Improving the Generalization of End-to-End Driving through Procedural Generation

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Abstract—Recently there is a growing interest in the end-to-end training of autonomous driving where the entire driving pipeline from perception to control is modeled as a neural network and jointly optimized. The end-to-end driving is usually first developed and validated in simulators. However, most of the existing driving simulators only contain a fixed set of maps and a limited number of configurations. As a result the deep models are prone to overfitting training scenarios. Furthermore it is difficult to assess how well the trained models generalize to unseen scenarios. To better evaluate and improve the generalization of end-to-end driving, we introduce an open-ended and highly configurable driving simulator called PGDrive. PGDrive first defines multiple basic road blocks such as ramp, fork, and roundabout with configurable settings. Then a range of diverse maps can be assembled from those blocks with procedural generation, which are further turned into interactive environments. The experiments show that the driving agent trained by reinforcement learning on a small fixed set of maps generalizes poorly to unseen maps. We further validate that training with the increasing number of procedurally generated maps significantly improves the generalization of the agent across scenarios of different traffic densities and map structures. Code is available at https://decisionforce.github.io/pgdrive.

I. INTRODUCTION

In recent years there has been rapid progress of autonomous driving in both industry and academia [1], [2]. Due to the public safety concerns it is impossible to directly train and test the driving systems in the physical world [3]. A common practice is to develop and validate the driving prototypes in simulators. Meanwhile, compared to the conventional modular approach, there is a recent interest in the end-to-end approach for autonomous driving, where the entire driving pipeline is replaced by a single deep neural network and trained with a massive number of data or interactions with the environment. For example, sufficient training data have been collected in simulator to train end-to-end driving via Imitation Learning [4] or Reinforcement Learning [5].

Many realistic driving simulators have been proposed to support the development, training, and validation of autonomous driving systems. Simulators such as CARLA [6] and SUMMIT [7] contain driving scenarios with realistic visual appearances. Particularly, CARLA enables the fine-grained rendering of the real world with realistic weathers and lighting conditions. Other simulators like Flow [8], Duckietown [9], and Highway-env [10] either focus on learning high-level decisions or only contain simplistic driving scenarios. It is known that deep neural networks can overfit training data easily [11], [12], thus the driving agent trained on a fixed set of scenarios in the simulators might have difficulty generalizing to new scenarios. Furthermore, the existing simulators lack sufficiently diverse designs of the maps and scenarios. For example, CARLA consists of only about ten towns while Highway-env contains six typical traffic scenarios. Training deep neural networks on such simulators might lead to overfitting and poor generalization of learned driving agent.

To evaluate and improve the generalization of end-to-end driving, we introduce PGDrive, an open-ended and highly configurable driving simulator. PGDrive integrates the key feature of the procedural generation (PG) [13], where a diverse range of executable maps can be procedurally generated from pre-defined elementary road blocks. Such maps can be used to train and test the end-to-end driving agents for examining their generalization ability. Specifically, PGDrive contains multiple building blocks such as Straight, Ramp, Fork, Roundabout, Curve, and Intersection, with configurable settings such as the road’s curved angle and the number of lanes. Following the procedural generation and predefined rules, these building blocks can be randomly selected and assembled into an environment for the driving agent to interact with. Furthermore, the kinematics of target vehicle and traffic vehicles are also configurable for emulating various traffic flows and transportation conditions. Thus the procedural generation feature of the PGDrive allows us to customize the training set, examine different emergent driving behaviors, and improve the model’s generalization across scenarios. PGDrive is built upon Panda3d and the Bullet engine [14] with optimized system design. It can achieve up to 500 simulation steps per second when running a single instance on PC. Fig. 1 illustrates one generated map with multiple building blocks, and the interface of the PGDrive.

Based on the proposed PGDrive simulator, we study the generalization of the end-to-end driving. We first validate that the agent trained on a small fixed set of maps generalizes poorly to new scenarios. The experimental result further shows that training with more environments, the learned reinforcement learning agents can generalize better to unseen scenarios in terms of less collision rate and traffic violation. It demonstrates the benefit of procedural generations brought
by PGDrive. More experiments indicate that the other configurable parameters such as the density of traffic flow as well as the kinematic coefficient also impact the generalization. We open-source the simulator to facilitate the research of end-to-end driving.

