Evaluating the Robustness of Deep Reinforcement Learning for Autonomous and Adversarial Policies in a Multi-agent Urban Driving Environment

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ABSTRACT

**Background:** Deep reinforcement learning is actively used for training autonomous and adversarial car policies in a simulated driving environment. Due to the large availability of various reinforcement learning algorithms and the lack of their systematic comparison across different driving scenarios, we are unsure of which ones are more effective for training and testing autonomous car software in single-agent as well as multi-agent driving environments. **Aims:** A benchmarking framework for the comparison of deep reinforcement learning in a vision-based autonomous driving will open up the possibilities for training better autonomous car driving policies. Furthermore, autonomous cars trained on deep reinforcement learning-based algorithms are known for being vulnerable to adversarial attacks. To guard against adversarial attacks, we can train autonomous cars on adversarial driving policies. However, we lack the knowledge of which deep reinforcement learning algorithms would act as good adversarial agents able to effectively test autonomous cars. **Method:** To address these challenges, we provide an open and reusable benchmarking framework for systematic evaluation and comparative analysis of deep reinforcement learning algorithms for autonomous and adversarial driving in a single- and multi-agent environment. Using the framework, we perform a comparative study of five discrete and two continuous action space deep reinforcement learning algorithms. We run the experiments in a vision-only high fidelity urban driving simulated environments. **Results:** The results indicate that only some of the deep reinforcement learning algorithms perform consistently better across single and multi-agent scenarios when trained in a multi-agent-only setting. For example, A3C- and TD3-based autonomous cars perform comparatively better in terms of more robust actions and minimal driving errors in both single and multi-agent scenarios. PPO IMPALA from a discrete action space and DDPG TD3 from a continuous action space show to be effective algorithms for training adversarial agents and exposing failure scenarios in autonomous car software. **Conclusions:** We conclude that different DRL algorithms exhibit different driving and testing performance in different scenarios, which underlines the need for their systematic comparative analysis. The benchmarking framework proposed in this paper facilitates such a comparison.

KEYWORDS

deep reinforcement learning, multi-agent systems, autonomous cars, autonomous driving, adversarial reinforcement learning

1 INTRODUCTION

Autonomous cars (ACs) are complex decision-making systems that are unfortunately prone to errors [16]. They commonly use machine/deep learning algorithms as part of decision-making software, which are known to be difficult to validate [29, 40]. Therefore, ACs need comprehensive training and evaluation in order to minimize risk to the public. For the same reason, autonomous driving (AD) research is nowadays performed within simulated driving environments (also used by the state-of-the-art industrial solutions like Tesla [44] and Comma ai [43]), as they provide flexibility for testing and validating AD without posing any danger to the real world. However, we observe three specific challenges in training and validating ACs in the existing simulation environments.

First, while the majority of AD research is focused on using deep reinforcement learning (DRL) for training ACs in a simulated urban driving scenario [35][47][6][4][39], there is a lack of comparison among DRL algorithms for vision-based urban driving scenarios. Having such a benchmark of commonly used DRL algorithms can be useful for understanding why some algorithms perform worse than others in specific driving scenarios, which can lead to the improvements of the state-of-art DRL algorithms for AD.

Second, the majority of existing research trains ACs as non-communicating and independent single intelligent agents [52][42], therefore treating the ACs as a single-agent driving problem. However, in the near future AD will be a complex multi-agent problem [20]. By bringing more than one AC into a multi-agent environment we can evaluate how a non-stationary driving scenario affects AC's control decisions when interacting with other ACs. Existing comparative analyses of RL algorithms for AD are still limited to single agent driving environments [46][48], and there is no systematic study performed yet on which DRL models work best for AD in a multi-agent environment.

Third, a vast portion of existing research is actively focused on testing ACs trained on vision-based end-to-end systems. One of the ways to test their control behavior is using adversarial RL (ARL). In fact, DRL is proved to be vulnerable multiple times against adversarial attacks [45], and one of the solutions to this problem is to train the adversary as a separate physical driving model using DRL [8]. ARL can be used to not only find failure scenarios in ACs but also to improve their driving policies through retraining [49]. However, at the moment, we lack the support for training and systematically evaluating ARL algorithms to decide which ones are more effective in creating better adversarial AD agents able to find errors in ACs.
To address these three challenges, in this paper we provide an open and reusable end-to-end benchmarking framework for DRL and ARL algorithms in a complex urban multi-agent AD environment. The framework enables us to bring competitive and independent driving agents in both discrete and continuous action space environments. We validate the framework by performing a comprehensive comparative study of the robustness of DRL algorithms for urban driving policies in both single-agent and multi-agent AD scenarios. In addition, we train adversarial driving agents with the same DRL algorithms to evaluate and compare their effectiveness in finding errors in ACs.

The key contributions in this paper are:

1. We provide an end-to-end benchmarking framework for the systematic evaluation of DRL-based AC driving policies in complex vision-based urban driving environments.
2. The framework supports training and validating AC’s driving policies in both single- and multi-agent driving scenarios.
3. The framework enables training and evaluating the effectiveness of ARL driving agents in finding errors in AC’s driving policies.
4. Using the framework, we perform a comprehensive comparative study of five discrete and two continuous action space DRL algorithms for AD in vision-only high fidelity urban driving simulated environments.
5. Drawing from the study results, we suggest some research directions on improving the robustness of DRL algorithms for AD.
6. The implementation of our benchmarking framework, as well as all experimental results are open and reusable, which supports the reproducibility of research in the AD domain.

