Towards Personalized Learning for Traffic Agents in the Driving Environment: Methodological Perspective

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1 Introduction

Heterogeneity has been a longstanding characteristic of human-driven vehicle traffic. It is set to be compounded by the growing adoption of automated vehicles (AVs) and the emergence of mixed traffic. The behaviors exhibited by AVs differ among themselves and notably with human driven vehicles (HDVs), highlighting the complex and heterogeneous nature of mixed traffic.

Central to our work here is the challenge of data-driven learning under such heterogeneity. Specifically we recognize that some methods of aggregating data across diverse traffic agents (e.g., different human drivers) to develop predictive models (e.g., driving models) encounter significant limitations. Such methods often fail to accommodate the distinct behaviors and preferences of individual agents. Misalignment between how traffic agents desire to behave versus how we model them to can mislead both data-driven predictions and traffic-scientists alike.

We propose a framework that employs a personalized modeling[1] approach to learn models for traffic agents[2]. This approach is motivated by (i) the heterogeneous nature of driving data and challenges it poses on data-driven learning, and (ii) the distinctive requirements of mixed-traffic environments, which demand effective human-machine coexistence and behavioral alignment.

Personalization offers a valuable opportunity to identify and utilize behavioral differences among traffic agents, and leverage them for improved downstream analytics (i.e., operation management).

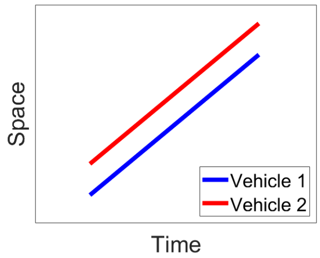
2 Learning Personalized Agents

2.1 Motivation: Toy Example

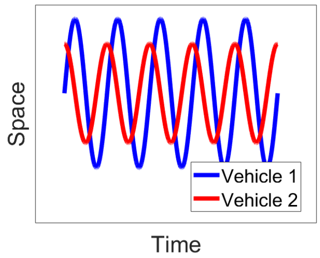
We begin with a simplified example that illustrates the challenges of learning amidst data heterogeneity stemming from diverse traffic agent behaviors. Hereon after, we will focus on traffic as AVs or HDVs, and in car-following (CF) scenarios.

[1]personalization refers to models that adapt their learning to agents' behavior and preferences

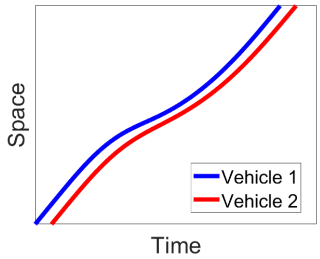
[2]by traffic agents we mainly refer to HDVs and AVs, yet we leave the notation general as the modeling framework is not restricted to particular agents. For instance, bicyclist can be seen as traffic agents.



(a) *Equilibrium*



(b) *Wave Response*



(c) *Car Following*

Figure 1 – *Behavior Difference*

We consider the following problem setup (Figure 1) where CF trajectories (Figure 1c) can be decomposed into an equilibrium state (Figure 1a) and a sinusoidal response function (with compound waves) (Figure 1b). The response function holds information on the CF behavior of an HDV/AV; in other words, how a vehicle responds to stimulus from the environment (e.g., traffic oscillations). This decomposition is of unique interest as we can isolate the heterogeneity in behavior to the characteristics of wave response, which if compared across different vehicles represents different driving behaviors.

Interestingly, we can discover from such composition that building a data-driven model by aggregating driving data from different wave response functions can lead to loss of inference. We can examine this phenomenon through a stylized mathematical example. Consider that vehicle response (Figure 1b) is defined by a sine function $f_{\theta_v}(x) = \sin(2\pi(x + \theta_v))$, where $\theta_v \in \mathsf{uniform}[0, 1]$ is vehicle-dependent. Essentially, vehicles have similar behavior but with a phase shift (often common in AVs control logic (Kontar *et al.*, 2021)). Now training a global model implies minimizing the risk

$$\min_{\boldsymbol{w}} \mathbb{E}_v[||f_{\boldsymbol{w}} - f_{\theta_v}||_2^2] \,.$$

where, f_w is the global model parameterized by weight $\boldsymbol{w}$ and and $||\cdot||_2$ is a functional on $[0, 1]$ defined as: $||f||_2^2 = \int_0^1 f(x)^2 dx$. We then have

