ANTI-CARLA: An Adversarial Testing Framework for Autonomous Vehicles in CARLA

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Abstract— **Despite recent advances in autonomous driving systems, accidents such as the fatal Uber crash in 2018 show these systems are still susceptible to edge cases. Such systems need to be thoroughly tested and validated before being deployed in the real world to avoid such events. Testing in open-world scenarios can be difficult, time-consuming, and expensive. These challenges can be addressed by using driving simulators such as CARLA instead. A key part of such tests is adversarial testing, in which the goal is to find scenarios that lead to failures of the given system. While several independent efforts in adversarial testing have been made, a well-established testing framework that enables adaptive stress testing has yet to be made available for CARLA. We therefore propose ANTI-CARLA, an adversarial testing framework in CARLA. The operating conditions in which a given system should be tested are specified in a scenario description language. The framework offers an adversarial search mechanism that searches for operating conditions that will fail the tested system. In this way, ANTI-CARLA extends the CARLA simulator with the capability of performing adversarial testing on any given driving pipeline. We use ANTI-CARLA to test the driving pipeline trained with Learning By Cheating (LBC) approach. The simulation results demonstrate that ANTI-CARLA can effectively and automatically find a range of failure cases despite LBC reaching an accuracy of 100% in the CARLA benchmark.**

I. Introduction

Advancements in Machine Learning (ML) have led to significant progress in the levels of autonomy achieved by Autonomous Vehicles (AVs) [1]. However, recent accidents such as Tesla's autopilot crashes [2] and the fatal Uber self-driving car accident [3] demonstrate that current AV systems still can fail. To address this, testing and validating such systems before deploying them into real-world operations has received increasing attention. To determine failure cases of a system before they happen on the road, it is crucial to generate adversarial test cases that can fail the system. For example, a scene with complex lighting can be an adversarial test case for a controller based on visual perception. Generating such test cases in the real world can be expensive, slow, and often infeasible. Hence, recent research has been increasingly focusing on using synthetic data from simulators such as AirSim [4], LGSVL [5], Deepdrive [6], and CARLA [7]. CARLA is particularly focused on autonomous driving and is a widely used option in academia and industry for this domain [8]–[11].

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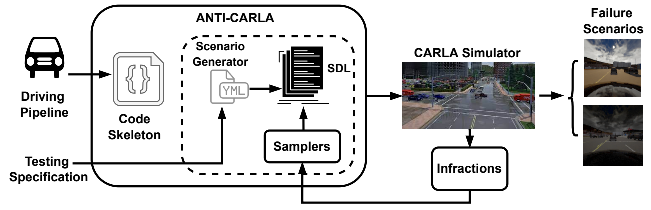


Fig. 1: Overview of ANTI-CARLA, the proposed adversarial testing framework integrated into the CARLA simulator. Given an arbitrary driving pipeline, the user specifies the desired test conditions and the framework automatically generates adversarial test cases.

Traditionally, testing is restricted to a set of handmade scenarios with the goal of satisfying safety standards such as ISO26262 [12]. However, manually creating test cases is tedious and requires significant human labor. Recently, there has been substantial ongoing work in automating the test case generation process. Domain-Specific Modeling Languages (DSMLs) such as Scenic [13], and MSDL [14] are being developed for describing what a test case should contain. They provide a mechanism for describing the test conditions, the variable parameters and their distribution, which is required for generating the test cases. These parameters are then sampled from their distribution ranges using state-of-the-art sampling algorithms such as random search, grid search, and Bayesian optimization search for generating suitable test cases. Despite this progress, the availability of frameworks that combine these components and allow straightforward test case generation is severely limited.

Only few frameworks have been proposed that focus on generating test cases for autonomous driving [15]–[18]. These frameworks are built on custom simulators that are not open-source or available for use. We address this issue and propose ANTI-CARLA, a framework for automated adversarial testing, evaluation, and exploration of the performance of AVs within the open-source CARLA simulator. It provides a skeleton that allows for plugging in and testing any autonomous driving pipeline. It includes an Scenario Description Language (SDL) for describing the test conditions and a simple interface for specifying test conditions. The overall workflow of the framework is shown in Figure 1. Given a driving pipeline and testing specifications, ANTI-CARLA automatically generates adversarial scenarios that fail the system. Due to its flexible and modular structure, any driving system can be evaluated. The main contributions of this paper are as follows.

- We combine a mapping mechanism for an arbitrary AV system, a test specification, and samplers [19], [20] into

ANTI-CARLA, which generates adversarial test cases for the AV system in CARLA.