2 RELATED WORK

In AD research, there are only few benchmarks for evaluating the performance of RL-based AD models. Vinitsky [48] proposes a benchmark for DRL in mixed-autonomy traffic. While the benchmark involves four scenarios: the figure eight network, the merge network, the grid, and the bottleneck, it evaluates a limited number of RL algorithms (two gradient-based and two gradient-free). In addition, the authors do not consider ARL in their work, although dealing with adversarial attacks is a great challenge in AD research. Finally, the proposed benchmark is specific to connected AD research. Stang [46] proposes another benchmark for RL algorithms in a simulated AD environment. As a limitation, this benchmark focuses on a simple lane-tracking task, and furthermore, evaluates only off-policy RL algorithms. In contrast, our work evaluates both on-policy and off-policy algorithms, and further allows comparing the performance of DRL algorithms in a complex urban environment. As another limitation, both [48] and [46] only support DRL benchmarking for single-agent AD environments.

Li [24] introduces a driving simulation framework called MetaDrive and performs a benchmarking of RL algorithms for AD. While the authors use five different driving scenarios, they only evaluate two RL algorithms (PPO and SAC). The proposed work also lacks any research on dealing with adversarial attacks on driving policies. The work could also benefit from using realistic visual rendering as provided by the CARLA framework in our work. Palanisamy [36] proposes a multi-agent urban driving framework in which one can train more than one AC. Using IMPALA, a connected AC policy is trained within the CARLA simulator. However, as a limitation, the work is restricted to connected AD problem only.

Furthermore, there are frameworks proposed for training and testing autonomous vehicles. For example, FITENTH framework [33] with three racing scenarios and baselines for testing and evaluating autonomous vehicles. However, the framework does not support dealing with ARL. Han [17] proposes an off-road simulated environment for AD with realistic off-road scenes, such as mountains, deserts, snowy fields, and highlands. While realistic environments are useful for evaluating the generalization abilities of AD models, the work is limited to single-agent AD environments.

3 DEEP REINFORCEMENT LEARNING FOR AUTONOMOUS DRIVING

Reinforcement learning (RL) is mainly modeled as a formulation of the Markov Decision Process (MDP), where the desired goal of the agents in a certain environment is to learn an optimal policy. This goal is achieved by maximizing cumulative reward after interacting with an environment. The MDP model consists of \( M(S, A, P, R, \gamma) \), where \( S \) is a set of agents’ state and \( A \) is a set of discrete or continuous actions. \( R : S \times A \rightarrow \mathbb{R} \) is a reward function value returned against every action \( A \), whereas \( \gamma \) is the discount rate applied to the future reward values. Lastly, the MDP model consists of a \( P : S \times A \rightarrow S \) as the transition probability which describes the stochastic probability distribution of the next state \( s' \in S \) given actions. Following the basics of the MDP model, the agent is dependent on the previous state only to make the next decision. Such a system obeys Markov property during RL control decisions.

Reinforcement learning has achieved great results over the past few years due to the advancements in DRL. In DRL, the MDP model is solved by using deep neural networks to learn weight parameters \( \theta \) over the time span of environment exploration. DRL models consist of a policy \( \pi \) which is responsible for taking an action given a state \( \pi(a|s) \) and a value function \( v_{\pi} \) for estimating maximum reward given the current policy \( s \in S \). Traditional RL fails at solving high-dimensional state space problems and therefore deep neural networks enable the possibility of learning a function approximation over large input and action state spaces to solve complex problems. The policy and value functions in DRL are therefore learned using the defined deep net models to estimate future actions. In our work, the DRL algorithms we choose to benchmark are based on a model-free approach. In model-free RL, the policy \( \pi \) and value function \( v_{\pi} \) is learned directly by interacting with the environment without taking model dynamics and the transition probability function of every state space into consideration.

Next, we provide a brief descriptions of the DRL models we use for the training and validation of AD in a simulated urban environment. These models are chosen on the basis of i) popularity in the DRL-based AD research community and ii) coverage of discrete as well as continuous action space (for multi-agent testing purposes).

3.1 DRL Algorithms for Autonomous Driving

3.1.1 Discrete Action Space. 

\[(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)\]
**Proximal Policy Optimization (PPO):** PPO [41] is a DRL algorithm, which also serves as one of the extensions to the policy gradient (PG) algorithms. Vanilla PG faces the problem of high gradient variance, and therefore PPO solves it by adding constraints like clipped surrogate objective and the KL penalty coefficient. Such improvements made PPO a very easy choice in the domain of DRL over the past few years.

In terms of vision-based AD, the authors in [35] use PPO as an RL algorithm to train a driving policy using synthetic simulated RGB images. The trained policy is transferred to real-world testing experiments for analyzing the perception and control perspective of the AC. Another authors in [18] uses PPO for proposing a road detecting algorithm in an urban driving environment. They carry out experiments in a Udacity racing game simulator [3] as well as in a small OpenAI gym Carracing-v0 environment [7].

**Advantage actor-critic (A2C):** A2C [23] is a synchronous version of the A3C RL algorithm. A2C is designed to solve problems associated with A3C regarding how individual actors can update the global parameters and thus it can lead to non-optimal solutions. In A2C, a coordinator is introduced in order to bring consistency to the actors so that all the actors can work with the same policy in the next iterations.

Jaafra proposed [19] to addresses an AD problem using CARLA autonomous simulator for training their DRL agent. Using an actor-critic architecture, the driving policy takes RGB images as input and learns to take action outputs within an urban driving environment.

**Asynchronous Advantage Actor-Critic (A3C):** A3C [39] is a well-known gradient descent-based RL algorithm. Following the on-policy technique, it focuses on using two neural networks - actor and critic. An actor is responsible for making actions while the critic aims for learning a value function. A3C takes this approach by keeping a global critic model while making multiple actor models for parallel training.