$$\begin{aligned}
&\arg\min_{f_{\boldsymbol{w}}} \mathbb{E}_{\theta_v}\left[\int_0^1 \left(f_{\boldsymbol{w}}(x) - \sin(2\pi x + 2\pi\theta_v)\right)^2 dx\right] \\
&= \arg\min_{f_{\boldsymbol{w}}} \mathbb{E}_{\theta_v}\left[\int_0^1 f_{\boldsymbol{w}}(x)^2 - 2f_{\boldsymbol{w}}(x)\sin(2\pi x + 2\pi\theta_v)dx\right] \\
&= \arg\min_{f_{\boldsymbol{w}}} \mathbb{E}_{\theta_v}\left[\int_0^1 f_{\boldsymbol{w}}(x)^2 dx\right].
\end{aligned}$$

Which admits a unique minimizer $f_w(x) = 0$ for all $x \in [0, 1]$, since $\mathbb{E}_{\theta_v}[\sin(2\pi x + 2\pi\theta_v)] = 0$. Clearly, such global modeling under heterogeneity is far from truth and essentially learns nothing. This highlights the need for a modeling technique that can isolate behavioral heterogeneity. We refer to this hereafter as personalization modeling; where the goal is to decompose data into common information (i.e., Fig. 1a) and unique patterns (i.e., Fig. 1b). Consequently, identifying unique patterns holds important usage at the intersection of: human-AV interaction (in the context of mixed traffic) and behavioral alignment of AV to human preferences.

2.2 Learning Heterogeneous Features

We follow the same philosophy of the data decomposition shown in Fig. 1c, to build a modeling framework that identifies common and unique patterns in driving data. The modeling framework finds its roots in Principal Component Analysis (PCA) and Matrix Factorization (MF) techniques.

Consider $\boldsymbol{V}$ data sources representing driving data from different vehicles. Each vehicle has dataset $\{\boldsymbol{D}_{(v)}\}_{v=1}^{V}$, where $\boldsymbol{D}_{(v)}$ represent observations from vehicle v. Here $\boldsymbol{D}_{(v)}$ contains typically driving data information of the vehicle's speed, acceleration, and positioning, as well as any other contributing information (e.g., neighboring vehicle kinematic data). We note that such approach has no limitation on data type or number of observations, but the only consideration is that vehicles should have the same feature space. Accordingly, each driving data observation $\boldsymbol{d}_{(v)}$, from vehicle v is modeled as a decomposition of K_1 shared components and $K_{2,(v)}$ unique components:

$$\boldsymbol{d}_{(v)} \sim \sum_{k=1}^{K_1} \psi_{(v),k}\boldsymbol{c}_k + \sum_{k=1}^{K_{2,(v)}} \Psi_{(v),k}\boldsymbol{u}_{(v),k} + \epsilon_{(v)} \tag{1}$$

Where $\psi_{(v),k}$ and $\Psi_{(v),k}$ are the principal components scores. What is of specific interest to us are the principal components $\boldsymbol{c}_k$ and $\boldsymbol{u}_{(v),k}$. Specifically, we compile $\boldsymbol{C} = [\boldsymbol{c}_1, \cdots, \boldsymbol{c}_{K_1}]$ representing the principal component scores of common features, and $\boldsymbol{U} = [\boldsymbol{u}_{(v),1}, \cdots, \boldsymbol{u}_{(v),K_2}]$ the principal component scores of unique features. In other words, the $\boldsymbol{C}$ holds common driving information between vehicles, while $\boldsymbol{U}$ records unique patterns specific for each vehicle.

In the PCA methodology, the principal components must be orthogonal:

$$\begin{cases} \boldsymbol{c}_{k1}^{\top}\boldsymbol{c}_{k2} = \mathbf{I} \\ \boldsymbol{u}_{(v),k1}^{\top}\boldsymbol{u}_{(v),k2} = \mathbf{I} \\ \boldsymbol{c}_{k1}^{\top}\boldsymbol{u}_{(v),k2} = \mathbf{I} \end{cases} \tag{2}$$

Accordingly, in PCA the objective is to minimize the following loss function while solving for $\boldsymbol{C}$ and $\boldsymbol{U}$, and subject to constraints presented in Eq. 2

$$\min_{\boldsymbol{C},\boldsymbol{U}_{(v)}} \quad \frac{1}{2}\sum_{v=1}^{V}\frac{1}{n_v}\left\|\mathbf{D}_{(v)} - \hat{\mathbf{D}}_{(v)}\right\|_2^2 \tag{3}$$

2.3 Model Demonstration

For demonstration illustrated in Figure 1, our goal is to learn common and unique features of CF trajectories from different vehicles. Specifically, we envision a common feature to be a neutral trajectory while unique features are those oscillatory perturbations to the trajectory, which hold behavioral differences.