- We develop a domain-specific SDL that allows for modeling different testing scenarios for the AV, defined in terms of its operating conditions.
- We use ANTI-CARLA to evaluate the state-of-the-art Learning By Cheating (LBC) controller [21]. Despite LBC achieving an accuracy of $100\,\%$ in parts of the CARLA challenge, ANTI-CARLA generates several operating conditions that fail the controller.

The rest of this paper is organized as follows. In Section II, we summarize related research. We discuss the problem formulation in Section III and introduce the proposed framework in Section IV. In Section V, we evaluate the framework by generating fail cases for the LBC controller and analyzing them. Section VI concludes. The source code of this work will be published alongside this paper under `https://github.com/scope-lab-vu/ANTI-CARLA`.

II. Related Work

In this section, we discuss related work. First, we introduce how test cases can be described and sampled. Then, we summarize existing frameworks that allow for generating test cases for a given driving pipeline. Finally, we summarize state-of-the-art driving pipelines for CARLA.

A. Test Case Description and Sampling

For testing software, test case generation has been a relevant research field for decades [22]. The field of AV testing has only recently started gathering interest. Domain-specific SDLs have been increasingly used for specifying the testing conditions [13], [23], [24]. For example, Scenic [13] is a popular language integrated with the CARLA simulator for setting up different scenarios. MSDL [14] is a language predominantly used in the industry to specify scenarios. Over the last years, several other languages such as SceML [24] have been developed to enhance the capabilities during testing.

To cover the operating conditions space, these languages are integrated with probabilistic samplers. One of the most widely adapted approach is the grid sampler. A previously identified risky scenario is used as the initial condition, and the grid around it is searched to sample new scenarios [25]. This approach requires prior information of the risk scenes and can be labor-intensive. Uniform random sampling does not require this prior information [18]. Other recent improvements include intelligent sampling techniques such as incremental sampling, importance sampling, and adaptive sampling, borrowed from other fields such as uncertainty quantification and design space exploration [26]. Zhao et al. [27] used importance sampling to learn the parameters affecting the performance of the system under test, generating increasingly varied test cases that fail the system.

We integrate both passive and active samplers into our framework. Due to the modular design of ANTI-CARLA, other intelligent samplers [26] can be integrated easily.