A3C has been used in [51] for training an AC policy in a virtual environment that can work in a real-world situation as well. By using synthetic images as an input, the policy learns to drive in an urban scenario using the proposed DRL method. Another work by the authors in [47] also uses A3C by combining RL with image semantic segmentation to train an AC driving policy. Using the TORCS [1] racing simulator, their goal is to lower the gap between virtual and real models while training an RL agent. A3C is also used in [21] where the authors created an end-to-end driving approach without detailed perception tasks on input images.

**Importance Weighted Actor-Learner Architecture (IMPALA):** IMPALA [15] uses actor-critic technique, but with the twist of decoupling actors. Following a V-trace off-policy approach, IMPALA’s main objective is to scale up the DRL training capability by adding multiple independent actors. The actors, in this case, are meant to generate experience trajectories for the policy to learn, while the learner tries to optimize not only the policy but also the value function.

An author in [36] proposes a multi-agent urban driving framework in which one can train more than one AC. Using IMPALA, the author performs training of connected AC policy within the CARLA simulator.

**Deep Q Networks (DQN):** DQN [31] fall into the category of value-based methods, where the goal is to learn the policy function by going through the optimal action-value function. DQN uses off-policy and temporal differences (TD) to learn state-action pairs by collecting episodes as experience replay. Using the episodic data, samples from the replay memory are used in order to learn Q-values, as a neural network function approximation. DQN is one of the foundation models in the upbringing of DRL and there are many improved versions of DQN implemented by overcoming the existing flaws.

DQN is used in [14] for training an AC in a Unity-based urban driving simulator. The authors use camera and laser as their input sensors for training the driving policies. Another work in [6] uses DQN for first training a driving agent in simulation to test its navigation capabilities in both simulated and real-world driving situations. DQN is also utilized in [50] for learning to steer a vehicle within a realistic physics simulator. Given the camera input feeds, their DQN based agent is aiming for following lanes with minimal offroad steering errors.

**3.1.2 Continuous Action Space.**

**Deep Deterministic Policy Gradient (DDPG):** When it comes to a continuous action space, DDPG [25] is the most widely used algorithm in the DRL research. DDPG is a model-free and off-policy approach falling under the actor-critic algorithms. It extends DQN by learning a deterministic policy in a continuous action space using actor-critic framework.

DDPG is extensively used in the field of training autonomous vehicles within simulated driving scenarios [4]. Authors in [39] uses DDPG to construct a DRL model for learning to avoid collisions and steering. DDPG is also used in [22] for learning a lane following policy within driving simulation using continuous action space.

**Twin Delayed DDPG (TD3):** TD3 [15] extends the idea of DDPG in a continuous action space algorithms by tackling issues regarding overestimation of the Q-learning function found in the value-based and actor-critic methods. This results in both improving the learning speed and model performance of DDPG within a continuous action setting.

TD3 is extensively used in urban driving scenarios for training AC agents. As a model-free approach, TD3 is used in [10][9] for learning an AD policy within an urban simulated environment. The authors proposed a framework for learning complex driving scenarios using a visual encoding to capture low-level latent variables. Another work in [28] also uses TD3 in to overcome the challenges of driving in an urban simulated environments.

**3.2 Multi-agent Autonomous Driving**

While introducing multi-agent AD agents, we need to consider an environment where agents do not have access to all the states at each time step. Such types of environments are found in the field of robotics and ACs where an agent is limited to the sensory information gathered by its hardware. Therefore, the existing MDP can be termed as a Partially Observable Markov decision process (POMDP) [34]. Furthermore, the current formulation of POMDP can be reformulated as Partially Observable Stochastic Games (POSG) [12] by defining a DRL control problem as a tuple
We divide our driving policies into $\pi$ and $\alpha$. In POSG, we can incorporate multi-agent scenarios using Markov Games [27] where multiple agents are interacting with the environment. An actor $i \in I$ receives its partial observations from a joint of observation state $o_t \in O_t$ at each time step $t$. Following the traditional MDP approach, each actor uses its learned policy function $\pi_i : O_t \mapsto A_t$ to perform actions $a_t \in A_t$. As a return, each actor gets a desired reward value $r_t \in R_t$.

3.3 Adversarial Reinforcement Learning

ARL is a new branch of RL where adversarial algorithms are trained such that they create perturbation attacks against a victim. The desired objective of ARL is to find failure outputs in the victim when the victim is exposed to such adversaries. The victim ACs are obtained from experimental evaluation as described in Section 5.2.1 and 5.2.2. In our work, the adversarial agents are trained as physical driving agents, as opposed to victim ACs in a competitive urban driving environment. Such driving adversaries have no white box access to the input, output, or model weights of victim ACs. By following a zero-sum game strategy, they learn a policy that produces adversarial output actions that appear as natural observations for victim ACs, thus fooling them into errors.

4 END-TO-END BENCHMARKING FRAMEWORK

In this section, we provide the details of the DRL benchmarking framework as well as an explanation of the reward function, hyperparameters, and driving policies. The implementation of the framework is available at 1.

4.1 Driving Policies

We divide our driving policies into $\pi_{AC}$ and $\pi_{\alpha}$. $\pi_{AC}$ represents the policy of AC driving agents that are trained using one of the 7 selected DRL algorithms, whereas $\pi_{\alpha}$ is the policy for adversarial driving models on the same DRL algorithms. Policies and their associated algorithms are mentioned in Table 1. Their usage is thoroughly explained in Section 5.2.

