Robustness and Adaptability of Reinforcement Learning based Cooperative Autonomous Driving in Mixed-autonomy Traffic

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Building autonomous vehicles (AVs) is a complex problem, but enabling them to operate in the real world where they will be surrounded by human-driven vehicles (HVs) is extremely challenging. Prior works have shown the possibilities of creating inter-agent cooperation between a group of AVs that follow a social utility. Such altruistic AVs can form alliances and affect the behavior of HVs to achieve socially desirable outcomes. We identify two major challenges in the co-existence of AVs and HVs. First, social preferences and individual traits of a given human driver, e.g., selflessness and aggressiveness are unknown to an AV, and it is almost impossible to infer them in real-time during a short AV-HV interaction. Second, contrary to AVs that are expected to follow a policy, HVs do not necessarily follow a stationary policy and therefore are extremely hard to predict. To alleviate the above-mentioned challenges, we formulate the mixed-autonomy problem as a multi-agent reinforcement learning (MARL) problem and propose a decentralized framework and reward function for training cooperative AVs. Our approach enables AVs to learn the decision-making of HVs implicitly from experience, optimizes for a social utility while prioritizing safety and allowing adaptability; robustifying altruistic AVs to different human behaviors and constraining them to a safe action space. Finally, we investigate the robustness, safety and sensitivity of AVs to various HVs behavioral traits and present the settings in which the AVs can learn cooperative policies that are adaptable to different situations.

Index Terms—Behavior Planning, Cooperative Driving, Mixed-autonomy, Reinforcement Learning, Robustness

I. INTRODUCTION

THE development of autonomous vehicles (AVs) is on the verge of passing beyond the laboratory and simulation tests and is shifting towards addressing the challenges that limit their practicality in today’s society. While there is still need for further technological improvements to enable safe and smooth operation of a single AV, a great deal of research attention is being focused on the emerging challenge of operating multiple AVs and the co-existence of AVs and human-driven vehicles (HVs) \cite{1}, \cite{2}. A realistic outlook for the adoption of autonomous vehicles on the roads is a mixed-traffic scenario in which human drivers with different driving styles and social preferences share the road with AVs that are perhaps built by different manufacturers and hence follow different policies \cite{3}, \cite{4}. In this work, we seek a solution that can ensure the safety and robustness of AVs in the presence of human drivers with heterogeneous behavioral traits.

Connected & autonomous vehicles (CAVs) via vehicle-to-vehicle (V2V) communication allow vehicles to directly communicate with their neighbors, creating an extended perception that enables explicit coordination among vehicles to overcome the limitations of an isolated agent \cite{5}–\cite{11}. While planning in a fully AV scenario is relatively easy to achieve, coordination in the presence of HVs is a significantly more challenging task, as the AVs not only need to react to road objects but also need to consider the behaviors of HVs \cite{3}, \cite{4}, \cite{12}. We start by identifying the major challenges in the domain of behavior planning and prediction for AVs in mixed-autonomy traffic. As a preliminary, it is important to distinguish between the individual traits of a human driver, e.g., aggressiveness, conservativeness, risk-tolerance, and their social preferences, e.g., egoism and altruism. Despite the correlation between the two categories, they arise from different natures and also lead to different behaviors in mixed traffic. As an example, an aggressive driver is not necessarily egoistic and selfish, but their aggression might limit their capability to cooperate with other drivers and take part in a socially desirable coexistence with AVs \cite{13}–\cite{15}. First, one major challenge is that human drivers are heterogeneous in their individual traits and social preferences, which makes the autonomous vehicle behavior planning extremely difficult, as it is challenging for the AV to predict the type of behavior it is going to face when dealing with a human driver. Additionally, relying on real-time inference of HVs’ behaviors is not always viable as the interaction time between vehicles can be short-lived, e.g., two vehicles that meet in an intersection. Second, the driving task involves complex interactions of agents in a partially observable and non-stationary environment, as HVs do not follow a stationary policy and change their policies in real-time according to the other vehicles’ behaviors.

In a pursuit to alleviate the challenges of this co-existence and enable social navigation for AVs, existing works either rely on models of human behavior derived from pre-recorded driving datasets \cite{16}, \cite{17} or defining social utilities that can enforce a cooperative behavior among AVs and HVs \cite{2}, \cite{18}. Other works focus on rule-based methods that use heuristics and hand-coded rules to guide the AVs \cite{19} or probabilistic driver modeling \cite{20}–\cite{22}. While this is feasible for simple situations, these methods become impractical in complex scenarios. The majority of the existing literature relies on simulated environments or human-in-the-loop simulations, which limits the capabilities of modeling the interactions of human drivers with AVs and implementing the heterogeneity of human behaviors. This shortcoming hinders the applicability of the resulting solutions as they are often limited.

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to the human behaviors with which they have interacted during the training. In order to accommodate for this, some of the proposed policies in the literature take an overly-conservative approach when interacting with humans [23]. Not only this approach leaves the AVs vulnerable to other aggressive drivers, especially in competitive scenarios such as intersections, but can also cause traffic congestion and potential safety threats [1], [24].

This study builds on our prior work in [3] and aim to develop a safe and robust training regimen that enables the AVs to work together and influence the behavior of human drivers to create socially desirable traffic outcomes, regardless of humans’ driving individual traits and social preferences. Furthermore, we emphasize the importance of safety in social settings and constrain the AVs’ policies to remove high-risk actions that can cause safety threats. Our work in this paper is built on the following key insights. First, we rely on learning from experience in a decentralized reinforcement learning framework that optimizes for a social utility, and exposes the learning agents to a wide spectrum of driver behaviors. By doing so, the resulting agents become robust to the behavior of human drivers and are able to handle cooperative-competitive behaviors regardless of HV’s level of aggression and social preference. Second, a safety prioritizer is proposed to avoid high-risk actions that can undermine driving safety. The overview of our methodology is presented in Figure 1.

Ultimately, the focus of this paper is on exploring the safe and robust decision-making problem in a mixed-autonomy MARL environment, in inherently competitive driving scenarios, such as the ones illustrated in Figure 2, where cooperation is required for safety and efficiency. The purpose is not to fully solve the autonomous driving problem, but instead, use it as an example to investigate the effectiveness of societal concepts from psychology literature within the MARL domain. Further work is required to use these ideas on real roads. Nevertheless, we are encouraged to see altruistic AVs that are safe, robust, and can learn to influence humans in a desired way without the limitations of current solutions [3], [25]–[29].

