Goal-constrained Sparse Reinforcement Learning for End-to-End Driving

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Abstract—Deep reinforcement Learning for end-to-end driving is limited by the need of complex reward engineering. Sparse rewards can circumvent this challenge but suffers from long training time and leads to sub-optimal policy. In this work, we explore full-control driving with only goal-constrained sparse reward and propose a curriculum learning approach for end-to-end driving using only navigation view maps that benefit from small virtual-to-real domain gap. To address the complexity of multiple driving policies, we learn concurrent individual policies selected at inference by a navigation system. We demonstrate the ability of our proposal to generalize on unseen road layout, and to drive significantly longer than in the training.

I. INTRODUCTION

Deep reinforcement learning (RL) has successfully solved some of the most challenging tasks and off the charts performance in games like Atari [34], Go [50] and Dota 2 [3] has shown its potential to solve complex decision making problems even for long term gains. Considering these results, RL has been used to solve real life robotics applications like manipulation [12], [21] and autonomous driving [39], [5]. However, most of the approaches are domain dependent and cannot be generalized across tasks.

Traditionally rule-based approach addressing tasks like autonomous driving requires complex engineering [22] and greedy search based algorithms [35]. Learning to drive with reinforcement learning (RL) is an alternative since the optimal policy is optimized from reward. However, RL commonly employs reward shaping [37], [26], [54], [45] – an extensive manual tuning subsequently prone to human bias [18]. In real life, humans are often rewarded only when the task is complete. Sparse reward follows the same analogy and is domain independent, hence easily transferred to new tasks. However, lack of feedback signals makes sparse reward RL difficult to train [14], [59], and to the best of our knowledge no work yet address end-to-end driving with sparse reward. Only [44], [15] experiment longitudinal driving task in simulation, without any lateral action.

We instead address this lack and learn the full car control with a goal-constrained sparse reinforcement learning framework, shown in Fig. 1. Because driving forms a natural curriculum where difficulty scales with the traveled distance, we train our method in a curriculum learning fashion with simultaneous and control modules can be trained sequentially or concurrently. At inference, a navigation system handles the decision at intersections (e.g. which direction to go), subsequently switching to the ad-hoc policy. Instead of the often used front-view images [38], [19], [25] or multi-modal observation space [42], we train using only navigation view maps and learn a compact world model [13] from the latter. Both world model (VAE) and RL policy (Proximal Policy Algorithm [49]) are trained simultaneously. Considering that with sparse reward the RL policy is trained online where the latent space used is optimized after each episode, the task is very challenging. Hence, we experiment in a simulated environment without other road users, already significantly more complex than previous attempts [44], [15]. The main contribution of our work are:

- **RL driving with navigation maps only.** Instead of front-view images, we leverage navigation maps, having smaller domain gaps and better generalization capacity.
- **Policies from goal-constrained binary sparse reward.** Benefiting from curriculum learning and our revert strategy, we learn the full car control of individual driving policies with goal-constrained binary sparse reward.
- **Flexible perception and control learning.** Our perception and control modules can be trained sequentially or simultaneously, therefore balancing the benefit of policy training from pixels or from a compact world model.

II. RELATED WORKS

End-to-end driving with RL. As it requires a trial-and-error process, the common RL strategy involves training virtual agents with simple rewards, in a model-based RL fashion.

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Reward shaping is of the utmost importance since it provides a supervision signal for the network, and was subsequently extensively discussed in [36], [6], [29], [23]. Dense (i.e. frame-wise) reward are commonly applied, by penalizing velocity [23], [28] along with road-car angle [33], distance to center [19], [29], [55], [32], distance from destination [9], car collisions [9]. Some works also optimize comfort accounting for steering and throttle [5] and traffic rules [28].

The main limitation of dense reward is that it acts as an expert to imitate, limiting the discovery [30] and preventing human-like behavior – like taking a turn from inside [19].

We refer to the recent survey [52] for details.

On input representations, most RL methods learn directly control mapping from front-view cameras [29], [55], [19], [56] though [40] relates that this limits the transferability to real world. Rare works employ navigation maps and only for imitation learning [16], or robot navigation [4].

Different from the literature, we learn multiple individual policies for the end-to-end driving task from navigation maps only, thus benefiting from higher generalization capability.

Sparse reward RL. Relying on sparse reward is difficult to optimize, hence often applied in conjunction of other training strategies. For example, [57], [46] use auxiliary tasks to prevent suboptimal policy and encourage exploration. The latter can be employed as a meta reward learning strategy [1]. Intrinsic rewards are also used, in the form of sub-goals [7] and demonstrations [58]. Of interest, note that to ease the binary reward feedback, exploration is enforced which is mostly suitable in finite observation space. Instead, driving has an infinite observation space meaning to unwanted exploration further slowing the training. To leverage some exploration despite observation space, we employ goal-constrained curriculum learning which we now review.

Curriculum learning. Curriculum is traditionally employed [10], [47], [48] as a way to break down complex tasks into simple ones of increasing complexities [27], [53] – similarly to human learning [24]. It has been reintroduced for deep learning [2], leading to many extensions [60], [31], [11], [41]. Controlling the complexity of curriculum is the key element and sophisticated strategies are used like teacher guided [11], self play [51] or the use of GANs for goal generation [17], [43].

To the best of our knowledge, no work yet addressed driving from sparse reward, possibly relating to the complexity of sparse reward in long-horizon tasks [20] and structured environment like road layout. However, sparse reward main benefit is to let the network discover efficient driving strategy. We now present our method addressing end-to-end driving with RL from sparse binary reward in a curriculum fashion.

