Development of A Safe, Profitable, and Fair Robotaxi Deployment Strategy

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FINAL REPORT

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DISCLAIMER

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Problem Statement:

The deployment of autonomous vehicles (AVs) has been troubled by the soaring cost of operations and the public's concerns about the safety and fairness issues potentially brought by the new mobility. As leading companies such as Waymo and Uber which have obtained permits to commercialize their robotaxi fleets domestically and overseas, it is urgent to investigate deployment strategies that are sustainable for companies to run their business and beneficial to the public.

This project aims to develop a safe, profitable, and fair deployment strategy for robotaxis by studying the possibility of deploying a fleet of autonomous vehicles with different functionalities. The temporospatial requirement for AVs will be analyzed using the traffic primitives method and synthesized with transportation demands. In this project, we visualize the complexity of the possible situations and the risk level on the whole Pittsburgh City level. Strategies will be developed to minimize the costs by commanding AVs with different functionalities to appropriate routes while maintaining an appropriate safety standard. In addition, we incorporate inverse general-sum non-cooperative dynamic games to estimate human drivers' intrinsic utility function and therefore obtain a model of social norms that can be used to improve the safety and social compliance of AVs.

To ensure safety and lay the foundation of autonomous vehicles deployment, this project first leverages past research on labeling the city's roads with different risk levels based on large-scale real-world datasets of Pittsburgh city, including multi-dimensional and multi-fidelity data [1]. The identification of typical driving scenarios is based on Dirichlet-Process-Gaussian-Process [3,4].

From the game-theoretical perspective, we study socially compliant driving behaviors based on human driving data. Here we understand social norms as "mental representations of appropriate behavior". A social norm often consists of social conventions that can be explicitly or implicitly learned under certain social contexts, which serves as guidelines for how humans and autonomous vehicles should behave.

Methods:

The first-stage analysis is based on the Argoverse tracking Dataset [1], which is collected from onboard sensors such as lidars and cameras of AVs in Pittsburgh City. The dataset contains the location, type, and bounding box of surrounding objects. The second-stage analysis is based on the Interstate 80 (I-80) Freeway trajectory of the eastbound traffic during rush hour from the Next Generation Simulation (NGSIM) dataset [6]. The dataset contains vehicle information such as length and type, and kinematic information such as position, speed, headings, etc., with a resolution of 10 frames per second. The trajectories are smoothened using simple vehicle dynamics. We focus on the highway on-ramp merging scenario in this project.

We use a hierarchical Bayesian nonparametric model with a high-level manager as a Direchlet Process (DP) [3] that serves as a prior and helps select low-level executors, and low-level executors as Gaussian Processes [2] that model different types of multi-vehicle interaction scenarios. Note that DP releases the assumption that the algorithm designer will enumerate all the possible intersection scenarios or will provide a preset total number of possible scenarios. It allows a growing number of clusters based on the data collected. More concretely, given a relative location pair (x,y) as the input, a GP model outputs a Gaussian distribution for a 2-dimensional random variable that represents the velocity in two directions. We further use the number of clustered scenarios corresponding to the map layout as a sign of the risk level. To improve scalability, we used a sparse GP [5] and implemented the DPGP algorithm based on GPyTorch [4].

We also studied the social norm as the guidance for Robotaxi deployment. Specifically, we modeled social norms as parameters of average human beings' intrinsic utility function. According to [7], a stable social norm must constitute a Nash equilibrium. Therefore, we first learned the social norms from human driving data, assuming that human actions form a Nash equilibrium. At evaluation time, the learned parameters can be used to predict vehicle trajectories. Then the distance between predicted trajectories and true trajectories is calculated. The distance represents how much the vehicles' actions deviate from social norms.