II. RELATED WORK

Autonomous Driving. The research on autonomous driving can be divided into two categories: the modular and the end-to-end approaches [2]. In the modular approach, the driving pipeline is composed of sub-modules such as perception, localization, planning, and control module [2]. The advantage for the modular design is the interpretability, where one can easily identify the module at fault in case of a malfunction or unexpected system behavior. However, it takes enormous human efforts to design and maintain the pipeline, and it might also suffer from the internal redundancy caused by manual designs [3].

On the other hand, one popular end-to-end approach for autonomous driving is to utilize the Imitation Learning (IL) to drive a car by mimicking an expert [3]. The accessibility of large amounts of human driving data [15] makes the IL approach work well for simple tasks such as lane following [16] and obstacle avoidance [17]. Nevertheless, the training data might be biased towards particular location, road layout, or weather [18], while the accident cases can rarely occur in the training data but deserve significant attention [3]. In contrast to the aforementioned approaches, Reinforcement Learning (RL) gains attention recently as another approach of end-to-end driving. RL is able to discover task-specific knowledge by interaction with the environment [19], thus the needs for elaborate design and domain knowledge are greatly alleviated. Meanwhile, RL agent learns through the exploration of the environment thus does not limit its capacity to the training data. Based on the strengths, more and more attention has been paid to the RL-based solutions [20].

Driving Simulators. Due to public safety and the cost, it is impossible to train and test the driving models in the physical world in a large scale to collect enough data. Therefore, simulators have been used extensively to develop and validate the autonomous driving research. The simulators CARLA [6], GTA V [21], and SUMMIT [7] realistically preserve the appearance of the physical world. For example, CARLA not only provides perception, localization, planning, control modules and sophisticated kinematics models, but also renders the environment in different lighting conditions, weather and the time of a day shift. Thus the driving agent can be trained and evaluated more thoroughly. Other simulators such as Flow [8], TORCS [22], Duckietown [9] and Highway-env [10] abstract the driving problem to a higher level or provide simplistic scenarios as the environments for the agent to interact with. However, most of the existing simulators have a limited number of maps thus fail to provide the diverse training environments for the agent to learn and generalize. It remains challenging to evaluate the generalization of the trained agents. To address the generalization issue, we integrate the procedural generation (PG) in the proposed simulator to generate a huge amount of diverse training and test data.

Procedural Generation. Procedural Generation (PG) or Procedural Content Generation (PCG) are first adopted in video game industry [13]. It refers to the practice of utilizing algorithms to automatically generate game content including levels, maps, racing tracks, etc [23], [24], [25]. Many machine learning concepts like data augmentation [26], [27], domain randomization [28], [29] and Generative Adversarial Network [30] have been proposed to help design PG algorithms, making the game playable and alleviating the burden.
of game designers. The machine learning community also becomes interested in applying PG to improve the learning models [31]. Researchers have utilized PG to generate abundant training samples along with various training settings to help relieve data over-fitting, enable lifelong learning with lifelong generation [32], [33], [34], and help agents adapt to real world from learning in simulated settings [35], [36].

**Generalization.** Attaining generalization from training has long been a focus of machine learning research [37], [38], [39]. A common feature of a model with weak generalization ability is, despite the excellent performance on the training dataset, the model tend to have a significant performance drop when dealing with unseen data [40], [41]. The weak generalization can be caused by various factors, such as biased sampling or the limited number of training data. The overfitting, especially for the deep neural networks, is also a common issue [42]. In reinforcement learning (RL), overfitting exists but is usually overlooked. In most RL settings such as Deep-Q networks on Atari games [43], the training and testing are conducted in the same environment and thus the agents are prone to memorizing specific features in the environment [11]. Nichol et al. [44] propose to measure generalization performance by training and testing RL agents on distinct sets of levels in a video game franchise, which reveals the limitation of “training on the test set” paradigm. Cobbe et al. [12], [45] propose to use PCG to generate many distinct levels of video games and split the training and test sets to quantify the generalization of agents and find that when increasing the number of training environments, the test performance increases. We follow a similar training and testing pipeline and shows that the diversity of environments have a significant impact on the generalization ability of end-to-end driving.