Our main contributions are:

- We begin by formulating the mixed-autonomy traffic as a stochastic game and introduce a general decentralized framework for training cooperative AV, that optimizes for a social utility while prioritizing safety and allowing adaptability.
- A novel training regimen is introduced that robustifies the AVs’ capability in creating socially desirable outcomes with regards to human drivers’ behavior.
- We proposed a safety prioritizer that constrained the policy of cooperative AVs to ensure the safety of their behavior via masking the Q-states that lead to high-risk outcomes.

II. LITERATURE REVIEW

MARL has received a lot of attention from the research community in recent years. MARL algorithms that assume separately trained agents perform poorly due to the intrinsic non-stationarity of the environment [30]. Some efforts to solve this issue assume that all agents observe the global state [31] or that they can share their states with their neighbors [32]. These assumptions address the non-stationarity challenge; however, they are unfeasible on real roads [33]. Authors in [34]–[36] take steps to address this challenge and [34] propose a centralized critic that reduces the influence of non-stationarity during the learning process. Xie et al. consider a MARL approach that learns latent representations of the agent’s policies, modeling agent strategies that depend on long interactions, alleviating the non-stationary effect, and enabling better performance and co-adaptation [37]. [38] further investigates the impact of interactions on agent’s modeling. Authors in [39] present a RL agent that learns to acquire social norms from public sanctions using a decentralized framework.

A. Driver Behavior and Social Navigation

Social navigation in mixed autonomy has shown the potential of collaboration among AVs and HVs [40]. Current works in social navigation tackle the MARL cooperation by assuming the nature of agent interactions [41], [42] or by directly modeling or classifying human driver behaviors [43]–[45]. Different methods to predict or classify driver behaviors are based on driver attributes [46], graph theory [47], game
theory [1] and data mining [48]. Toghi et al. release a maneuver-based dataset and propose a model that can be used to classify driving maneuvers [28]. Authors in [44] present an approach to modeling and predicting human behavior in situations with several humans interacting in highly multi-modal scenarios that could allow AVs to predict human reactions. [43] can be referred for a comprehensive study on modeling and prediction in multi-agent traffic scenarios.

In [49] and [4] the driving patterns of humans are learned from demonstration through inverse RL. An approach based on imitation learning is proposed by [16] to learn a reward function for human drivers and demonstrates how AVs can manipulate human behaviors. In [50] a centralized game-theory model for cooperative inverse reinforcement learning is proposed. Several works take a more abstract and traffic-level perspective [51]–[53]. Differently, we rely on implicitly learning from experience altruistic behaviors that facilitate AVs’ coordination without the need for a human model or counting on their collaboration.

B. Safe and Robust Decision-Making

In addition to the socially advantageous behavior of altruistic AVs, it is important to consider robustness and safety. Safety is essential for AVs and is particularly important for AVs trained using RL. We need to prioritize safety; as coordination is often coupled with risk, in many situations there exists a safe action that produces lower rewards, and a risky action that produces higher rewards if agents coordinate [54], [55], however, the risky action increases the probability of crashes when synchronization fails. In particular, AVs using trained RL algorithms may not always behave safely as the trained models may choose unsafe actions [23]. In that direction, several works take a pure reward shaping approach to avoid collisions. While this is a common practice in RL, safety is not implicitly prioritized and AVs using those RL algorithms may not behave safely in some scenarios, as the agents could choose dangerous actions due to function approximation.

To address this challenge, the idea of safe RL is proposed in [23] to improve safety in unseen driving environments in which the RL algorithm behaves unsafely. [56] presents a rule-based decision-making framework that examines the trajectories given by the controller and replaces the actions causing collisions. Nagesh Rao et al. [57] includes a short-horizon safety supervisor to substitute risky actions with safer ones. Nevertheless, these studies consider oversimplified and non-realistic environments. The work in [58], [59] utilizes a Q-masking approach to prevent collisions, removing the actions that could result in a crash. Chen et al. present a novel priority-based safety supervisor to significantly reduce collisions [60].

In this work, we leverage these approaches to improve the safety of the altruistic agents while also training the cooperative agents to be robust to different driver behaviors and scenarios using a decentralized reward function, local actions, and assuming partial observability. We consider a general setup where AVs and HVs with different behaviors coexist as in Figure 2. Particularly, the figure represents two common traffic situations where vehicles are either required to efficiently merge to a lane or exit the highway without colliding with other vehicles. In an ideal cooperative setting, the vehicles should proactively decelerate or accelerate to make adequate space for the vehicles to safely merge/exit and avoid deadlock situations, while also being robust to different scenarios and behaviors and ensuring safety in decision-making.

III. PROBLEM FORMULATION

The MARL problem can be formulated as a centralized or decentralized problem. A centralized controller that assigns a central joint reward and joint action is straightforward. Nevertheless, such assumptions are impractical in the real world. Therefore, this study focuses on a decentralized controller where agents have partial observability and consequently, the problem is formulated as a partially observable stochastic game (POSG) defined by \((\mathcal{T}, \mathcal{S}, \{\mathcal{A}_i\}_{i \in \{1, \ldots, N\}}, \{\mathcal{O}_i\}_{i \in \{1, \ldots, N\}}, P, \{R_i\}, \gamma)\) where

- \(\mathcal{T}\): a finite set of agents \(N \geq 2\).
- \(\mathcal{S}\) : a set of possible states that contains all configurations that \(N\) AVs can take (probably infinite).
- \(\mathcal{A}_i\): a set of possible actions for agent \(i\).
- \(\mathcal{O}_i\): a set of observations for agent \(i\).
- \(P\): a state transition probability function from state \(s \in \mathcal{S}\) to state \(s' \in \mathcal{S}\), \(P(s = s'|s = s, A = a)\).
- \(R_i\): a reward function for the \(i\)th agent, \(R_i(s, a)\).
- \(\gamma\): a discount factor, \(\gamma \in [0, 1]\).