We consider a discrete-time N-player generals-sum non-cooperative dynamic game defined over a fixed time horizon K. The system dynamics is known as a nonlinear function

$$x_{k+1} = f_k\left(x_k, u_k^1, \ldots, u_k^N\right), \quad x_1 = \bar{x}$$

We assume that any agent is minimizing the cost function

$$J^i\left(u^1, \ldots, u^N, \theta^i\right) \triangleq \sum_{k=1}^{K} g^i\left(x_{k+1}, u_k^1, \ldots, u_k^N, x_k, \theta^i\right)$$

where the stage-wise cost function g is a linear combination of M basis functions such that

$$g^i\left(x_{k+1}, u_k^1, \ldots, u_k^N, x_k, \theta^i\right) \triangleq \sum_{j=1}^{M} \theta_j^i g_j^i\left(x_{k+1}, u_k^1, \ldots, u_k^N, x_k\right)$$

The control sequences constitute an open-loop Nash equilibrium solution to the N-player general-sum non-cooperative dynamic game if and only if inequalities

$$\begin{aligned} J^1\left(u^{1*}, u^{2*}, \ldots, u^{N*}, \theta^1\right) &\leq J^1\left(u^1, u^{2*}, \ldots, u^{N*}, \theta^1\right) \\ J^2\left(u^{1*}, u^{2*}, \ldots, u^{N*}, \theta^2\right) &\leq J^2\left(u^{1*}, u^2, \ldots, u^{N*}, \theta^2\right) \\ &\vdots \\ J^N\left(u^{1*}, u^{2*}, \ldots, u^{N*}, \theta^N\right) &\leq J^N\left(u^{1*}, u^{2*}, \ldots, u^N, \theta^N\right) \end{aligned}$$

hold for all agents. Therefore, in inverse N-player general-sum game non-cooperative dynamic game, we want to recover the unknown parameters $\theta^i = \theta^{i*}$ given the trajectory x^* and u^{i*} . The problem can be formulated as

$$\begin{aligned} &\underset{\theta^1, \theta^2}{\text{minimize}} \quad L \triangleq \sum_{k=1}^{K} \|Cx_k - y_k\|^2 \\ &\text{subject to} \qquad x_{k+1} = f_k(x_k, u_k^{1*}, u_k^{2*}) \quad \forall k \in 1, \ldots, K-1 \\ &J_1\left(\mathbf{x}, \mathbf{u}^{\mathbf{1}*}, \mathbf{u}^{\mathbf{2}*}, \theta^1\right) \leq J_1\left(\mathbf{x}, \mathbf{u}^{\mathbf{1}}, \mathbf{u}^{\mathbf{2}*}, \theta^1\right) \quad \forall \mathbf{u}^{\mathbf{1}} \in \mathbf{U}^{\mathbf{1}} \\ &J_2\left(\mathbf{x}, \mathbf{u}^{\mathbf{1}*}, \mathbf{u}^{\mathbf{2}*}, \theta^1\right) \leq J_2\left(\mathbf{x}, \mathbf{u}^{\mathbf{1}}, \mathbf{u}^{\mathbf{2}}, \theta^1\right) \quad \forall \mathbf{u}^{\mathbf{2}} \in \mathbf{U}^{\mathbf{2}} \end{aligned}$$

Although we write the optimization problem in this form, to solve this optimization problem actually involves bi-level optimization. The top level is to find θ1 and θ2 that minimizes the difference between the predicted trajectory and noisy measurements. The lower level is to find the optimal control input sequences that form Nash equilibrium given the θ1 and θ2 selected by the top level optimization. Since solving Nash equilibrium involves solving a coupled optimization problem which is nontrivial, we replace the lower level optimization problem of the Nash equilibrium with the necessary (but not complete) conditions for the Nash equilibrium. We can then reformulate the bilevel optimization as a single level optimization can be efficiently solved by state-of-the-art nonlinear optimization solvers such as IPOPT solver implemented in CasADi [8].

Findings:

Our main results include the traffic scenario clustering method, a method to study the human drivers' intrinsic utility function and social norms for safer and social compliant Robotaxi deployment. More specifically, we analyzed the driving risk levels of Pittsburgh City based on the Argoverse Dataset by modeling the scenario as Dirichlet Process Gaussian Process. In the analysis of social norms, we verify our method by a simple illustrative example to show that our method can recover the ground truth parameters and reconstruct the trajectories. Then we deploy our method on a real-world dataset, NGSIM, to show that it can reconstruct the parameters even with relatively more complicated cost features and a long time horizon.

Conclusion:

We argue that a trustworthy robotaxi is expected to have the ability to (1) handle a dynamic number of surrounding vehicles in a complex intersection scenario and (2) infer the utility function of others for accurate predictions. We address the first problem using a hierarchical Bayesian nonparametric model and the second one with inverse dynamic games. For future work, we will do extensive experiments to test the robotaxi agent in simulators such as CARLA.

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