Table 1: Driving Policies and their associated symbols for ACs and adversaries.

| DRL Algorithm | AC Policy | Adversarial Policy |
|---------------|-----------|--------------------|
| PPO           | $\pi_{AC}$-PPO | $\pi_{\alpha}$-PPO |
| A2C           | $\pi_{AC}$-A2C | $\pi_{\alpha}$-A2C |
| AC3           | $\pi_{AC}$-AC3 | $\pi_{\alpha}$-AC3 |
| IMPALA        | $\pi_{AC}$-IMPALA | $\pi_{\alpha}$-IMPALA |
| DQN           | $\pi_{AC}$-DQN | $\pi_{\alpha}$-DQN |
| DDPG          | $\pi_{AC}$-DDPG | $\pi_{\alpha}$-DDPG |
| TD3           | $\pi_{AC}$-TD3 | $\pi_{\alpha}$-TD3 |

4.2 Deep Neural Network Model

A pictorial description of the DRL benchmarking framework can be seen in Figure 1. Each driving agent, whether an AC or adversary, receives partial input state observation of 84x84x3 dimension images through the front camera sensors. Cameras are mounted as part of the driving agents, and during each time step of the simulation environment, cameras capture the input state observations which serve as an input layer to the DRL model. The input layer is then passed to the convolutions and connected hidden layers for extracting important features before they are passed to the output layer of the architecture. ACs as well the adversary driving policies predict the control actions at the output layer based on the 3-dimensional input images at each time step.

Since our seven selected DRL models work on a discrete as well as a continuous action space, the output layer of the architecture predicts 9 distinct action values for the discrete action space and 2 float values for the continuous action space policies. These output actions can be summed into three vehicle control commands: Steer, Throttle, and Brake. Reverse and hand brakes are disabled for our experiments.

4.3 Reward functions

As described in Section 3, each agent in a POMDP setting is following MDP. Thus, the driving policies receive reward $R$ at each time step of the simulated environment while collecting trajectories of the tuple $(S, R, A)$. $R$ is the reward value returned while performing action $A$ on the current state observations $S$ which helps in improving the driving policies $\pi$.

For our experiments, we define two different types of reward functions. The first reward function $R_{\text{AC}}$ is used by the DRL AC policies $\pi_{\text{AC}}$ during the training phase. As opposed to that, we define $R_{\alpha}$ as the second reward function which is used by the DRL adversarial policies $\pi_{\text{\alpha}}$. $R_{\text{AC}}$ aims to maximize the driving performance of an AC agent by keeping safety in check. $R_{\text{AC}}$ can be formulated as:

$$R_{\text{AC}} = (D_t - D_1) + (F_t) / 10 - 100.0(CV_t + CO_t) - 0.5(I\alpha_t) + \beta$$

where $D$ is the distance covered and $F$ is the speed of the AD agent. $CV$ and $CO$ represent a boolean value for collision with another vehicle and road objects respectively. Lastly, $I\alpha$ refers to the boolean value for offroad steering of the AC model. The $\beta$ at the end of the reward functions is a constant used to encourage AC models in driving ground truth road. Ground truth in our case refers to the start and end coordinates of the environment which are assigned to each driving agent during training and testing phase. It is clear from the equation that AC driving policies are penalized against collisions and offroad steering decisions in policy training.

On the other hand, the adversary reward function $R_{\alpha}$ can be defined as:

$$R_{\alpha} = (D_t - D_1) + (F_t) / 10 + 5.0(CV_t + CO_t) + 0.05(I\alpha_t) + \beta$$

where $R_{\alpha}$ is designed to aim for maximizing a positive reward against collision and offroad steering errors in ACs while training adversarial driving policies.
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Autonomous Driving
Deep RL Agents
Observations
Action
Steer
Throttle
Reward
Multi-agent Autonomous
Driving Environment
Discrete Action
Space
Continuous Action
Space
Discrete (9)
Box (2) Brake

Figure 1: End-to-end DRL benchmarking framework for AC and adversary agents. An agent receives an input observation image of 84x84x3 which is passed to a DRL model. Actions are selected at the output layer of every agent and are performed in the next time step of the simulation in order to obtain a reward and a new observation state.

4.4 Hyperparameters
We select hyperparameters by going through the literature of the best implementations for DRL in AD. Since we are using seven different DRL implementations for training their driving policies, each of the algorithms requires separate hyperparameter tuning. The details of the hyperparameters for all the AC and adversary agents are provided in the anonymous repository.

There are some common hyperparameter configurations used for defining the training and testing scenarios of the driving policies. The hyperparameters used in the training phase of the ACs and adversaries are shown in Table 2. Based on a DRL algorithm and its interaction with the environment, the number of episodes and steps per training iteration varies a lot. During the testing phase, as explained in Section 6, we run 50 total episodes, each having 2000 simulation steps in one environment setting and 5000 simulation steps in another environment setting per driving agent.

Table 2: Hyperparameters for the training of AC the adversarial driving agents.

| Hyperparameter               | AC   | Adversarial |
|------------------------------|------|-------------|
| Total Training Iterations    | 200  | 100         |
| Training Steps per episode   | 2048 | 2048        |
| Total Training steps         | 40000000 | 20000000   |
| Learning Rate                | 0.0005 | 0.0005  |
| Batch Size                   | 128  | 128         |
| Optimizer                    | Adam | Adam        |

5 COMPARATIVE STUDY
In this section, we present a comparative study of the performance of seven DRL algorithms for AD, including the description of the simulation frameworks for the training and testing of AC agents.

The research questions in our work evaluate:

**RQ1:** Which DRL-based ACs act better (or worse) in a single-agent as well as multi-agent competitive environment when trained in a multi-agent-only scenario?

**RQ2:** Which DRL-based adversarial agent is more effective in finding failure scenarios for victim ACs while driving against the best performing ACs?