We show this in Figure 2. Specifically, we simulate a set of 5 CF trajectories for AVs, with a common HDV leader profile. We design the AVs to have different behavior by tweaking their control parameter set (i.e., creating a range of aggressive, moderate, and conservative behaviors). The control parameters are based on $K_{(v)} = [k_s \quad k_v \quad k_a]$, where k_s is the spacing gain, k_v relative speed, and k_a is acceleration gain. In the simulation we have $K_1 = [1 \quad 1 \quad -3]$, $K_2 = [3 \quad 3 \quad -1.2]$, $K_3 = [0.5 \quad 0.5 \quad -1.2]$, $K_4 = [1.5 \quad 1.5 \quad -0.8]$, and $K_5 = [2 \quad 2 \quad -0.8]$ [3]. Note that the dataset for each of these vehicles has the same feature space, this is a requirement for the model presented here. Then we solve for the common and unique feature spaces. Specifically, we learn $\boldsymbol{C}$ and $\{\boldsymbol{U}\}_{i=1}^{5}$. We then project a vehicle's data into these common and unique subspace learned (e.g., solving $\boldsymbol{U_1}\boldsymbol{U_1}^{\top}\boldsymbol{D_1}$) to output the unique patterns for each vehicle. The results in Figure 2 show how CF behavior of each vehicle can be represented by a common feature trajectory and a unique response pattern to it – akin to deviation from the equilibrium. The unique patterns here represents behavioral difference for each vehicle.

[3]For the sake of space we do not discuss the AV control system in the simulation, but it follows from our work in (Kontar *et al.*, 2021). In short the controller is a linear-feedback controller, that generates different response behavior by tweaking the controller gain parameters.

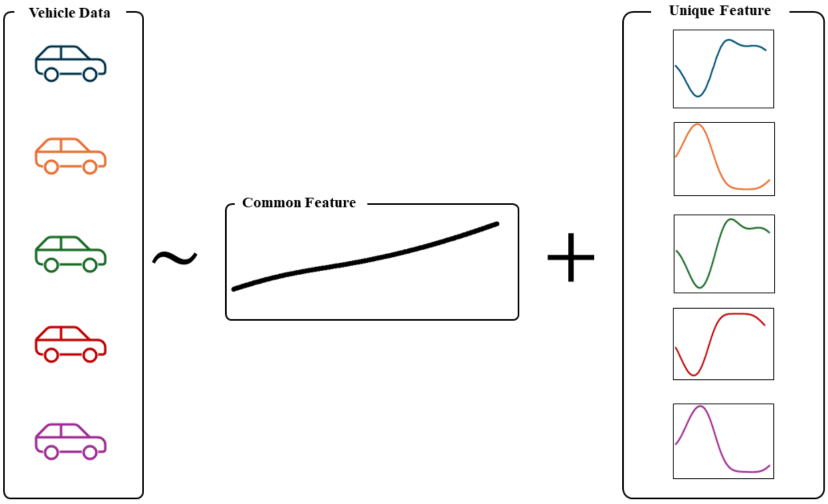


Figure 2 – *Extracting Common and Unique Features for Each Vehicle Dataset*

3 Discussion and Planned Work

In this abstract we focus mainly on the methodological perspective; however the complete work has two principal objectives:
Mixed traffic operations: The goal here is to design AV's CF models with embedded knowledge on unique human behaviors. Following the methodology presented here we can learn unique representation of human driving data (e.g., from NGSIM), and embed such knowledge into an AV training process similar to what we show in the demonstration. We hypothesize that doing so enhances AV's situational awareness by enabling better prediction of other traffic agents on the road. We will test this hypothesis in mixed traffic simulation environments.
Alignment of AV design to human preference: Unique features of human driving can be incorporated to align AV behavior with human preference, creating a personalized driving experience for humans inside AVs.

References

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