It should be noted that the agents have no access to the exact environmental state but only a local observation which is correlated with the state, increasing the difficulty of solving the POSG. The POSG can be described as follows: at every time step \(t\), \(s_t\) is the state of the environment, each agent senses the environment and obtains a local observation \(o_i : \mathcal{S} \rightarrow \mathcal{O}_i\), based on \(o_i\) and its stochastic policy \(\pi_i\), it selects an action from the action space \(a_i \in \mathcal{A}_i\). As a result, the agent
moves to the next state $s'$. The goal of each agent $i$ is to optimally solve the POSG by deriving a probability distribution over actions in $A_i$ at a given state, that maximizes its cumulative discounted reward over an infinite time horizon, and find the corresponding optimal policy $\pi^*: S \to A_i$.

An optimal policy maximizes the action-value function, i.e.,

$$\pi^*(s) = \arg \max_{a} Q^*(s, a)$$

where $Q^*(s, a) := \mathbb{E}_r[\sum_{k=0}^{\infty} \gamma^k R(s, a)|s_0 = s, a_0 = a]$. The optimal action-value function is determined by solving the Bellman equation

$$Q^*(s, a) = \mathbb{E}[R(s, a) + \gamma \max_{a'} Q^*(s', a')|s_0 = s, a_0 = a].$$

### A. Double Deep Q-Network (DDQN)

We use Double Deep Q-Network (DDQN) as the function approximator to estimate the action-value function, i.e.,

$$\hat{Q}(.; w) \equiv Q(.) \quad \text{(with weights } w)$$

DDQN improves Deep Q-Network (DQN) by decomposing the max operation in the target into action selection and action evaluation, mitigating the over-estimation problem. The idea is to periodically sample data from a buffer and compute an estimate of the Bellman error or loss function, written as

$$\mathcal{L}(w) = \mathbb{E}_{s,a,r,s'|R_{\text{update}}}[(\text{Target} - \hat{Q}(s, a; w))^2]$$

$$\text{Target} = R(s, a) + \gamma \hat{Q}(s', a', \phi; w)$$

The DDQN algorithm then applies mini-batch gradient descent as $w_{k+1} = w_k - \alpha \nabla_w \mathcal{L}(w)$, on the loss $\mathcal{L}$ to learn the approximation of the value function ($\hat{Q}(.)$). The $\nabla_w$ operator denotes an estimate of the gradient at $w_k$, $w$ are the weights of the online network and $\hat{w}$ are the weights of the target network which are updated at a lower frequency ($\text{Target}_{\text{update}}$).

### B. Driving Scenarios

Our goal is to study driving scenarios where the absence of coordination by the AVs compromises safety and efficiency. Additionally, we aim to investigate adaptability among competitive scenarios and driver behaviors. For this purpose, we define a set of scenarios $\mathcal{F}$ and choose highway merging and exiting ramp as the base scenarios where a mission vehicle (merging/exiting) attempts to complete its task in a mixed-traffic environment as in Figure 2.

We design the merging and exit scenarios such that cooperation is required for safety. AVs must coordinate and neither of them alone can realize a safe and smooth traffic flow, i.e., only one AV will not make the merging/exiting possible without the coordination of the other AVs. The altruistic AVs must learn to account for the interests of all the vehicles, coordinate, make sacrifices and guide the behavior of humans to allow for a safe merging/exiting while also adapting to different traffic situations safely. For instance, in Figure 2, the AV1 must learn to sacrifice and slow down (compromising its own utility) to guide the traffic of aggressive HVs, creating a safe corridor for the merging/exiting vehicle, while the other AVs have to accelerate to make space for the mission vehicle. The merging and exiting scenarios are defined as $f_m, f_e \in \mathcal{F}$ respectively. We select such situations because of their intrinsic closeness and competitive characteristics, since the merging/exiting vehicle’s local utility conflicts with that of the highway vehicles.

### C. Social Value Orientation and Altruistic AVs

Social Value Orientation (SVO) characterizes the individual’s preference to account for the interests of others vs. their own interest [1]. The behavior of a human or an AV can fluctuate from egoistic to absolutely altruistic based on the importance given to the utility of others. The SVO of humans is uncertain, therefore we depend on AVs instead to guide the traffic towards more socially advantageous goals. Formally, the SVO angle $\phi$ of an AV, determines how the AV balances its own benefit against that of others. In terms of rewards, we can define the total reward $R_i$ of an AV as:

$$R_i(s, a) = \cos \phi_i \gamma^{ego} + \sin \phi_i \gamma^{social},$$

where $\gamma^{ego}$ is the AV’s specific reward (egoistic) and $\gamma^{social}$ is the overall reward of other vehicles (social) respect to the $i^{th}$ AV [2], [3]. The SVO angle can be changed from $\phi = 0$ (purely egoistic) to $\phi = \pi/2$ (purely altruistic). Nevertheless, none of the two extremes is optimum, and a point in between yields the most socially advantageous result, defined as the optimal SVO angle $\phi^*$. SVO helps explain the behaviors that allow the mission vehicle to merge or exit in Figure 2. Without SVO, the mission vehicle in Figure 2 could cause traffic congestion or an unsafe situation. AVs need to consider SVO, since HVs can not communicate that directly, and we should not expect HVs to cooperate.

### D. Driving Behaviors

The challenge of simulating diverse behaviors can be framed as the problem of obtaining the suitable range of parameters that can generate the heterogeneous behaviors within the simulator. Many studies from social traffic psychology establish that driving behavior falls between aggressive and conservative. Nonetheless, the precise definitions differ between studies [13]. In general, the term “aggressive driving” covers a range of unsafe driving behaviors like overspeeding or running red lights. However, the causes of aggressive driving come in various forms and are not always obvious. Some are due to undesirable roadway situations, while others are individual traits or states of mind. Furthermore, there is a relationship between aggressiveness and egoism, as egoistic drivers usually do not yield and also tend to engage in speeding, risk-taking, and similar aggressive behaviors. While there is a correlation between these terms [13]–[15], for the purpose of this paper, we separate egoism from aggressiveness by characterizing social preferences and individual traits.