### III. PGDrive Simulator

We introduce a new driving simulator PGDrive, which can generate an unlimited number of diverse driving environments through procedural generation. We compare PGDrive with other popular driving simulators in Table I. PGDrive has the key feature of procedural generation, and allows customizing many settings such as the traffic flow and the vehicles’ models. Besides, fine-grained camera, Lidar data generation and realistic 3D kinematics simulation are also supported. PGdrive is highly efficient. Each PGDrive instance runs in a single process and thus can be easily parallelized. Single PGDrive process can run up to 500 simulation steps per second without rendering on a PC.

As shown in Fig. 3, random interactive driving environments can be assembled from the basic road blocks. In each environment, the objective of the target vehicle, namely the vehicle that are controlled by the agent, is to reach the destination while avoid colliding with other vehicles and violating traffic rules. In the following parts, we introduce the technical details of the PGDrive and the process of procedural generation.

| Simulator          | Unlimited | Traffic | Custom Vehicle | Lidar or Camera | Realistic Kinematics |
|--------------------|-----------|---------|----------------|-----------------|---------------------|
| CARLA [6]          | ✓         | ✓       | ✓              | ✓               | ✓                   |
| GTA V [21]         | ✓         | ✓       | ✓              | ✓               | ✓                   |
| Highway-env [10]   | ✓         | ✓       | ✓              | ✓               | ✓                   |
| TORCS [22]         | ✓         | ✓       | ✓              | ✓               | ✓                   |
| Flow [8]           | ✓         | ✓       | ✓              | ✓               | ✓                   |
| Sim4CV [46]        | ✓         | ✓       | ✓              | ✓               | ✓                   |
| Duckietown [9]     | ✓         | ✓       | ✓              | ✓               | ✓                   |
| PGDrive (Ours)     | ✓         | ✓       | ✓              | ✓               | ✓                   |

#### A. Simulation Engine

PGDrive is implemented based on Panda3D [14] and Bullet Engine. Panda3D is an open-sourced engine for real-time 3D games, visualization, and simulation. Its well-designed rendering functions enable PGDrive to construct a realistic display for monitoring and producing the camera data. Bullet Engine is a physics simulation system that supports advanced collision detection, rigid body motion, and kinematic character controller, which empower efficient and accurate physics simulation in PGDrive.

**Physical and Visualization Model.** To improve the simulation efficiency and fidelity, all the elements in PGDrive, such as the lane line, vehicles and even the Lidar lasers, are constructed by two internal models: the physical model and the visualization model, which utilizes the Bullet Physics Engine and Panda3D’s render module, respectively. Powered by Bullet Engine, the physical model is a box shape rigid body that can participate in the collision detection and motion calculation. For example, the collision between the physical models of the vehicle’s wheels and the solid white line in the ground indicates the vehicle is driving out of road. The collision of Lidar ray and rigid body can be use to compose the observation of Lidar sensor. The visualization model, which is loaded to Panda3D’s render module, provides fine-grained rendering effects such as light reflection, texturing and shading. We adopt the open-sourced 3D models as the visualization model of vehicles. As shown in Fig. 1, there are 5 vehicle types available for creating the target or traffic vehicles. The vehicle’s physical model is inherited from the BulletVehicle 3D model in Bullet Engine, allowing it to slip, tilt even rollover when steering. It contains rich configurable parameters, such as the wheel friction, max suspension travel distance, suspension stiffness, wheel damping rate and so on, supporting the customization of a vast range of vehicles in the environments created by PGDrive.