We evaluate the driving performance of victim ACs using four Driving Performance Metrics:

- **CC:** the amount of collision with another driving vehicle
- **CO:** the amount of collision with road objects
- **OS:** offroad steering percentage from its driving lane
- **SPEED:** the forward speed of the AC agent.

The first three metrics are used together for showing the overall driving safety capabilities of an AC policy, while the fourth metric is used for an in-depth understanding of the driving behavior of specific AC agents.

5.1 Driving Environment
To train our AC agents in a partially observable urban environment we use Town03 map from Carla with Python API [5]. This environment is configured for training multi-agent ACs and testing the same ACs in a single and multi-agent scenario. The same environment is also used for training the adversaries against the best-performing AC. The details of the training and testing configurations for our experiments are mentioned in Section 5.2.

5.1.1 Driving Environment 1 (env_1). We use four-way intersection as our first driving environment from the Town03 map. The driving setting is perfect for validating multi-agent AC policies in a single scenario. All the independent non-communicating driving agents are spawned closer to the intersection in all three scenarios as mentioned in Section 5.2.

5.1.2 Driving Environment 2 (env_2). The second environment has independent non-communicating agents spawned close to the


Scenario 1: Training and testing of multi-agent ACs.

First, we train AC policies $\pi_{AC}$ in a multi-agent driving environment. There are DRL-based as well as a few auto-controlled cars driving around each of the AC agents representing human drivers from real-life scenarios. We train $\pi_{AC}$ policies using the reward function $R_{AC}$ described in Section 4.3. The performance of AC policies that are trained in the first scenario is shown in Figure 3. By training the $\pi_{AC}$ policies for a fixed number of iterations, almost every AC policy converges faster except the $\pi_{AC}$-IMPALA and $\pi_{AC}$-TD3 based policy. $\pi_{AC}$-A3C based DRL policies get to a state stable max episodic reward after a few training episodes.

Next, for testing and validating ACs in a multi-agent Scenario 1 all seven DRL-based ACs drive next to each other, as well as around auto-controlled cars, therefore acting as independent non-communicating competitive driving agents, illustrated in Figure 4(a). The driving performance of each AC is evaluated against the four Driving Performance Metrics.

Scenario 2: Testing of single-agent ACs.

After training all seven DRL-based ACs for a number of episodes in a multi-agent Scenario 1, we validate the driving performance of each AC policy in a single-agent driving environment, illustrated in Figure 4(b). Testing in a single-agent scenario is important in order to validate the driving capability of AC policies in similar driving situations but with no cars around. Just like in Scenario 1, ACs’ driving performance is validated based on the four Driving Performance Metrics.

Scenario 3: Training and testing of driving adversaries against the best performing AC.

In the third scenario, we introduce adversarial driving agents to our experiments, illustrated in Figure 4(c). For training the adversarial policy, we select the best performing DRL-based AC policies from Scenario 1 and 2. We train every policy $\pi_{\alpha}$ by keeping its weights constant during the adversarial training. The number of training iterations for each adversarial agent is kept lower than the number of iterations used for AC policy training. As mentioned in Section 4.3 we use $R_{\alpha}$ as a reward function for training the seven adversaries.

Finally, we use the seven trained adversaries to test the driving behavior and control decisions of the best performing AC agents (evaluated in Scenario 1 and Scenario 2) in a competitive multi-agent scenario. The goal is to see which DRL-based adversarial policy is the most effective in leading victim ACs into failure states.

All three scenarios are illustrated in Figure 4.

5.3 Simulation Setup

The proposed benchmarking framework uses the following open libraries/frameworks:

CARLA [11] is an urban driving simulation framework designed for training and validating autonomous vehicles. CARLA is famous for its highly integrated Python API and access to high-fidelity urban driving environments. We use the 0.9.4 version.

RLlib [32] is a very fine-tuned and scalable DRL framework library. RLlib gives the opportunity to access more than one DRL policy graph and its hyperparameters for creating a non-shared multi-agent system. We use versions 0.8.0 for IMPALA and 0.8.5 for rest of the 6 DRL algorithms.

Macad-gym [37] is an open-source framework that connects CARLA, RLlib, and Open AI’s Gym toolkit [7]. We have modified the framework by adding adversarial training and competitive multi-agent driving functionalities required for our experiments. We use the 0.1.4 of version.

Tensorflow [2] is one of the leading frameworks used to create deep learning-based algorithms. We use version 2.2.0 within the RLlib library.

6 RESULTS & ANALYSIS

In this section, we discuss the experimental results for testing DRL AC policies. For collecting the results, we run 50 testing episodes in both single and multi-agent scenarios to take an average among the Driving Performance Metrics explained in Section 5. In each
6.1 RQ1: Testing AC policies in a single and multi-agent scenario

We first look into the performance comparison among the 5 discrete and 2 continuous action space DRL AC policies. Each of the AC agents is trained with a fixed number of episodes and their model convergence performance has been discussed in Section 5.2.1. Now we use the same training environment and analyze their driving behavior in both single and multi-agent scenarios.

The evaluation results of the driving performance of DRL-based AC agents are presented in Table 3 using three Driving Performance Metrics: CC, CO, and OS. AC policies having values closer to 0 are driving error-free, while those near to 1 have a higher failure state. The results of these three metrics should be analyzed jointly with the fourth metric: SPEED. This is because a car could have no collision and offroad steering errors due to being stationary. Therefore, we provide Figure 5, which shows an AC’s driving speed per timestep in a testing simulation. For displaying all the episodic results, we took an average of both Scenario 1 and 2 for every DRL AC policy across each environment setting.