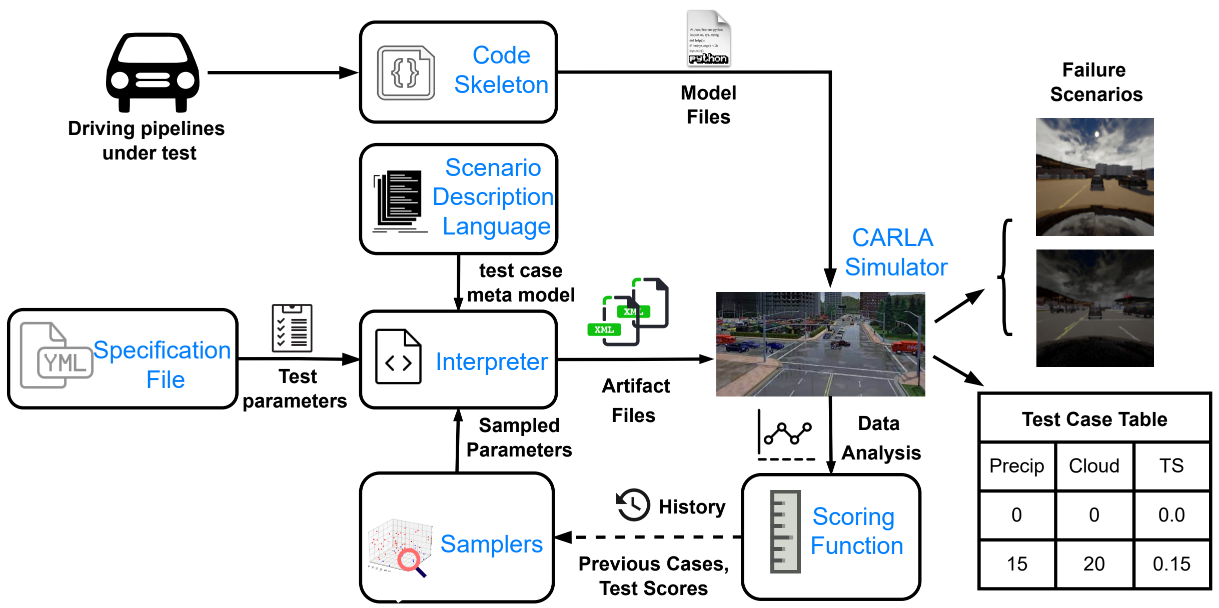
B. Testing Frameworks

Simulation-based testing frameworks allow generating test cases for a given system. A framework consists of two main components: a mechanism for describing test cases, and a mechanism for generating test cases. Tuncali et al. [28] presented a testing framework built using their MATLAB tool called S-TaLiRo. The tool provides an optimization engine and a stochastic sampler to automatically sample test cases across the search space generated from the testing specification. The same authors later presented a simulation-based adversarial testing framework called Sim-ATAV [29], which performs adversarial testing in the scenario configuration space of perception-based AVs. Son et al. [17] proposed an Advanced Driver Assistance Systems (ADAS)-testing framework based on co-simulation of Siemens Amesim and Prescan software. The testing is driven by several handmade scenarios derived from safety standards such as ISO26262. The Paracosm framework [18] allows users to describe complex driving situations as programs. It provides a systematic approach for exploring the search space and contains a coverage metric to quantify the coverage. For Grand Theft Auto, a simulation-based harness for AV is available [15]. It includes a testbench that performs sampling using simulated annealing to sample the next simulation parameters based on the AV's performance in the current simulation. While all of these works focused on AV testing, they are implemented either in proprietary simulators or in limited custom scenarios.

To the best of our knowledge, no framework is readily available for testing AVs in open-source simulation. Despite CARLA being a widely used simulator across academia and industry, a flexible framework for testing AVs is currently not available for CARLA. This motivates the introduction of ANTI-CARLA, an automated testing framework with adversarial samplers that can be used to test an arbitrary driving pipelines with minimal effort.

C. Autonomous Driving Pipelines

The proposed framework is designed to generate fail cases for a given autonomous driving pipeline. A range of controllers that perform well in CARLA is available. The Transfuser approach [30] uses transformers to fuse LIDAR and camera input. The World-on-Rails pipeline [31] only relies on camera images. It simplifies the driving task by assuming that the vehicle does not influence the environment, then uses reinforcement learning to obtain a driving policy. Finally, the LBC approach [21] is also based on visual input. First, a teacher agent with complete access to internal simulator information is trained to imitate expert trajectories. Next, the actual controller is trained to imitate the teacher agent's trajectories. By learning from a teacher who was "cheating" by having complete information, the student network is capable of learning highly accurate driving strategies. LBC achieved an accuracy of $100\,\%$ on the original CARLA benchmark [21]. Current benchmarks are thus not always capable of identifying weaknesses of a controller, demonstrating the need for adversarial testing as offered by ANTI-CARLA.



Test Case Table

Precip	Cloud	TS
0	0	0.0
15	20	0.15

Fig. 2: Overview of the ANTI-CARLA framework for generating test cases that fail an AV system in the CARLA simulator. The driving pipeline and the test specifications are taken as inputs by the framework to generate failure test cases that can be post processed to analyze the problems with the system.

While any controller could be used, we select LBC as a representative state-of-the-art approach to evaluate with ANTI-CARLA.

III. Problem Formulation

Formally, the problem can be defined as follows. We have a simulator Sim that is given the current environment E_t, an AV with a driving controller C, and the current state of the AV $state_t$. The state of the vehicle $state_t \in \mathbb{R}^n$ describes the position, speed, steering angle etc. of the vehicle. The current environment E_t can be defined in terms of a set of temporal variables such as weather, traffic density, the time of day that change over time and a set of spatial variables that describe roadway features. These features are characterized by waypoints w denoted by a two-dimensional matrix of latitude and longitude. These waypoints can be mapped to different road segments that constitute a track on which the AV is tested. Further, the controller C is a function that perceives the environment using measurements from multi-modal sensors such as a camera, LIDAR, Radar, etc. to compute actuation controls of speed, throttle, and brake. The control signals are sent to the simulator, which generates the next state of the vehicle $state_{t+1}$ by running the controller C under the given environment variables E_t: $Sim(state_i, E_i, C) = state_{i+1}$. An ordered sequence of n consecutive states $state_i$, $i \in \{t-n, ..., t\}$ is considered a *scene*. The simulator has some infraction function I that records for each state its infractions $I(state_t) \in \mathbb{R}_n$. A scoring function TS assigns a score to the entire scene: $TS(scene) = \sum_{k=t-n}^{t} I(state_t)$. Then, we want to solve the following problem.

Problem. *Given a simulator Sim, a driving controller C and some conditions on the environment E, generate a set of scenes that results in high infraction scores TS.*

The conditions on E allow to specify what kind of test cases should be generated. To solve this problem, we need a mechanism for specifying those conditions, a search mechanism to find an environment that leads to a high infraction score S, and a mechanism for integrating a given controller C into the given simulator Sim. In the next section, we introduce ANTI-CARLA as an implementation for these requirements.