**Perception.** Low-level sensors and high-level traffic information can be provided by PGDrive. For low-level sensors, an unlimited number of RGB cameras, Depth cameras and Lidar can be added with adjustable parameters, such as field of view, size of film, focal length, aspect ratio and the number of lasers. The captured images and point clouds can be fed
to the agent as input to simulate the data collected in real-world. Meanwhile, the high-level observation, namely the abstraction of surroundings, including the road information such as the bending angle, length and direction, and opponent vehicles’ information like velocity, heading and profile, can also be provided as input directly without perception noise, thus enables the development of driving pipeline with the assumption that the perception is solved.

Road and Traffic System. The driving scene in PGDrive contains a sophisticated road network and traffic flow. The road network, which is the static region that allows the vehicles to drive in, is represented by a set of nodes, i.e. joints, and the roads that interconnect nodes. The road is a concatenation of straight lanes, circular or spiral lanes laid between two nodes. Each lane has its properties such as length, width and curvature, and preserves several spawn points where traffic vehicles can be added. A larger road network can be constructed by attaching two or more road networks to the same node or joint. A route between two arbitrary nodes can be searched to form the navigation route. It can be either fed to target vehicle as navigation information, or used to find the paths between the spawn points and the destinations for the traffic vehicles calculated by A∗ algorithm.

A large number of traffic vehicles are created to form the traffic flow. They cruise in the scene from their spawn points to their own destinations powered by the IDM model and perform lane-changing based on Bicycle Model [47]. To simulate different traffic conditions such as empty road or traffic jam, we maintain a traffic manager which creates traffic vehicles by randomly selecting the vehicle type, kinematics coefficients, target speed, behavior types (aggressive or conservative), spawn points and destinations. The traffic manager can adjust the traffic density by triggering new traffic vehicles by randomly selecting the vehicle type, kinematics coefficients, target speed, behavior types (aggressive or conservative), spawn points and destinations. The traffic manager can adjust the traffic density by triggering new traffic vehicles after they arrive at their destinations.

B. Elementary Road Blocks

We introduce the concept road block, which is the elementary traffic component that can be assembled into a complete map by the procedural generation algorithm. Each block contains multiple nodes, i.e. the joints in the road network, multiple lanes that interconnect nodes, and at least one socket. The socket is the anchor to connect other blocks, which is usually a straight road. When connecting to an existing block, a newly added block will rotate and adjust its direction such that one of its socket can fit the target socket of the existing block. Each block can preserve several sockets. For instance, Roundabout and T-Intersection have 4 sockets and 3 sockets, respectively. The concept of socket allows us to develop the PG algorithm that can connect blocks easily, which is introduced in Section III-C. Apart from the above properties, a block-specific parameter space is defined to bound the possible parameters of the block, such as the number of lanes, the lane width, and the road curvature and so on. Each block also has a trigger zone to detect the target vehicle’s arrival and to trigger the traffic manager to spawn traffic vehicles at the spawn points, which are the specified locations in the lanes that are randomly chosen when creating the map. Fig. 2 shows 7 typical road block types. The detail of each block type is as follows:

- **Straight**: A straight road is configured by the number of lanes, lane length and lane width, and lane line types, namely whether it is broken white line or solid white line.
- **Ramp**: A ramp is a road with entry or exit existing in the rightest lane. Acceleration lane and deceleration lane are attached to the main road to guide the traffic vehicles to their destination.
- **Fork**: A structure used to merge or split additional lanes from the main road and change the number of lanes.
- **Roundabout**: A circular junction with four exits (sockets), whose radius is configurable. Both roundabout, ramp and fork aim to provide diverse merge scenarios.
- **Curve**: A curve block consists of a curved road and a straight road. The curve part can be a simple circular shape or clothoid shape to smooth the curvature variation.
- **T-Intersection**: An intersection that can enter and exit in three ways and thus has three sockets. The turning radius is configurable.
- **Intersection**: A four-way intersection allows bidirectional traffic. It is designed to support the research of unprotected-intersection.