We differentiate between social preferences and individual traits of drivers, as they lead to different behaviors. First, we characterize egoism and altruism as social preferences, and identify an egoistic driver as a selfish driver who accounts for his own utility independently from his aggressiveness. Second, we characterize aggressiveness and conservativeness as individual traits, and identify an aggressive driver as a driver whose actions cause aggressive behaviors. Social preferences such as egoism are characterized by their social goals and...
intentions, whereas individual traits such as aggressiveness are characterized by the consequences of their actions. In that sense, an egoistic driver is a self-centered driver characterized by a lack of social motivation, a driver that feels like he owns the road and does not consider the other drivers. Egoist drivers often engage in aggressive behaviors and while ego defensiveness is not the only cause of aggressiveness, it is still a main contributing factor of anger and aggressive driving [14], [15]. Despite the correlation between the two categories, they arise from different natures and lead to different behaviors. For instance, a driver could be egoistic and conservative. We could imagine a driver who drives cautiously in order to protect himself (selfish motivation/preference) and, as a consequence, behaves conservatively (outcome of his actions).

Formally, in our simulation, social preferences (egoism or altruism) are characterized by the AV’s SVO angular preference $\phi$; and individual traits (aggressiveness, conservativeness, etc) by the HV driver model parameters ($P$) as described in section IV-D. Based on the values of these parameters, a vehicle will exhibit aggressive or conservative behaviors. In our experiments, we assume the SVO of HVs to be unknown as they cannot communicate that directly. Finally, we define a set of behaviors $B$, i.e, aggressive, moderate and conservative, $b_a, b_m, b_c \in B$ based on the parameters ($P$) obtained in section IV-D.

E. Problem Formulation

We formulate the problem as the POSG defined; where the road is shared by a set of HVs $h_k \in H$, with an undetermined SVO $\phi_k$ and heterogeneous behaviors $b_k \in B$: a set AVs $i \in I$, that are connected together using V2V communication, controlled by a decentralized policy and sharing the same SVO, and a mission vehicle, $M \in I \cup H$ that is aiming to accomplish its mission (highway merging/exiting) and can be AV or HV. We focus on the multi-agent maneuver-level decision-making problem for AVs in mixed-autonomy environments, and study the following problems: how AVs can learn in a mixed-autonomy environment cooperative optimal policies $\pi(s)$ that are robust to different scenarios $f \in F$ and behaviors $b \in B$ while ensuring safety on the decision-making, and how sensitive is the performance of the altruistic AVs to the HVs behaviors.

As AVs are connected, we assume that they receive an accurate local observation of the environment $o_i \in O_i$, sensing all the vehicles within their perception range, i.e, a subgroup of HVs $H \subset H$ and a subgroup of AVs $I \subset I$. Nevertheless, AVs are unable to share their actions or rewards, and they take individual actions from a set of high-level actions $a_i \in A_i(|A_i| = 5)$. The goal of this work is to train AVs that learn how to drive in a mixed-autonomy scenario in a robust, efficient and safe manner while benefiting all the vehicles on the road.

IV. SAFE AND ROBUST ALTRUISTIC DRIVING

To drive in a mixed-autonomy environment in a robust and safe manner, we propose a MARL approach with a general decentralized reward function that optimizes for a social utility by inducing altruism in the agents: the general reward accounts for any anticipated vehicle’s mission, allowing it to be applied to different scenarios and tasks; and ensuring safety by adding a safety prioritizer. We train altruistic AVs that learn from experience to perform a task, account for the interests of all the vehicles, while being able to adapt to other traffic situations safely. We carefully design a decentralized general reward function, a suitable architecture, and a safety prioritizer to promote the desired safe altruistic behavior in AVs’ decision-making process. The overview of our approach as presented in Figure 1 and Figure 2 helps us to create intuition on these points, by introducing driving scenarios in which altruistic AVs lead to socially advantageous results while adapting to different traffic circumstances.

Action Space. We define a high-level action space $A$ of discrete meta-actions for decision-making. In particular, we select a set of five high-level actions as $a_i \in A_i = \{\text{Change to Right Lane, Change to Left Lane, Accelerate, Decelerate, Idle}\}$. These meta-actions are then converted into trajectories and low-level control signals, which ultimately control the vehicle’s movement.

Observation Space. We use a multi-channel VelocityMap observation ($o_i$) that embeds the relative speed of the vehicle with respect to the ego vehicle in pixel values, as in [2]. We represent the information in multiple semantic channels that embed: 1) the AVs, 2) the HVs , 3) the mission vehicle, 4) an attention map to highlight the position of the ego vehicle, and 5) the road layout. To map into pixels the relative speed of the vehicles, we use a clipped logarithmic function which improves the dynamic range and shows better results than a straightforward linear mapping. As temporal information is necessary for safe decision-making, we use a history of VelocityMaps successive observations to create the input state to the Q-network $\psi_i$.

A. Decentralized General Reward

We train the AVs from scratch using local observations and a decentralized reward structure and expect them to learn the driving task in different scenarios while accounting for individual diver’s missions. Consequently, we design a well-engineered general reward function that accounts for the social utility, traffic metrics and desired missions. The agent’s $I_i \in I$ local reward is defined as

$$R_i(s, a) = R^{ego} + R^{social}$$

$$R^{ego} = \cos \phi_i r_{i,a}(s, a)$$

$$R^{social} = \sin \phi_i \left[ \sum_j r_{AV}^{ij}(s, a) + \sum_j r_{HV}^{ij}(s, a) + \sum_k r_{AV}^{ik}(s, a) \right]$$

$$+ \sum_k r_{i,k}^{M}(s, a)$$

in which $R^{ego}, R^{social}$ represents the egoistic and social reward, $i \in I, a, j \in (I \setminus \{I_i\}), k \in H$. The term $r_i$ represents the ego vehicle’s reward obtained from traffic metrics and the angle $\phi$ allows to adjust the level of egoism or altruism. We decouple the social component in cooperation (the altruistic
behavior among AVs, i.e., AV’s altruism toward others AVs) and sympathy (AV’s altruism toward HVs) as they differ in nature. The sympathy term, \( r^\text{HV}_{i,k} \), considers the individual reward of the HVs, while the cooperation term, \( r^\text{AV}_{i,j} \), considers the individual reward of the other AVs, and are defined as

\[
r^\text{HV}_{i,k} = \frac{\mathcal{W}_k}{d_{i,k}} \sum_m \omega_m x_m \quad r^\text{AV}_{i,j} = \frac{\mathcal{W}_j}{d_{i,j}} \sum_m \omega_m x_m
\]

in which \( d_{i,k}/d_{i,j} \) represents the distance between the agent and the corresponding HV/AV, \( \lambda \) is a dimensionless coefficient, \( \mathcal{W}_k \) a weight value for individual vehicle’s importance, \( m \) are the traffic metrics that have been considered in the vehicle’s utilities (speed, crashes, etc.), in which \( x_m \) is the \( m \)-th normalized value and \( w_m \) is the weight associated to that metric. The term \( r^M \) accounts for the reward of the vehicle’s mission. A mission is defined as any desired specific outcome for a particular vehicle, as merging, exiting, etc.

