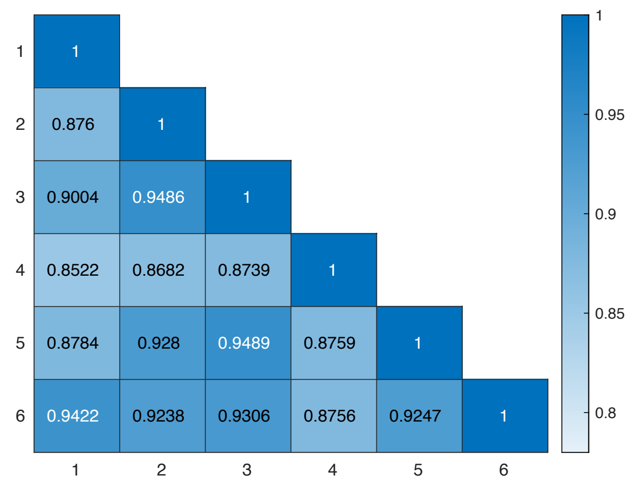

Fig. 6. Quantitative analysis of the overlap between predicted routes for the different ego vehicles in Table Iaveraged over 10 time instants and seven randomly selected origin-destination pairs in the example road network in Fig. 2 when the traffic is congested.

on driving history and crowdsourced connected vehicle data for particular traffic conditions.

Although the six ego vehicles characteristics are different as in Table I, the predicted optimum paths can coincide, as shown in Fig. 4 for a particular time instant for the example road network in Fig. 1, because of the limited number of major road segments between the origin-destination pair in the small urban area.

D. Quantitative results

The personalized route predictions for the six different ego vehicles in Table I are averaged over different time instances during the SUMO simulation and over seven randomly selected origin-destination pairs, and presented through the confusion matrices in Figs. 5 and 6, which quantify the percentage overlap of the predicted routes between the different ego vehicles. For instance, the $(i, j)^{th}$ element of the confusion matrices shows the averaged similarity between the predicted routes of Vehicle i and Vehicle j. Therefore, smaller off-diagonal elements of confusion matrix depicts more diverse route choices. Fig. 5 shows the confusion matrix for the time instances when the considered example traffic network in Fig. 2 is not congested, i.e., when most vehicles are in free flow and can make different decisions based on different characteristics in Table I. Fig. 6 shows the confusion matrix when the traffic network is congested. It can be seen that the overlap between the predicted routes becomes larger for the different ego vehicles when the traffic network becomes congested. However, in the non-congested state, when the different vehicles can choose different behaviors based on personal cost functions, the overlap between vehicle predictions is reduced.

The predicted routes at a particular time in Fig. 4 for the example road network show reasonable choices between the specific origin-destination pair. Furthermore, the different characteristics of the ego vehicles do lead to differences in the predicted routes, which is already constrained by limited number of choices in the small urban network. This shows the ability of the proposed algorithm to capture differences in preferences from individual driving histories. A more comprehensive quantitative evaluation averaged over multiple time instances and origin-destination pairs shows that the algorithm predicts different routes for the ego vehicles in less congested period of simulation in Fig. 5 when vehicles are free to make different decisions. On the other hand, in congested situation, when most major roads are blocked, the algorithm predicts more similar routes as shown in Fig. 6.

IV. Conclusions

This paper presented a personalized vehicle routing algorithm based on individual driving histories and using crowdsourced connected vehicle data. The algorithm developed a generalized approach to learn route choice models of individual drivers by providing a cost function based on driving history and connected vehicle data. The driving history of individual drivers captured individual route preferences, which can be based on more attributes than the commonly-used features of travel time and energy efficiency. SUMO simulations on a realistic road network showed the ability of the algorithm to predict personalized route choices for the same traffic conditions.

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