C. Procedural Generation from Blocks

In order to provide a diverse set of driving scenarios for learning the end-to-end driving agent, we use the Procedural Generation (PG) technique to automatically select and assemble the blocks into driving maps. We exhibit several procedurally generated maps under different number of blocks in Fig. 3. The procedural generation procedure
iterates over four steps: 1) randomly choosing a new block, 2) perturbing its setting, 3) randomly choosing a socket from previous block’s sockets list and 4) inserting the new block to this socket.

However, during the above process, adding a randomly selected block to the existing road network may cause conflicts, since the new block may have overlap with the existing blocks due to its random topology. To avoid the overlapping conflicts, we design a search-based PG algorithm to filter out incorrect maps and achieve efficient map generation, as illustrated in Algorithm [1]. We define a function named Block Incremental Generation (BIG), which recursively appends block to the existing network if feasible and reverts current block otherwise. Concretely, when creating a map, we maintain a stack to store temporary blocks and search for an available block to be the next block. We allow the current block to take T trials to generate a new block with random parameters, connecting to one of current block’s socket. If successful, we push the latest block into the stack and search for next block. Otherwise, we pop up the current block from the stack and take the previous block to continue searching.

We can follow more concrete rules to select blocks, assemble them to maps as well as build complex emergent road network at city level. Extending PGDrive to learn to generate realistic road structure from real HD maps is also possible. We leave those extensions to future work.

D. Interactive Environment for Reinforcement Learning

We turn the generated maps into interactive environments, where the end-to-end driving agent can be trained by Reinforcement Learning (RL) algorithms. We discretize the time into 0.1s intervals. After each 0.1s interval, we query the RL agent for a normalized action \( a_{RL} = [a_1, a_2]^T \in [-1, 1]^2 \) and then convert it to the steering, acceleration and brake signal. Concretely, the steering value is given by \( u_s = a_1 \times 40 \) (degree), and the direction (turning left or right) is determined by the sign of \( a_1 \). The acceleration and brake signal is determined by \( a_2 \). For \( a_2 > 0 \), we consider it denotes acceleration signal and apply \( u_a = a_2 \times 460 \) (hp) engine force to the target vehicle. If \( a_2 \leq 0 \), we treat \(-a_2\) as the brake signal and apply \( u_b = |a_2| \times 355 \) (hp) brake force to the vehicle. After applying the control signals \( u = [u_s, u_a, u_b]^T \) to the target vehicle, PGDrive advances the simulation for 0.1s and provides the following information to RL agent as the observation:

1) Lidar-like cloud points with 50 m maximum detecting distance, centering at the target vehicle. We use a vector of 240 length, whose entries are in \([0, 1]\) and represent the relative distance of obstacle in specified direction.
2) The sensory data of the ego vehicle including current steering, heading, velocity and relative distance to the left and right boundaries.
3) The navigation information including the relative position of the socket of next block and the relative heading of ego vehicle against the heading of current lane.
4) The opponent information including the relative positions and headings of the closest 4 traffic vehicles.

After stepping the environment, the reward function is computed from four ingredients as follows:

\[
R = c_1 R_{\text{disp}} + c_2 R_{\text{speed}} + c_3 R_{\text{steering}} + c_4 R_{\text{term}}.
\] (1)

The displacement reward \( R_{\text{disp}} = d_t - d_{t-1} \), wherein the \( d_t \) and \( d_{t-1} \), denotes the longitudinal coordinates of the target vehicle’s center in the current lane of two consecutive time steps. It denotes the projection of the vehicle’s displacement to the longitudinal coordination of current lane. This reward
Algorithm 1: Procedural Generation from Blocks

Input: Maximum number of tries in one block T,
Number of blocks in each map n
Result: A set of maps M

1 # Define the main function to generate a list of maps
2 Function main(T, n)
3 Initialize a empty list M to store maps
4 while M does not contain N maps do
5     Initialize a stack cur_map to store blocks
6     new_map, flag= BIG(T, cur_map, n)
7     if flag is True then
8         Append new_map to M
9     Return M