\[
r^M = \begin{cases} \frac{w_i}{(d_{i,j})^\mu}, & \text{if } f(j) \\ 0, & \text{otherwise} \end{cases} \quad r^M = \begin{cases} \frac{w_k}{(d_{i,k})^\mu}, & \text{if } f(k) \\ 0, & \text{otherwise} \end{cases}
\]

The function \( f(v) \) is an independent function to evaluate the mission: \( f(v) \) return true if the vehicle \( v \) has a mission defined and the mission has been accomplished in the recent time window. \( \mu \) is a dimensionless coefficient, \( w_i/w_k \) are weights for individual vehicle’s mission (importance of the mission). This allows to define a general reward independent of the driving scenario and mission goals for different vehicles.

In our experiments, a HV can be assigned a merging mission or a highway exiting mission, as referred to in Figure 2.

**B. Deep MARL architecture for Cooperative Driving**

We use a 3D Convolutional Neural Network (CNN) with a safety prioritizer as presented in Figure 3. The 3D CNN acts as a feature extractor and uses a history of VelocityMap observations to account for the temporal information.

To tackle the non-stationarity of MARL, we train the agents in a semi-sequential approach, as in [2]. The agents are trained independently for \( N_{\text{iterations}} \) iterations while freezing the policies of the remaining AVs, \( w^- \). Subsequently, the other agents’ policies are updated with the new policy, \( w^+ \). To improve sample efficiency and train the agent safely, reducing episode resets due to imminent collisions, we use a safety prioritizer that, in the cases where the action selected by the agent policy is unsafe, selects a safe action and stores the unsafe action \( a_t \) and the related state in the RM with a suitable penalty on the reward \( r_{\text{unsafe}} \) for the unsafe state-action pair. Those pairs are not removed so the agent can also learn from unsafe experiences. The experience \((s_t, a_t, r_{\text{unsafe}}, \emptyset)\) is stored in RM with a terminal next state \( \emptyset \), the target for this unsafe pair \((s_t, a_t)\) is \( \text{Target}(s_t, a_t)^{DDQN} = r_{\text{unsafe}} \). The details of the safety prioritizer are given in the next section IV-C.

**Algorithm 1** summarizes the overall methodology of our safety prioritized deep MARL architecture. Additionally, we do not initiate the learning process until the replay buffer is filled with a minimum number of sample simulations. Moreover, inspired by [62] and [2], we update our experience replay buffer to compensate for the highly skewed training data. Balancing skewed data is a common practice in machine learning and is beneficial in our MARL problem as well.

**Algorithm 2.** During action selection of the agent \( I_i \), once an action \( a_t \) is chosen, the safety prioritizer checks if the action is safe by computing a safety score for \( N_{\text{steps}} \) of planning.

We utilize the time-to-collision (ttc) as a safety score. If \( \text{safety}_\text{score} < \text{safety}_\text{th} \) the action is unsafe and we need to select a safe action. The selection of a safe action is presented in **Algorithm 3**.

**Algorithm 3.** The safe action selection is different in training and testing. During training, to encourage exploration, we remove the unsafe actions and keep the random action selection following the current exploration policy on the remaining actions. During testing, we follow the greedy policy in the subset of safe actions \( a_t = \max_{a' \in \mathcal{A}_{\text{safe}}} Q(s_t, a'; w) \). It should be noted that the algorithm does not choose the safest of all possible actions, as that action may lead to particularly conservative behaviors that can compromise traffic efficiency;
we instead remove the imminent unsafe actions and follow the priority given by the learned altruistic policy. If it happens that all possible actions are unsafe, we return the action priority given by the learned altruistic policy. If it happens that we instead remove the imminent unsafe actions and follow the in which

model considers two main criteria, the safety prioritizer, achieving higher traveled distance while learning; and during testing the decision-making is based on the prosocial learned policy with minimum intervention from the safety prioritizer, achieving higher traveled distance while avoiding collisions.

D. Modeling Driver Behaviors

We model the longitudinal movements of HVs using the Intelligent Driver Model (IDM) [63], while the lateral actions of HVs are based on the MOBIL model [64]. The MOBIL model considers two main criteria,

The safety criterion ensures that after the lane change, the deceleration of the new follower \( a_n \) in the target lane does not exceed a safe limit, i.e., \( a_n > -b_{\text{saf}} \).

The incentive criterion determines the advantage of HV after the lane change, quantified by the total acceleration gain, given by

\[
a_{\text{ego}}' - a_{\text{ego}} + \sin \phi_{\text{ego}} \left( a_n' - a_n \right) + (a_n' - a_n) > \Delta a_{\text{th}} \tag{6}
\]

where \( a_o, a_n \) and \( a_{\text{ego}} \) represent the acceleration of the original follower in the current lane, the new follower in the target lane, and the ego HV, correspondingly, and \( a_o', a_n', \) and \( a_{\text{ego}}' \) are the equivalent accelerations considering that the ego HV has changed the lane, \( \sin \phi_{\text{ego}} \) is the politeness factor. Finally, the lane change is performed if the safety and incentive criterion are mutually satisfied.

The IDM Model determines the longitudinal acceleration of a HV \( v_k \) as following,

\[
v_k = a_{\text{max}} \left[ 1 - \left( \frac{v_k}{v_k^s} \right)^\delta - \left( \frac{d^*(v_k, \Delta v_k)}{d_k} \right)^2 \right] \tag{7}
\]

where \( T_0^k, d_k, a_{\text{max}}, \) and \( a_{\text{des}} \) are the safe time gap, the minimum distance, the comfortable maximum acceleration, and deceleration, correspondingly.