6.1.1 env_1: From Table 3, it is clear that in a multi-agent scenario, A3C algorithm-based policy $\pi_{AC\_\_A3C}$ performs better with no collision with other vehicles and zero offroad steering errors. We can also see in Figure 5 that A3C overall performs consistently throughout the testing episodes with both high and low speed values. $\pi_{AC\_\_IMPALA}$ and $\pi_{AC\_\_A2C}$ although have no collision and offroad steering percentage in the table, they perform the worst among DRL based policies when we analyze the results in Figure 5. In the figure, we can see that A2C and IMPALA-based AC policies did not move forward after the starting number of steps and therefore stayed at one position during the entire testing phase. This results from $\pi_{AC\_\_IMPALA}$ and $\pi_{AC\_\_A2C}$ avoiding any collision and offroad steering errors by standing still, making it the worst-performing agents during our experiments. The rest of the 2 discrete action space AC driving policies work almost the same, dropping the performance after going halfway through the testing episodes as shown in the figure. The table also shows that $\pi_{AC\_\_PPO}$ and $\pi_{AC\_\_DQ}$ based AC policies had no collision with DRL and auto-controlled vehicles, but were driving offroad most of the testing phase resulting in collisions with footpaths and other road objects.

In the same scenario using continuous action space, $\pi_{AC\_\_TD3}$ performs much better than $\pi_{AC\_\_DDPG}$ with less collision percentage and no offroad steering error states. We see supporting behavior in the figure 5 as well for Scenario 1 where $\pi_{AC\_\_TD3}$ covers more distance $\pi_{AC\_\_DDPG}$ while performing multi-agent testing.

To answer RQ1 in-depth, DRL AC policies trained in a multi-agent scenario are now brought in a single-agent scenario. The goal is to see how much does driving in a single-agent urban setting affect the performance capabilities of each AC agent. Using the same four Driving Performance Metrics we display our results using Table 3 and Figure 5.

The driving performance of AC policies drops significantly when tested in a single-agent environment. Comparatively, A3C-based policy $\pi_{AC\_\_A3C}$ performs better than the rest of the AC policies in a single-agent setting, which is consistent with the results from a multi-agent scenario. Similarly, $\pi_{AC\_\_A3C}$ joins $\pi_{AC\_\_IMPALA}$ as the worst-performing AC policies while driving in a single-agent scenario. Both policies have zero collision and offroad steering error since they were unable to perform control decisions as shown in Figure 5.
Table 3: Comparison of the behavior of AC driving agents in terms of collision and offroad steering error percentage when tested both in a single (Scenario 1) and multi-agent (Scenario 2) environment.

| Scenario 1 | CC | CO | OS | Scenario 2 | CC | CO | OS |
|------------|----|----|----|------------|----|----|----|
| env_1      | 0.0 0.0 | 0.0 0.0 | 0.0 0.0 | env_2      | 0.0 0.0 | 0.0 0.0 | 0.0 0.0 |
| CC         | 0.0 0.0 | 0.0 0.0 | 0.0 0.0 | CO         | 0.015 0.0 | 0.0 0.0 | 0.0 0.0 |
| OS         | 0.697 0.0 | 0.0 0.0 | 0.0 0.0 | OS         | 0.0 0.0 | 0.0 0.0 | 0.0 0.0 |

Figure 5: Comparison of the behavior of AC driving agents in terms of forward speed when tested both in a single and multi-agent scenario. The first row represents AC policies tested in env_1 and the second row represents the same policies tested in env_2.

\( \pi_{AC-POO} \) and \( \pi_{AC-DQN} \) based AC agents drop their driving performance after taking a few steps in the testing episodes as plotted in the figure. \( \pi_{AC-POO} \) started off well but after a few simulation steps, its driving decision capabilities dropped when getting closer to a four-way intersection.

On the other hand, \( \pi_{AC-TD3} \) had more offroad steering errors than \( \pi_{AC-DDPG} \), but it kept moving forward towards the destination unlike \( \pi_{AC-DDPG} \) which stopped at an earlier episodic steps of testing.

6.1.2 env_2: To test the driving robustness of AC policies in an unseen environment we use env_2. In the multi-agent setting (Scenario 1), for \( \pi_{AC-POO}, \pi_{AC-A3C}, \) and \( \pi_{AC-DQN} \), the overall factors of collision and offroad steering increased compared to the results in env_1. Within discrete action space algorithms, once again \( \pi_{AC-A3C} \) performs better than the rest of the AC policies.

The same pattern applies to continuous action space algorithms when tested in the multi-agent scenario of env_2. \( \pi_{AC-TD3} \) although performs better in comparison, but just like \( \pi_{AC-DDPG} \), it results in more failure trajectories while performing episodic runs.

In a single-agent testing Scenario 2, \( \pi_{AC-POO} \) and \( \pi_{AC-DQN} \) faced many offroad steering trajectories compared to the multi-agent scenario. Whereas \( \pi_{AC-A3C} \) also had the same effect of many offroad steering errors, in comparison, it had fewer road objects collision rates.

For continuous algorithms, \( \pi_{AC-DDPG} \) and \( \pi_{AC-TD3} \) performed slightly better in a single-agent unseen driving. Just like in env_1, \( \pi_{AC-TD3} \) yields fewer failure driving states while covering more distance and speed in comparison with \( \pi_{AC-DDPG} \).

By combining the results of Scenarios 1 and 2 for env_2, we can visually see that the driving performance of \( \pi_{AC-POO} \) and \( \pi_{AC-DQN} \) remained almost the same as in env_1, \( \pi_{AC-A2C} \) and \( \pi_{AC-IMPALA} \) similarly fail to perform in env_2.