IV. Proposed Framework

In this section, we show the proposed adversarial testing framework for the CARLA simulator. An overview is shown in Figure 2. Next, we discuss each component in more detail.

A. Scenario Generator

The first component of the proposed framework is a scenario generator. It includes a Scenario Description Language for modeling scenarios as well as specification files for specifying and selecting testing parameters. In this setup, a test case is defined in terms of a scene which is a time-series trajectory of the system's path in the environment that lasts 30 s to 60 s. The scene is represented using the environmental conditions (E) and the AV system's parameters (A). E is a set of spatial variables such as regions of a track and temporal variables such as the weather and traffic density. A includes information like the starting position, onboard sensors and actuators. Together, E and A form the testing parameter set. The value for some of these parameter can be sampled from specified distributions. Physical constraints and maximum step change constraints limit the speed at which the parameters can evolve. For example, the time of day has a fixed rate at which it can change. Including these constraints during sampling results in more meaningful scenes as shown in our previous work [20].

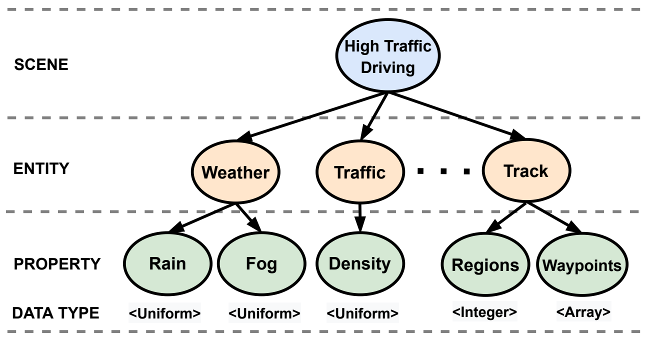


Fig. 3: Example for the structure of the proposed meta-model.

Scenario Description Language: We have designed an SDL in the textX [32] meta-language for modeling a scene. A grammar contains the rules for describing scene in the meta-language. A meta-model contains the actual description of a scene. A visualization of the structure of the meta-model is shown in Fig. 3. A scene s is a collection of entities $\{e_1,e_2,...,e_k\}$ that represent different environmental conditions and agent parameters. For example, the scene *High Traffic Driving* is specified by its *Track* as well as its *Weather* and *Traffic* conditions. Entities are further specified by a set of properties $\{p_1,p_2,...,p_m\}$. For example, the *Weather* can have the properties *Rain* and *Fog*. Each property has a name n and a data type t. For example, *Rain* is a uniform distribution, while the *Waypoints* are an array of integers. Special data types such as distributions can again have properties, e.g. the range of a uniform distribution. The meta-model allows for a structured description of any desired scene in the CARLA simulator.

Specification Files: We also provide a set of specification files with the scene parameters that can be selected by the user. These files serve as an abstract representation of the SDL modeling concepts. Based on the user's selection of the sampler, the selected parameters are sampled from their respective distributions. The remaining parameters are assigned default values. We divide the information into three specification files. First, the user selects a scene specifier. We show an excerpt of the scene specifier file in Figure 4. It specifies which town to use as a map, which track to drive, the distributions for the weather traffic density, pedestrian density, and the sampling constraints. The user also specifies which infraction metric to use and at which frequency data should be recorded. Second, an agent specifier is needed, which includes agent-related information such as the available controllers, list of sensors and their positions, and the sensor data that can be recorded. Third, a sampler specifier determines which sampler to use from a list of available samplers.

Finally, the language has an interpreter as shown in Fig. 2. It connects the specification files, the SDL, and the probabilistic samplers discussed in the following section. First, the interpreter extracts the parameters that require sampling and the fixed parameters from the specification files. It then sends the parameters that need sampling to the sampler.

```
Scenario Description{
    town: 5 //Available towns 3 and 5
    track: 1 // 1 track available for each town
       regions: 5 //Each town has 5 regions
    weather:  //Weather parameters and distribution range
      cloudiness: [0,100]
      precipitation: [0,100]
      time-of-day: [-90,90]
    pedestrian_density: [0,3]
    traffic_density: [0,10]
    Constraints: //A constraint on the rate of change in
         parameter values
        weather_delta: 2
        traffic_delta: 2
        pedestrian_delta: 1
    Infraction_Metrics: //Infraction metrics to be
         recorded
        Infraction Penalty: true
        Off-road Driving: true
        Route Deviation: false
    Record Frequency: 5Hz } //Frequency of data recording
```

Fig. 4: Excerpt of a scene specification file. The specification files describe the available inputs, the user then only has to select a value for each concept.