The typical parameters for MOBIL model are \( \sin \phi_e = 0.5, \Delta a_{th} = 0.1 \frac{m}{s^2} \) and \( b_{\text{saf}} = 4 \frac{m}{s^2} \). Table I shows typically used parameters of the IDM model [63].

| Parameter | Value | \( T_0^k \) | \( d_k \) | \( a_{\text{max}} \) | \( a_{\text{des}} \) | \( \delta \) | \( d^* \) |
|-----------|-------|-----------|---------|----------------|----------------|--------|--------|
| \( \text{m/s} \) | 1.5 | 1 | 1 | 1 | 4 |

Heterogeneous Driver Behaviors. Though those parameters are typical used for IDM and MOBIL models, they simulate just one behavior. In order to generate diverse behaviors \( B \), we frame the task of simulating diverse behaviors as the problem of obtaining the appropriate range of parameters (\( P \)) that can generate those behaviors. To achieve that, we leverage a behavior classifier and iteratively simulate the parameters and classify the behaviors, mapping parameters to behaviors.

To classify the behaviors we represent traffic using a traffic-graph at each time step \( t, G_t \), with a set of edges \( E(t) \) and a set of vertices \( V(t) \) as functions of time, i.e., the positions of vehicles \( (\mathcal{H} \cup \mathcal{I}) \) represent the vertices. The adjacency matrix \( A_t \) is given by \( A(k, m) = d(v_k, v_m), k \neq m \), in which \( d(v_k, v_m) \) is the shortest travel distance between vertices \( k \) to \( m \). Then we use centrality functions [47] to classify the behavior (level of aggressiveness) resulted from \( P \), and then use those simulation parameters \( P \) to model behaviors within the simulator with varying levels of aggressiveness. The centrality functions are defined as,

Closeness Centrality: the discrete closeness centrality of the \( k \)th vehicle at time \( t \) is defined as,

\[
C^k_C[t] = \frac{N - 1}{\sum_{v_m \in V(t) \setminus \{v_k\}} d^*(v_k, v_m)}, \tag{9}
\]

where \( N = |\mathcal{H} \cup \mathcal{I}| \). The more central the vehicle is located, the higher \( C^k_C[t] \) and the closer it is to all other vehicles.

Degree Centrality: the discrete degree centrality of the \( k \)th vehicle at time \( t \) is defined as,

\[
C^k_D[t] = \left| \{ v_m \in V(t) \} \right| + C^k_D[t - 1] \tag{10}
\]

such that \( (v_k, v_m) \notin \mathcal{E}(\tau), \tau = 0, \ldots, t - 1 \) in which \( N_k(t) = \{ v_m \in V(t) \} \), \( A_t(k, m) \neq 0, v_m \leq v_k \) represents the set of vehicles in the proximity of the \( k \)th vehicle, given that \( v_m \leq v_k \); and \( v_m, v_k \) denote the velocities of the \( m \)th and \( k \)th vehicles. The more new vehicles seen by vehicle \( k \) that meet this condition, the higher \( C^k_D[t] \).

With the centrality functions we can measure the Style Likelihood Estimate (SLE) for different driver styles [47]. We consider two SLE measures. The SLE of overtaking and sudden lane-changes (\( SLE_t \)) and the SLE of overspeeding (\( SLE_o \)). The \( SLE_t \) and \( SLE_o \) can be computed by measuring the first derivative of the centrality functions as,

\[
SLE_t(t) = \left| \frac{\partial C^k_C(t)}{\partial t} \right|, SLE_o(t) = \left| \frac{\partial C^k_D(t)}{\partial t} \right| \tag{11}
\]

The maximum likelihood \( SLE_{\text{max}} \) is calculated as \( SLE_{\text{max}} = \max_{t \in \Delta t} SLE(t) \).
Using those functions, we can approximately quantify and classify driver behaviors in our simulation. The intuition behind that is that an aggressive driver may frequently overspeed or perform sudden lane changes; while overspeeding the $C_D(t)$ monotonically increases (higher SLE$_b(t)$) and during sudden lane changes the slope and the extrema of $C_C(t)$ changes values. Thus higher values of SLE$\_\text{max}$ are related to increased levels of aggressiveness. Conversely, conservative drivers are not inclined towards those aggressive maneuvers, and the degree centrality will be relatively flat, thus SLE$_b(t) \approx 0$ for conservative drivers.

We use these metrics as approximations of the driver’s level of aggressiveness. In order to compute the suitable values for our simulation, we iteratively simulate the parameters from IDM and MOBIL models, and for each set of parameters, we quantify the resulting behavior in the simulation (using those metrics). Mapping the parameters $\mathcal{P}$ to behaviors (quantified in the simulation for those parameters). The estimated simulation parameters that simulate conservative, moderate and aggressive behavior in our scenarios are presented in Table II.

**TABLE II:** Estimated simulation parameters that simulate conservative, moderate and aggressive behavior in our scenarios.

| Model | Parameter | Aggressive | Moderate | Conservative |
|-------|-----------|------------|----------|--------------|
| MOBIL | $\sin \phi_c$ | 0 | 0.3 | 1 |
|       | $\Delta \sigma_{th}$ | 0 m/s$^2$ | 0.1 m/s$^2$ | 0.4 m/s$^2$ |
|       | $b_{safe}$ | 12.0 m/s$^2$ | 6.0 m/s$^2$ | 2.0 m/s$^2$ |
| IDM   | $\alpha$ | 0.5s | 1s | 3s |
|       | $\delta_0$ | 1 m | 2 m | 3 m |
|       | acc$_{max}$ | 7.0 m/s$^2$ | 3.0 m/s$^2$ | 1.0 m/s$^2$ |
|       | acc$_{des}$ | 12.0 m/s$^2$ | 7.0 m/s$^2$ | 2.0 m/s$^2$ |

The desired velocity $v^*$ is set to 30m/s and the acceleration exponent $\delta = 4$.