In summary, the experimental results of testing AC policies in a single and multi-agent scenario indicate that the A3C and TD3-based driving agents perform better than the rest of the DRL agents in both single and multi-agent scenarios within two driving environment settings, answering RQ1.

Next, we use \( \pi_{AC-A3C} \) and \( \pi_{AC-TD3} \) policies for training our adversarial driving policies \( \pi_{A} \) in Scenario 3, as described in 5.2.3. The same A3C and TD3-based victim AC agents are evaluated using the trained adversaries in 6.2.

6.2 RQ2: Effectiveness of adversarial driving policies in finding failure driving scenarios for victim ACs

We now compare which of the seven DRL algorithms perform better as adversaries. A successful adversarial driving agent is the one that is able to disturb the driving behavior of a victim AC, thus resulting in exploring more failure cases for the victim AC. The victim ACs are \( \pi_{AC-A3C} \) for a discrete and \( \pi_{AC-TD3} \) for a continuous action space. For evaluating the effectiveness of each adversarial policy \( \pi_{A} \) we use the same four Driving Performance Metrics.
Table 4 describes the collision and offroad steering error percentage of $\pi_{AC-A3C}$ and $\pi_{AC-TD3}$ victim AC agents against each of the seven DRL-based adversarial agents. Figure 6 further shows the driving speed of these two victim AC policies under adversarial attacks.

6.2.1 env_1: The PPO-based adversarial policy ends up finding most of the failure states in the $\pi_{AC-A3C}$-based victim AC compared to the rest of the adversaries. $\pi_{\alpha-PPO}$ adversary affects the driving performance of $\pi_{AC-A3C}$ by pushing it into colliding with other vehicles in the environment. $\pi_{AC-A3C}$ did not have a single vehicle collision while testing without adversaries, as shown in Table 3. This shows that the PPO algorithm is a good choice for training adversarial agents which can later be used for testing and validating AC agents. $\pi_{\alpha-PPO}$ adversary also affected the driving performance of SUT by discovering a few cases of offroad steering failure states. In Figure 6a, we can see the effects of the $\pi_{\alpha-PPO}$-based adversarial policy on speed of the $\pi_{AC-A3C}$-based victim AC in env_1. The speed of $\pi_{AC-A3C}$ driving agent on average drops after passing halfway through the testing episodes. This implies that the PPO-based adversarial agent was able to control the decision of the $\pi_{AC-A3C}$-based victim AC, leading it into error states, hence a decline in speed of the victim agent. The rest of the four DRL-based adversaries from a discrete action space perform somewhat weaker compared to $\pi_{\alpha-PPO}$, where other than a few cases by $\pi_{\alpha-A3C}$ none of them forced the victim AC to a vehicle collision failure state.

Moving towards the continuous space, TD3 itself became a better adversary in a two-player game against the $\pi_{AC-TD3}$-based victim AC. Within env_1 it drove the victim AC policy more towards failure cases compared to the $\pi_{\alpha-DDPG}$-based adversary. The presence of adversarial policy within the observation state of $\pi_{AC-TD3}$-based victim AC resulted in more offroad steering errors and collisions in the victim AC policy actions. Figure 6b also depicts that, i.e. due to the adversarial attacks of $\pi_{\alpha-TD3}$, there is an increase of unstable driving performance of the $\pi_{AC-TD3}$-based victim AC, leading toward no speed control decisions for the rest of the episode steps.

6.2.2 env_2: We observe slightly different results while using the same adversarial agents against the $\pi_{AC-A3C}$-based victim AC in a new driving environment env_2. Among all the discrete algorithms, $\pi_{\alpha-IMPALA}$ performs most effectively as an adversarial driving agent. Figure 6c shows the impact of adversary $\pi_{\alpha-IMPALA}$ on the the driving speed of the $\pi_{AC-A3C}$-based victim AC, where the speed of the victim AC policy drops with time during the episodic testing.

In the continuous action space, env_2 brings new findings for the $\pi_{AC-TD3}$-based victim AC against both adversaries. As shown in Table 4 $\pi_{\alpha-DDPG}$ works better as adversarial driving policy in the new driving environment against the victim AC agent during testing, which in turn leads to higher collision and offroad steering percentage. Figure 6d also shows the same effects where the $\pi_{AC-TD3}$-based AC policy fails to overcome the $\pi_{\alpha-DDPG}$ natural observational attacks. $\pi_{\alpha-DDPG}$ forces the $\pi_{AC-TD3}$-based AC policy into higher collision and offroad steering error states, resulting in no speed control decisions from the AC policy in majority of the episode steps.

In summary, the experimental results of evaluating the effectiveness of adversarial driving policies in findings errors in victim ACs indicate that PPO and IMPALA in discrete action space as well as TD3 and DDPG in continuous action space algorithms are the most effective adversarial driving agents, answering RQ2. These adversarial agents were able for expose failure states within AC policies across two different driving environments.

Table 4: Collision and offroad steering error percentage of the best-performing victim AC policies ($\pi_{AC-A3C}$ and $\pi_{AC-TD3}$) when tested against the seven adversarial cars.

| Scenario | CC  | OS  | CO  | OS  | CC  | OS  | CO  | OS  |
|----------|-----|-----|-----|-----|-----|-----|-----|-----|
| env_1    | 0.1518 | 0.0  | 0.0625 | 0.0  | 0.0  | 0.1756 |
| env_2    | 0.0  | 0.0  | 0.09764 | 0.0271 | 0.0  | 0.0  | 0.0  |
| OS       | 0.1817 | 0.1893 | 0.2502 | 0.2033 | 0.04 | 0.1903 | 0.7193 |

Figure 6: Driving speed of the best-performing victim AC agents $\pi_{AC-A3C}$ and $\pi_{AC-TD3}$ when tested against adversarial cars in env_1 (1st row) and env_2 environments (2nd row).