The sampler generates a value for these parameters from their distribution ranges. Finally, the sampled parameters and the fixed parameters are parsed to the SDL meta-model to generate artifact files that drive the simulator.

B. Adapter Glue Code

The framework also requires a driving pipeline under test. Integrating different pipelines is not straightforward since they might not have the right interface to be used "as in" the framework. For example, driving pipelines developed outside of CARLA may not be directly used in the simulator because of CARLA's strict interface requirements in the sensors and actuators. They may need to be "adapted" to meet the interface expectations of the simulator [33]. To address this, we generate an adapter that interfaces the driving pipeline code with the sensors and actuators in the format required by the simulator's API as shown in Figure 5. The adapter is synthesized from the agent specification file, which has a list of sensors required by the driving pipeline, its positions, and the sampling rates.

The adapter reads the available sensors from the autonomous agent class in the simulator's API and extends it with the sensors requested in the specification file. Thus, a code structure for the requested sensors in the desired positions is generated and provided to the driving pipeline code. Also, the actuators required by the simulator are read from the API and made available in the code. With the required sensors and actuators available through the adapter, the user needs to provide the driving pipeline code. There are specific directories for any utility files and model weights of the controller, which are linked with the code skeleton. The user only needs to handle this interface for setting up their controller correctly. If the actuators and sensors are not properly set up, the simulator will throw an error. In future work, we will include an automatic check for ensuring a correct-by-construction setup between the code, sensors, and actuators.

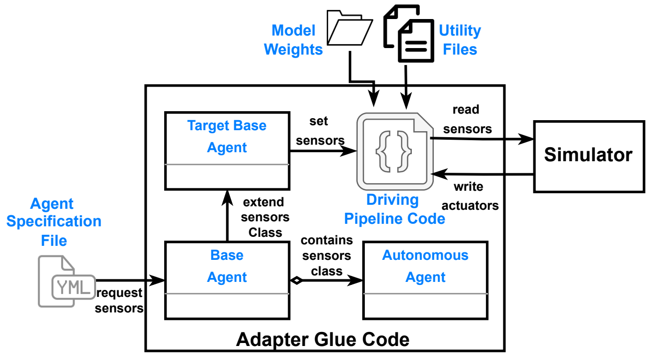


Fig. 5: An illustration of the adapter glue code that interfaces the sensors and actuators of CARLA to the code of the AV system.

C. Scoring Function

For evaluating the driving proficiency of the AV system in the generated scene, the framework also provides a scoring function called test score TS. The scoring is performed based on all of the infractions performed by the system in a given scene. Infractions measured in CARLA include route deviation, lane violation, traffic rule violation, running a stop sign, running a red light, and off-road driving. Each infraction I_k is assigned a weight w_k. In the current setup, these weights are set to the values used in the CARLA challenge [34]. However, they can be varied depending on the current use case. The infractions are then combined into the weighted score as shown in Equation 1:

$$TS = \sum_{k=1}^{n} w_k \cdot I_k \tag{1}$$

The test score TS generated from the infractions is stored along with the test case parameters in a test case table as shown in Figure 2. These test cases and the scores are used online to drive the active samplers towards regions of the search space that have previously resulted in high test scores. The table can also be used to perform an offline post-analysis to identify the failure conditions of a given controller, allowing to retrain and improve the controller.

D. Samplers

We have integrated several samplers to perform search-based test case generation. Here, a sampler is interfaced to the SDL through an interpreter, which provides it with the names, distribution, and the current value of the parameters. We included two kinds of samplers available in the framework.

First, we implemented several passive samplers since they are fast and widely used. They do not use the feedback of previous results in the sampling process. *Random Search*, uniformly samples the parameter value from their respective distributions at random. *Grid Search* exhaustively searches all of the combinations of the parameters in a given grid. *Halton Sequence Search* [19] is a pseudo-random technique that samples the parameters using co-primes as their bases. While these samplers perform well, their non-feedback sampling approach results in a directionless search that could miss several important failure test cases. Further, they do not balance the exploration vs. exploitation of the search space, which is required for generating diverse failure cases [20].