**E. Computational Details and Hyperparameter**

We customize the OpenAI Gym environment in [65] to suit our particular driving scenario and MARL problem. The PyTorch implementation of our architecture on average takes 3.1GB of memory for 4 agents and 18 HVs. Using a GPU NVIDIA Tesla V100. The training process is repeated several times to ensure convergence of the experiments to a similar policy. The network is trained for $N_{\text{episode}} = 10,000$ taking on average 8 hours and a forward pass during testing requires on average 15ms. We utilize 3,200 GPU-hours for our simulations. Table III lists our simulation and training hyper-parameters.

**TABLE III:** Simulation and training hyper-parameters.

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| $N_{\text{episode}}$ | 10,000 | $e$ decay | Linear |
| RM buffer size | 8,000 | Initial exploration $\epsilon_0$ | 1.0 |
| Batch size | 32 | Final exploration | 0.05 |
| Learning rate $\alpha_0$ | 0.0005 | Optimizer | ADAM |
| Target update | 300 | Discount factor $\gamma$ | 0.95 |
| $|R|$ | 18 | $|Z|$ | 4 |

Finally the adaptation error is a weighted sum function of the safety ($C(\%)$) and efficiency ($DT(m)$) performance of the AV when trained and tested in different scenarios/behaviors. Defined as,

$$A_{\text{error}}(\%):= w_s \times (C(\%)) + w_e \times 100(1 - \frac{DT}{DT_{\text{max}}})$$

such that an adaptation between different situations that result in 0% crash and $DT = DT_{\text{max}}$ will have $A_{\text{error}} = 0\%$.

**A. Hypotheses**

In this section we examine the following hypotheses

- **H1.** The higher the level of aggressiveness in a mixed-autonomy scenario, the greater the impact of cooperation. Thus, we expect a higher performance gain ($PG$) when altruistic AVs face environments with higher level of aggressiveness.
- **H2.** Altruistic AVs agents using the decentralized framework can adapt to different driver behaviors and traffic scenarios without compromising the overall traffic metrics. However, the higher the similarity of testing scenarios to the ones seen during training ($f_{test}, b_{test}$) the lowest adaptation error ($A_{\text{error}}$).
- **H3.** With the inclusion of the safety prioritizer, we anticipate improvement in safety and efficiency. We expect that AVs will cause more crashes in the absence of a safety prioritizer ($safec_{th} = 0$).

**B. Analysis and Results**

Based on the hypotheses, we explore their correctness through the experiments in this section.
HV behaviors on the altruistic AV agents. We focus on
scenarios with a HV mission vehicle, with safe AVs that act
HV behaviors on the altruistic AV agents. We focus on
scenarios with a HV mission vehicle, with safe AVs that act
altruistically (AV_g) or egoistic (AV_E), in environments with
increasing levels of HVs aggressiveness. Figure 4 illustrates
the altruistic performance gain for increasing levels of HVs' aggressiveness for 2 AVs (left) and 4 AVs (right). It
demonstrates that the more aggressive the HVs are, the higher is
the impact/gain of cooperation.

Fig. 4: Sensitivity analyses measured by altruistic performance gain (PG) of AVs, the more aggressiveness of the HVs, the higher the impact/gain of cooperation.

Fig. 5: Lateral and longitudinal sensitivity analyses, the altruistic performance gain (PG) increase in both lateral and longitudinal directions.

1) Sensitivity analyses to HVs behaviors
To study the hypothesis H1 we investigate the effect of
HV behaviors on the altruistic AV agents. We focus on
scenarios with a HV mission vehicle, with safe AVs that act
altruistically (AV_g) or egoistic (AV_E), in environments with
increasing levels of HVs aggressiveness. Figure 4 illustrates
the altruistic performance gain for increasing levels of HVs' aggressiveness for 2 AVs (left) and 4 AVs (right). It
demonstrates that the more aggressive the HVs are, the higher is
the impact of cooperation and thus confirms the H1. This is
also observed in Figure 5 where the level of aggressiveness is
decomposed into lateral and longitudinal aggressiveness. Lateral and longitudinal aggressiveness is varied by changing the MOBIL and IDM parameters (Table II) from aggressive to
conservative. Figure 5 shows that the altruistic gain increases
in both directions, but is more pronounced in the longitudinal
direction. That is probably due to the simulated scenarios having more longitudinal maneuvers.

2) Domain adaptation of altruistic agents
Following the sensitivity analysis, we investigate the domain
adaptation of the AVs to validate the H2. Figure 6 shows
how the altruistic AVs learn to adapt to different scenarios and behaviors, based on an adaptation score. For the experiments, AVs are trained in different scenarios $f_i \in F$ in the presence of HVs with different behaviors $b_k \in B$ and tested in other scenarios $f_j \in F$ and behaviors $b_l \in B$. In our experiments, we consider two case study scenarios $f_m, f_e \in F$ (merging/exiting) in environments with three different HVs behaviors $b_a, b_m, b_c \in B$ (aggressive, moderate, conservative) see Table II; and a mixed behavior environment, in which
HVsa re created randomly and their behaviors are selected based on a uniform distribution over the behaviors in $B$, given equal probability to the defined behaviors. In total, we
have eight combinations of scenarios and behaviors, namely:
$(f_m, b_{mix}), (f_m, b_a), (f_m, b_m), (f_m, b_c), (f_e, b_{mix}), (f_e, b_a), (f_e, b_m), (f_e, b_c)$.

The results are presented in Figure 6 as an adaptation
matrix, showing the $A_{error}$ for different domains, the $A_{error}$ is in percentage (%) and color-map in logarithmic scale to increase the perceived dynamic range for visualization. In
our analyses, the weights used for $A_{error}(\%)$ are $w_g = \frac{2}{3}$ and $w_e = \frac{1}{3}$, which weights the safety performance higher.
$DT_{max}$ is computed based on the maximum distance for each
situation. Additionally, Figure 7 and Figure 8 illustrate how the AVs adapt in terms of safety (measured by $C(\%)$) and efficiency (measured by $DT(m)$), separately.

The matrix shows the best performances in the diagonal as agents trained and tested in the same environment ($i = j$) experience during testing similar situations to the ones seen in training. The vehicles trained in the merging environment are able to perform the exiting mission for different behaviors, and vice-versa. It is interesting to notice that when trained in a conservative environment ($b_c$), the performance when tested in aggressive environments ($b_a$) is poor. We believe that the reason is that in conservative environments, the HVs yield the mission vehicle, and the AVs learn to rely on HVs to guide the traffic. This learned policy is valid in a conservative environment where one can expect the HVs to always create a safe space for the mission vehicle. However, the same is not valid in more aggressive environments, in which AVs have to guide the traffic to avoid dangerous situations. As a result, the performance of vehicles trained in a conservative environment and tested in an aggressive one is the worse.