10 # Define the Block Incremental Generation (BIG) helper
11 function that appends one block to current map if
feasible and return current map with a success flag
12 Function BIG(T, cur_map, n)
13     if cur_map has size n then
14         Return cur_map, True
15     for 0, ..., T-1 do
16         new_block = get_new_block()
17         Insert new_block to one of the previous
block's sockets
18         if new_block does not intersect with cur_map
19             then
20                 Push new_block to top of cur_map
21                 cur_map, flag= BIG(T, cur_map, n)
22                 if flag is True then
23                     Return cur_map, True
24                 else
25                     Pop the top element of cur_map
26         Return cur_map, False

28 # Randomly create a block
29 Function get_new_block()
30     Randomly choose a road block type and instantiate
31     a block new_block
32     Randomize new_block's parameter
33     Return new_block

is responsible for providing dense reward to encourage
agent to move forward. The speed reward $R_{speed} = v_t / v_{max}$
incites agent to drive fast. $v_t$ and $v_{max}$ denote the current
velocity and the maximum velocity (120 km/h), respectively.
To relieve agent from swaying the vehicle left and right,
we penalize it for large changes in the steering signal by
imposing a steering penalty $R_{steering} = |a_{t+1} - a_{t+1}| \cdot v_t / v_{max}$,
where $a_t$ is the normalized steering given by agent. We also
define a sparse terminal reward $R_{term}$, which is zero in the
whole episode except the last time step. At that step, we
will set $R_{disp} = R_{speed} = 0$ and assign $R_{term}$ according to
the terminal state. $R_{term}$ is set to +20 if the vehicle reaches
the destination, -10 for crashing others, and -5 for driving
out of the road. Finally, we use the weighted sum of these
reward functions as the final reward function as described in
Equation (1). We set $c_1 = c_4 = 1$ and $c_2 = c_3 = 0.1$. Sophisticated
reward engineering may provide a better reward function,
which we leave for future work.

IV. EXPERIMENTS

Equipped by the proposed PGDrive simulator, we conduct
experiments to first reveal the overfitting issue in the end-to-
end driving agent, and show the improvement of the general-
ization brought by the PG technique. We further investigate
the critical factors that affect generalization. We introduce
the performance metrics and the experimental settings as
follows:

1) Deterministic Scene: PGDrive can produce a determi-
nistic scene if the same random seed is given, which
allows us to split the generated maps into two sets: the
training set and test set, through using exclusive
random seeds.

2) Training Set: We use a set of seeds beyond index
200 to generate the maps. The number of training
environments is denoted as N.

3) Test Set: We use the seed 0 to 199 to generate 200
maps and fix them across all experiments. Each episode
will use one map.

4) Terminal States: An episode is terminated when four
possible states are reached for the target vehicle, (1)
Max Step: the episode exceeds the maximum time
steps; (2) Out of Road: the vehicle goes out of the road;
(3) Crash: the vehicle crashes with other vehicles and
(4) Success: the vehicle arrives the destination.

5) Success Rate: Defined as the proportion of episodes
that achieve Success. We will report the training suc-
cess rate as well as the test success rate separately.

The success rate is a more suitable performance measure-
ment when evaluating the generalization ability of the agent,
compared to the commonly used episodic reward. This is
because we have a large number of environments and each
of them has unique features such as the road length and
the traffic density, which are highly related to the reward
and may vary drastically across environments. Note that the
success rate is not the only criteria used to evaluate end-
to-end driving, there are other metrics such as the driving
speed, behavior smoothness, and energy consumption, which
will be explored in the future work. We fix the lane width
to 3.5m, the number of lanes to 3 and traffic density to 0.1
by default. All experiments are repeated five times and we
report the average results.

A. Results on Generalization

The overfitting happens if an agent achieves high perform-
ance in the training environments, but behaves poorly in
test environments that it has never encountered before. On
the other hand, a learned agent is considered to have good
generalization ability if it works well on unseen environments
and has small performance gap between training and test. We
conduct a series of experiments to evaluate the generaliza-
tion and investigate the improvement brought by procedural
generation.

We have 7 sets of training data, by varying the number
of included training environments (N) from 1 to 1000. The
test set remains fixed and the same for all trials. We train
an agent on each set separately and then evaluate on the test set. Fig. 4 and Fig. 5 show the progression of training and test performances over training steps, where each column indicates the performances on different training set.