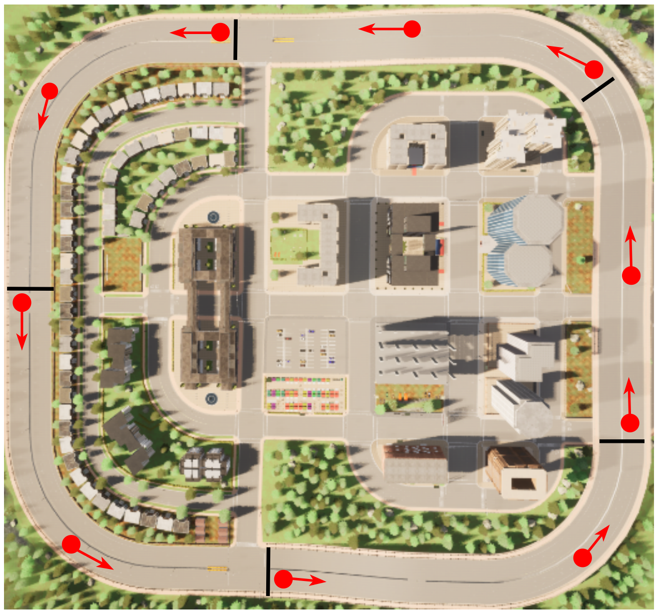


Fig. 6: An illustration of the track in CARLA's town5. The waypoints are highlighted by red arrows and the five regions are separated by black lines.

To overcome these limitations, we have also included two active samplers, *Random Neighborhood Search (RNS)* and *Guided Bayesian Optimization (GBO)* [20]. These samplers use the feedback of the AV system's previous performances when sampling the parameters for the current test case. The feedback uses the test score and the previously sampled parameters. In addition, they also capture constraints and correlations between the different test parameters. The *RNS* sampler extends the conventional random search with the kd-tree nearest neighborhood search algorithm [35]. This extension provides the random sampler with the capability to exploit. If the test case generated from randomly sampled parameters results in a high test score, the region around these parameter values are exploited. Otherwise, the parameters are again randomly sampled from the entire distribution. The *GBO* extends the conventional Bayesian Optimization sampler with constraints, which restrict the region where the acquisition function looks for the next sampling variables.

V. Evaluation

In this section, we present several experiments to evaluate the usability of ANTI-CARLA for adversarial testing. We use the framework to compare the adversarial test cases found by different samplers. Then, we compare the performance of the LBC controller to the Transfuser approach [30] on those test cases, analyze the failures and make suggestions on how to improve the LBC controller. The experiments were run on a desktop computer with AMD Ryzen Threadripper 16-Core Processor, 4 NVIDIA Titan XP GPUs, and 128 GiB RAM.

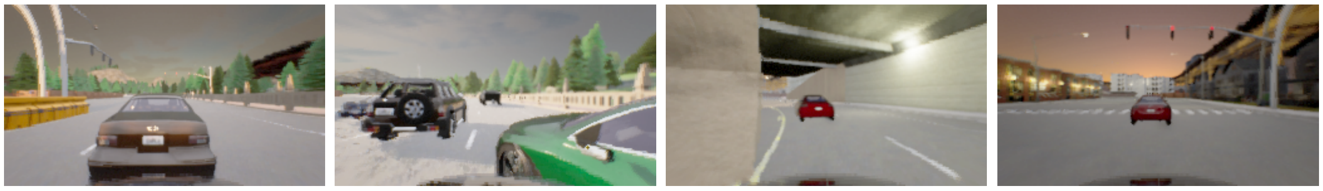

(a) Town5, t=1, c=10%, p=5%, d= 8° (b) Town5, t=10, c=70%, p=60%, d=24° (c) Town3, t=4, c=20%, p=0%, d= 60° (d) Town3, t=2, c=40%, p=0%, d=0°

Fig. 7: Screenshots of the test cases as captured by the forward looking camera of the AV. Descriptions of these scenes are provided below the images.

A. *Simulation Setup*

The proposed framework is integrated into the CARLA simulator. We used the CARLA challenge API [34] to create one closed loop track in both town5 and town3. We use LBC as the controller C under test. The geometry of the track is defined by ten waypoints as shown in Figure 6. We divide the track into several regions containing two waypoints each. For each track, we thus obtain five regions. We divided each track into regions to create shorter scenes in which we can vary the weather conditions as well as traffic and pedestrian densities. Each track can then have ten different environmental conditions. The length of the track and number of regions can be specified in the scene description file and can thus be changed with minimal effort in the code. We use the API to create and control the traffic and pedestrians in each scene. For evaluating each simulation, we record the driving score, the route completion score, and the test score TS based on the list of infractions available from the API.

Besides evaluating the performance of the driving pipeline, the framework also allows to evaluate the performance of the samplers used to generate adversarial test cases. We use the following two metrics.