On the other hand, an adequate performance adaptation
(lower $A_{error}$) is obtained when agents are trained in the
presence of all moderate HVs ($b_{m}$) or a mixed behavior environment ($b_{mix}$), in which AVs face situations where the
HVsa yield, but also situations that require learning how to
guide the traffic to optimize for the social utility. The results
from the domain adaptation matrix indicate that a moderate
or mixed environment is the most suitable for training robust AVs and show the adaptability of AVs to different situations, thereby confirming the H2 hypothesis.

It can be concluded that the adaptation between the environments is not reciprocal and the selection of the environment and situations should be considered during training, based on
the application needs and target situations. The adaptation matrices serve as reference and provide insights on domain
adaptation in mixed-autonomy traffic, the matrices present the
settings in which altruistic AVs can best learn cooperative
policies that are robust to different traffic scenarios and human
behaviors.

3) Transfer Learning
Together with domain adaptation we exploit transfer learning
to foster generalization while efficiently learning harder
tasks from trained models and therefore accelerate the learning. We study how the policies learned during merging can be
Fig. 6: The domain adaptation matrix with adaptation error ($A_{\text{error}}$) between different traffic scenarios and behaviors. AVs are trained (rows of the matrix) in different scenarios $f_i \in F$ in the presence of HVs with different behaviors $b_k \in B$ and tested (columns of the matrix) in other scenarios $f_j \in F$ and behaviors $b_l \in B$. Each pair $(f_i, b_k)$ is a combination of scenario and behavior. The lower $A_{\text{error}}$ the more suitable the adaptability between those domains.

Fig. 7: The domain adaptation matrix with crash percentage ($C(\%)$) between different traffic scenarios and behaviors. The lower $C(\%)$ the more suitable the adaptability in terms of safety (measured by $C(\%)$) between those domains.

Fig. 8: The domain adaptation matrix with distance traveled ($DT(m)$). Illustrating how the AVs adapt to other situations in terms of efficiency (measured by $DT(m)$).

Fig. 9: Transfer learning performance. Showing how policies learned during merging can be transferred to the exiting environment to speed up the learning process while achieving similar performance as when learning the task from scratch.

4) Safety

Finally, we compared state of the art architectures related to our approach [2], [3], [18], [61] in terms of safety and efficiency to validate H3. We trained the different architectures in the same situations and examined their performance under different levels of HVs behaviors. As noted in Table IV our safe altruistic agents consistently outperformed the other approaches, and the results are more notable when the level of aggressiveness is higher. We conclude that when using the safety prioritizer, immediate collisions are avoided reducing the overall number of crashes in the episodes.

transferred to the exiting environment. For that, we train AVs agents from scratch for the mission/task of merging AV$_{\text{merging}}$ (T1), train AVs agents to drive on a highway, and then use that model as the starting point to learn the merging task AV$_{\text{drive-to-merging}}$ (T2), train AVs agents for the exiting task and then use that model as the starting point to learn the merging task AV$_{\text{exiting-to-merging}}$ (T3); and apply the same procedure for the exiting task, learning to exit from scratch AV$_{\text{exiting}}$ (T4), after learned how to drive AV$_{\text{drive-to-exiting}}$ (T5) and after learned how to merge AV$_{\text{merging-to-exiting}}$ (T6). The results of the experiments are presented in Figure 9 and show that our transfer learning approach speeds up the learning process while achieving similar performance as when learning the task from scratch.
TABLE IV: Architectures’ performance comparison. Our safe altruistic AVs outperformed the others approaches.

| Approaches         | Aggressive HVs | Moderate HVs | Conservative HVs |
|--------------------|----------------|--------------|-----------------|
|                    | C (%) MF (%) DT (m) | C (%) MF (%) DT (m) | C (%) MF (%) DT (m) |
| Conv2D+DQN [61]    | 31.2 28.9 316 | 25.4 20.3 302 | 14.0 7.9 274 |
| Toghi et al. [2]   | 21.3 16.4 339 | 12.7 10.1 333 | 1.6 0.6 269 |
| Conv3D+A2C [18]    | 14.8 12.6 341 | 9.4 8.8 328 | 1.1 0.1 267 |
| Conv3D+DQN [3]     | 3.1 2.4 359 | 2.6 2.4 341 | 0.3 0.0 284 |
| Ours               | 0.2 0.1 397 | 0.1 0.1 354 | 0 0 281 |

VI. CONCLUSION AND FUTURE WORK

We study the problem of multi-agent maneuver-level decision-making in mixed-autonomy environments and investigate how AVs can learn cooperative policies that are robust to different scenarios and driver behaviors safely. Our altruistic AVs learn the decision-making process from experience, considering the interests of all vehicles while prioritizing safety and optimizing a general decentralized social utility function. We expose the settings for our MARL problem in which transfer learning and domain adaptation are more feasible, and conducted a sensitivity analysis under different HVs’ behaviors. Our safe altruistic AVs learn to coordinate and influence the behavior of HVs with socially advantageous results in diverse situations.

Limitations and Future Work. While we explored different aspects of social navigation in various environments and in the presence of diverse HVs behaviors, the HV models are not learned from real human drivers’ data and the traffic scenarios are limited to merging and exiting. Nevertheless, we speculate that our approach could be effective in realistic traffic situations by utilizing and learning from real human data and traffic scenarios. Additionally, extra emphasis is required on safety for this approach to be utilized in the real-world scenarios.

In future work, we plan to investigate more sophisticated architecture and state representations, as well as develop a more realistic simulation environment that incorporates data and traffic scenarios to handle complex interactions between HVs and AVs and diverse traffic agents such as bicycles or pedestrians. Despite the limitations, we are thrilled to see safe and robust social AVs on the road that learn from experience. We also anticipate applications of these ideas beyond driving, to general MA humans-robot interactions in which agents influence humans and cooperate safely for a socially advantageous outcome.

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