7 DISCUSSION AND OPEN RESEARCH DIRECTIONS

This section provides our observations and thoughts on the effectiveness and robustness of the seven evaluated DRL algorithms for their use in AD research, specifically, as AC agents and adversarial agents used for testing the driving agents.

PPO as AC, in general, did not perform better than the rest of the algorithms while driving in a single or multi-agent scenario. Standard PPO policies are often stuck at non-optimal actions while learning, since they are very sensitive to sparse high rewards. However, the same PPO algorithm with the adversarial reward function
acts well in learning the adversarial agent policy for \textit{env}_1. PPO as an adversary has been used before in [8] and exploring its further use for training in urban driving scenarios is a promising open research direction. Creating a more adversarial-focused reward function might be helpful in exposing the safety aspects of AC agents.

A2C as AC did not perform well at all. Despite having more advantages compared to the A3C, the algorithm needs more training episodes to fully learn an end-to-end driving policy. Therefore, it has a similar performance in training as A3C, but in testing, it fails to make actionable decisions. The same is the case with A2C as an adversary. The reason for such poor driving performance can be connected to the multi-agent scenario, where the AC policy fails to learn better in the training as well as in unseen driving environments. As A2C has not been explored much in AD research so far, this could be another future research direction.

A3C as AC performs the best in both single-agent and multi-agent environments. With its default implementation, the critic model seems to learn the value function well while actors are independently learning their driving policies in parallel. Although A3C works well in AC driving, it is affected by the noisy adversarial actions of the PPO and IMPALA adversary. This shows that the AC policy can be tuned more by using adversarial cars as part of the environment, making it a promising research direction to explore. A3C seems to work well where training is performed on input camera images [51][47][21] as in our case.

IMPALA has shown great results when used before in the same simulation environment [37], but the main difference in that work is that the authors implemented the IMPALA algorithm for training multi-agent ACs using shared connected AC weights. In our work, we train a non-shared multi-agent AC which shows to not only fail in single-agent testing but also in a multi-agent competitive scenario. The algorithm is unable to effectively use the trajectories gathered from actors that are decoupled from the learner. IMPALA algorithm has been successful in training adversarial agent policies, which opens up the opportunity for further research in this direction. For example, a promising open research direction is to explore the use of IMPALA for communicating and connected multi-agent ACs along with adversarial policy learning.

Default DQN is the most used algorithm within the DRL community and even in AD research, even though training ACs and adversaries using DQN in our case did not achieve good results. A lot of extensions have been proposed since the popularity of DQN in atari games. Therefore, one prosperous research direction is to explore the continuous action space as in DDPG [26].

DDPG is widely used for training AC policies [4][39][22], and we show that the improved DRL model TD3 performs better during single and multi-agent testing scenarios. The algorithmic advantages of the TD3 policy over DDPG really help in learning a multi-agent driving policy. At the same time, DDPG was useful as an adversarial agent in order to expose failure cases of the victim AC policy, which can further be explored for creating better attacks in continuous action space environments. This research direction has the potential for further investigation since one of the variants of DDPG has been successfully used in [49] for training decentralized-actor-and-centralized-critic actors in a multi-agent adversarial setting.

8 THREATS TO VALIDITY
Non stationary multi-agent driving environments. In multi-agent non-stationary environments, each agent’s transition probability and reward function depends on the actions of all the agents since they change every time with the actions performed by the agents. DRL research for AD is mainly focused on driving in a single-agent stationary MDP environment. Driving behavior is affected a lot when tested in a multi-agent scenario due to the non-stationary driving environment [38]. This is one of the key threats to the existing DRL-based AD research that is performed only in a single-agent scenario. As explained in Section 6.1, the driving performance of AC agents is affected significantly when they are exposed to more AC agents in a multi-agent setting.

Choice of driving scenarios. As mentioned in Section 5.1, we are using four-way intersection and T-intersection for testing AC agents in a single as well as a multi-agent scenario. The primary reason for selecting such scenarios is because they represent high-complexity driving scenarios, by facing cars from various directions in an intersection. However, the results are collected in the mentioned driving environments only. Our future research direction is to further investigate the driving performance of each AC and adversarial agent using different driving scenarios.

Choice of DRL algorithms. We have selected a total of seven DRL algorithms to test the robustness of AC and adversarial driving agents as described in Section 3.1. While there could be other suitable DRL algorithms, we have selected ours to cover a range of DRL categories, including value-based, policy-based, and actor-critic-based. Furthermore, our benchmarking framework relies on the Ray RLlib framework [32] which makes it possible to implement a competitive DRL-based multi-agent driving environment. At the moment, the choice of DRL algorithms also partly depends on which DRL algorithms work smoothly while integrated with Ray RLlib, Tensorflow [2] and CARLA specific versions [11].

Hyperparameters tuning. Hyperparameter tuning is considered a very sensitive part of training DRL policies, and to mitigate this threat, we have used the best hyperparameters reported in the past implementations in literature. Experimenting with hyperparameter tuning can be experimented further in future AD research.

9 CONCLUSION
In this work, we compare the robustness of DRL-based policies while training ACs and adversarial agents. By first training DRL AC policies in a multi-agent environment, we test their driving performance in both single and multi-agent scenarios. We analyze the robustness of AC policies using four evaluation metrics described in Section 6. In order to find more vulnerabilities in AC policies, the same DRL algorithms are used for training adversarial agents that can help in finding failure-driving scenarios for victim ACs. We use the best performing AC agents from our experiments as victim ACs to evaluate the effectiveness of adversarial policies in driving victim ACs into collision and offroad driving errors.

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