1) Failed Test Cases (FT): This score measures the efficacy of the samplers in generating failure test cases. It is calculated as the number of failed test cases N_{Fail} compared to the total number of sampled test cases N_{Total}:

$$FT(\%) = \frac{N_{Fail}}{N_{Total}} \cdot 100 \tag{2}$$

2) Total Execution Time: The overall time taken by the sampler to sample N_{Total} test cases and execute them in the simulator is a metric relevant for practice. This metric indicates any hidden overheads of the sampler in the framework.

B. *Results*

We generated 100 test cases each for the track in town3 and town5. Each test case represents a scene that lasts between 30 seconds to 60 seconds. We varied the environment parameters of cloudiness c, precipitation p, time of day d, and traffic density t to generate different test cases. We varied the cloudiness and precipitation in the range $[0, 100]$, the time of day in the range $[0, 90]$, and the traffic in the range $[0, 50]$. We used the initial conditions of $d = 0^\circ$ (dusk), $c = 0^\circ$, $p = 0^\circ$, and $t = 5$. To score the test cases, we computed a test score as $TS = R_i \cdot I_S$. Here, R_i is the route completion percentage of the i^{th} route, and I_S is the weighted sum of major infractions such as collision with pedestrians, collisions with vehicles, collisions with static objects, and minor infractions such as running a stop sign, running a red-light signal, and off-road driving. The weights for these infractions are taken directly from the CARLA challenge setup. To drive the test case generation process, we selected the commonly used random sampler as a baseline and compared it against the RNS sampler. The simulator was run in synchronous mode at a fixed rate of 20 frames per second. If a test case includes either a collision, infraction, or route in-completion, it is considered to be a failure test case.

Samplers	Town	Failed Test Cases (%)	Test cases with collisions (%)	Test cases with infractions (%)
Random	3	17	9	10
	5	13	7	8
RNS	3	27	13	15
	5	21	10	13

TABLE I: Test case statistics for the random and RNS sampler.

1) Visualization: First, we visualize several test cases by showing the frontal camera view from each scene. In Fig. 7, we show four exemplary test cases for LBC. Fig. 7-a is a nominal test case from town5 with low precipitation and dusk time of the day and low traffic. Fig. 7-b is a failed test case from town5 with high precipitation and traffic. A collision occurred when the controller tried to steer to the right lane. Fig. 7-c is a failed test case from town3 with no precipitation and low traffic. Here, the AV can be seen navigating a tunnel. Towards the end of the tunnel, the AV collides with a pillar. Finally, Fig. 7-d is another failed test case from town3, where the AV runs a red traffic light. These examples demonstrate that a diverse set of fail cases could be obtained.

2) Sampler Comparison: Table I shows the statistics of the collisions and infractions generated by the two samplers across all test cases. The RNS sampler generates a higher number of failed test cases than the random sampler. In general, the AV performed better in town5 than in town3. The track in town5 was shorter, had fewer traffic lights and stop signs, and did not have complex landmarks such as a tunnel or a round-about. The controller failed 13 % and 21 % of the test cases generated by the random and RNS sampler, respectively. Town3 has several traffic lights and a tunnel. Here, the controller failed 17 % and 27 % of the test cases generated from the random and RNS sampler, respectively. These fail cases occurred in the region that included the

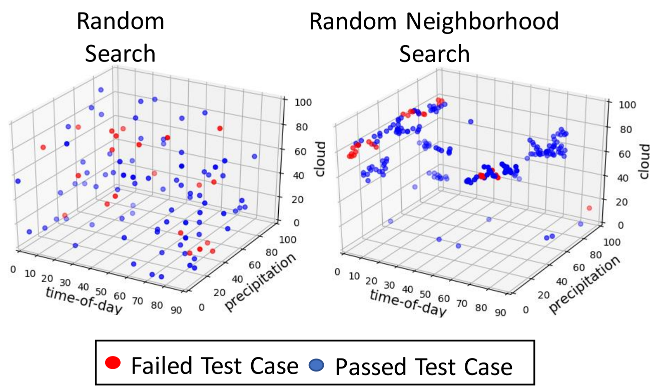


Fig. 8: Comparison of the 100 scenes sampled by the random and RNS samplers. The RNS sampler generates distinct clusters of failures. Plot axis: x-axis represents the time of day, y-axis represents the precipitation level and z-axis represents the cloud level.

tunnel as well as areas with traffic signs and stop signs nearby. The framework required 140 minutes to generate the test cases for town5 and 325 minutes for town3 when using the random sampler. With the RNS sampler, the execution times are 176 minutes for town5 and 384 minutes for town3. This shows that the more efficient RNS sampler does not add significant overhead, with both samplers requiring around five minutes per test case.