We train the agents with two popular RL algorithms respectively, PPO [48] (the result is shown in Fig. 4) and SAC [49] (the result is shown in Fig. 5), based on the implementation in RLLib [50]. Results of generalization are observed on both of the trained agents: First, the overfitting happens if the agent is not trained with a sufficiently large training set. From the first column where the agent is trained in a single map, we can clearly see the significant performance gap between the training set and test set. Even though the agent quickly converges to a high training success rate, the test success rate remains low. Second, the generalization ability of agents can be greatly improved if being trained in more environments. As the training environment number N increases, the final test performance keep increasing. The overfitting is alleviated and the test performance can match the training performance when N is higher than 40. We also train agent with the reinforcement learning algorithm Soft Actor-critic (SAC) [49] which yields similar results. The experimental results clearly show that increasing the diversity of training environments can increase the generalization of RL agents significantly, which validates the strength of the procedural generation introduced in PGDrive.

Fig. 6. (a) Agents demonstrate overfitting to the traffic density, wherein the “Fixed” agent means the density is set to 0.1, while the “Uniform” agent varying the traffic density from 0 to 0.4 during training. (b) Agents trained with wheel friction coefficient 0.6 have better generalization compared to those with 1.0 friction coefficient.

B. Factors Relevant to Generalization

We further evaluate the factors that may affect the generalization.

Impact of Traffic Density. We train two agents on the training set of the same 100 maps but with different traffic density. The first agent is trained with traffic density 0.1, called the “Fixed” agent. The second agent, called the “Uniform agent”, is trained with the traffic density varying from 0 to 0.4 uniformly. Averagely, the Fixed agent will encounter 10 vehicles, while the Uniform agent may meet 0 to 40 vehicles in training. We then evaluate these two trained agents in 7 sets of test environments, which share
the same group of unseen maps but with different fixed traffic density from 0 to 0.6, respectively. Fig. 6 shows that the Uniform agent can maintain a relatively high performance compared to the Fixed agent which fails completely in dense traffic scenarios. Besides, even in the environment with high traffic density that unseen during the training, namely 0.5 and 0.6, the Uniform agent can still outperform the Fixed agent. Therefore, training agent in more diverse environments in terms of traffic conditions can alleviate the overfitting and improve the safety and reliability of end-to-end driving.

Impact of Friction Coefficient. Fig. 6(b) shows the impact of the friction coefficient between the vehicle’s wheels and ground, which is an important parameter for driving. We consider two agents where one is trained on the ground with fixed 1.0 friction coefficient, so the maneuverability of the vehicle is good and the other is with 0.6. The result shows that the agent trained on slippery terrain due to the low friction achieves better generalization and can drive on road surfaces with different friction coefficients better than the agent trained in the easy environment. Therefore, we can train more robust agents by configuring the parameters of the environment that are not allowed to tune in some other simulators in the PGDrive.

Impact of PG.

We further conduct an experiment to show that an agent specialized on solving all types of blocks separately can not solve a complex driving map composed of multiple block types. We compare two agents: 1) PG Agent trained in 100 environments where each environment has 3 blocks, and 2) Single-block Agent trained in 300 environments where each environment contains only 1 block. We evaluate them in the same test set of the environments with 3 blocks in each. Fig. 7 shows that both agents can solve their training tasks, but they show different test performance. Agent trained on maps generated by PG performs better than agents trained on separate blocks. The results indicate that training agents in separate scenarios can not lead to good performance in complex scenarios. The procedurally generated maps which contain multiple blocks types lead to better generalization of the end-to-end driving.

V. CONCLUSION

We introduce the PGDrive, an open-ended and highly customizable driving simulator with the feature of procedural generation. Multiple elementary road blocks with configurable settings are first defined and then assembled into diverse driving environments by the proposed Block Incremental Generation algorithm. The experimental results show that increasing the diversity of training environments can substantially improve the generalization of the end-to-end driving.

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