Fig. 8 shows the test cases sampled by the random and RNS sampler plotted in the operating conditions space. The failed test cases are marked in red, and the test cases that passed without failures or collisions are marked in blue. The random sampler randomly samples the test cases across the search space. This makes it is hard to analyze common causes of the controller's failures. In contrast, the failed test cases generated by the RNS sampler occur in clusters, which makes it easier to hypothesize the causes of the failures. Fig. 8 shows that the controller had failures mostly in two operating conditions: (a) high precipitation and (b) dusk as the time of the day.

3) Controller Comparison: ANTI-CARLA can also be used to compare different controllers. We compare the performance of the Transfuser [30] controller to LBC using the track in town5. We ran the Transfuser and LBC for the same 100 test cases generated with the random sampler. The LBC and Transfuser controllers had 13 and 23 failed test cases, respectively. Fig. 9 shows a breakdown of the infractions caused by these controllers. Controller timeout is the main reason for the Transfuser's higher failure rate. This could be due to the expert policy used during training not being sufficient for handling all scenarios. Besides the frequent timeouts, the Transfuser had significantly fewer collisions and infractions than LBC. Both controllers struggled with detecting red traffic lights. The authors of Transfuser suggested that this is due to traffic lights being placed on the opposite side of intersections, which is difficult to detect in camera images [30]. These results show how ANTI-CARLA allows to identify weaknesses of different controllers by focusing specifically on adversarial test scenarios.

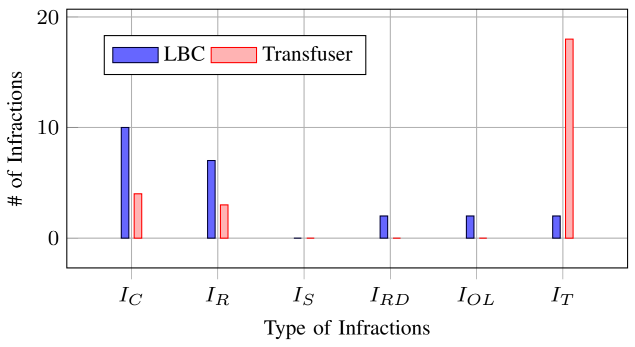


Fig. 9: Infractions caused by the LBC and transfuser controllers.

4) Recommendations: The previous sections show that LBC tends to crash into the leading vehicle in heavy rain or in unusual lighting conditions, caused either by the time of day or by entering a tunnel. The highest infraction scores are obtained for adverse weather conditions and challenging landscapes such as traffic lights, tunnels, and roundabouts. By identifying those main reasons for failures, several suggestions can be made for improving LBC. First, adding another sensor modality could make the perception more robust to rain or darkness. For example, LIDARs do not require sunlight and are less susceptible to rain. Second, the robustness of the camera-based perception could be improved by training the controller with more images taken in the adverse conditions of rain and at dusk.

VI. Conclusion

In this paper, we introduced ANTI-CARLA, an adversarial testing framework for the CARLA simulator that allows to automatically generate test cases that fail an arbitrary AV system. Testing frameworks available in the literature are either tailor-made for a specific use case or built on proprietary simulators. In contrast, ANTI-CARLA is an open-source extension to an open-source simulator. The framework integrates a Scenario Description Language for modeling test scenarios in terms of the system's operating conditions, sensor and actuator faults. A test specification file is used to specify and select the test conditions, infraction metrics, and samplers required for generating the test cases. The SDL is driven by an adversarial sampler that searches across the specified operating conditions space. We used this framework to test the popular Learning By Cheating controller and to compare different samplers. Then, we derived recommendations for improving LBC. We also used ANTI-CARLA to compare the performance of LBC to the Transfuser approach, allowing to identify weaknesses of each controller. While LBC achieved an accuracy of $100\,\%$ across several scenarios in the CARLA challenge, the proposed framework automatically found a range of scenes in which the controller fails.

There are some limitations of ANTI-CARLA. First, only individual, static scenes can be sampled. A temporal sequence of scenes leading up to each fail case is not available. Temporal and dynamic sampling should be explored and added to the framework. Second, the samplers could also be further improved. One potential direction is to use Reinforcement Learning to learn what changes in the operating conditions led to failures and then generate the sequence of scenes that resulted in the system's failure. Third, sensor faults as a testing parameter and the remaining towns available in CARLA will be added to the framework to allow for adversarial testing of any AV system in any environment.

For future work, the adversarial test cases could be used for a closed-loop training workflow as proposed in [36]. By training the controller with the obtained failure scenes and then sampling new failure scenes, the controller can be iteratively optimized. Further, parallelizing the framework by running multiple simulations at once would allow to scale the framework across a fleet of vehicles.

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