III. Method

Fig. 1 shows an overview of our reinforcement learning (RL) framework, where the agent interacts with Carla [9] virtual driving environment and predicts the continuous low level control of a car (steering, throttle, brake). There are important originalities of our proposal regarding the literature. Firstly, rather than front view images we rely on navigation views (i.e. top-view navigation maps) which prove smaller virtual-to-real gap. Secondly, to avoid the pitfall of model-based RL – where agents mimic the model, we only provide a sparse binary reward at the end of each episode: 1 if the goal is reached, 0 if not. This light supervision enables the discovery of unique driving features. Thirdly, we learn a compact world model enabling better policy learning, and train the whole pipeline in a curriculum fashion for separate policies (driving straight, turning left, turning right). For inference a simple navigation system apply policy switching.

The remaining of this section describes the architecture (Sec. III-A), our sparse reinforcement learning pipeline (Sec. III-B), and the training strategy (Sec. III-C).

A. Architecture

Our architecture is composed of two main modules: perception which provides a compact representation of the world, and control which predicts the full car control output.

The perception module takes as input a single navigation view map (256x256 RGB) output by Carla simulator. It is composed of a shallow Variational AutoEncoder (VAE) having 5 convs with increasing filters (32, 64, 128, 256, 256) as encoder, and 5 transpose convs (256, 128, 64, 32, 3) in the decoder. The latent space is a 256 dimension vector, hereafter referred as world model.

The control module takes as input the concatenation of the world model, with current speed and goal easily retrieved from Carla metadata, as illustrated in Fig. 1. It employs a shallow network consisting of 4 FC layers (512, 256, 128, 64 neurons) and a 2 neuron output layer with tanh activation to output steering and brake/throttle as scalars in [−1, +1]. The prediction is logically applied to the simulator before obtaining the next simulation step.

B. Sparse reinforcement learning

Instead of penalizing the agent with dense frame-wise reward, we define a goal to reach and only reward the agent (+1) if goal is reached before the episode termination. As such, our supervision signal is significantly weaker than existing dense reward end-to-end driving [52], but encourages self discovery. As other long-horizon tasks [20], learning driving is indubitably hard with a sparse reward. We employ thus curriculum learning strategy to break complexity, and use an on-policy Proximal Policy Optimization (PPO) as it is less sensitive to hyperparameters tuning while ensuring slow policy deviation during training. Given the changing goal distribution with curriculum, on-policy algorithm is more efficient than an off-policy, and recent work [62] demonstrated the benefit of PPOs for complex non-stationary environment. We now provide the reader with a brief background.

Proximal Policy Optimization (PPO). In short, considering a state $s_t$ and an action space $a_t$, PPO [49] optimizes network parameters $\theta$ using a surrogate objective $L(\cdot)$ with a stochastic gradient ascent to learn the best policy $\pi$, while
Goal constraints

The goal is being reached when the agent position is within a lateral radius $\rho$, as illustrated in Fig. 2b. We argue that similarly to [8], this prevents policy reversion upon failure. Importantly, we stop the training after 100m goal distance is reached.

In practice, we start the curriculum with a complexity of 1 (i.e. 1m goal) and increment/decrement it by 1 according to our curriculum. Upon goal completion the agent is rewarded ‘+1’ and the episode ends. If the goal is not reached before the episode terminates – without any reward. Importantly, we stop the training after 100m goal distance is reached.

C. Training strategy

Policy is trained as mentioned with a binary sparse reward if goal is completed before episode ends. The VAE module is trained in a standard self-supervised manner, with a binary cross entropy (BCE) reconstruction loss and a KL loss on the predicted distribution to enforce a normal in the encodings.

While training perception and policy sequentially is straightforward, we also investigate simultaneously training both. In the latter case, all frames observed during policy training are only stored in a buffer from which data is sampled to optimize the VAE.

Multiple policies. Because driving is complex to learn with a single policy, we instead consider driving as tasks ensemble and learn multiple unique policies, switched at inference. In details, we learn three independent polices for driving straight (SP), turning right (RP), turning left (LP). This not only helps simplifying the control module but also prevents integrating route information in the world model. At inference we use an external navigation system (e.g. global planning algorithm) to switch between these policies near intersections, as shown in Fig. 3.

IV. Experiments

We conduct our experiments at 10Hz on Carla [9] simulator, as it provides a range of high definition maps for virtual towns, and custom API calls to interact with the simulator. Navigation views maps are custom-built and rendered as 256x256 RGB images. Because these views have small domain gaps, we train only on three small sections of the track ‘Town01’ which encompass the scenarios of interest (straight and left/right turns). Evaluation is conducted on test tracks ‘Town01’ and ‘Town02’, in unseen areas, see Fig. 4a.

Considering the complexity of learning to drive from only maps input and sparse reward, our experiments are conducted in simulated environments having a single (ego) vehicle.

In the following, we first provide details on the experimental setup, and evaluate the performance when perception...
and policy are trained simultaneously which takes as little as 8 hours on a single GPU. Finally, we ablate our contributions and compare simultaneous and sequential training.

A. Experimental Setup

At each episode start, the agent are spawned with a random position on the road and orientation in \([-45^\circ, 45^\circ]\) w.r.t. the local road curvature. A buffer limit of 50000 is used and while the buffer is being filled, the perception and control modules optimizes the world model and policy, respectively. The V AE samples from the buffer and for every iteration optimizes the world model with a batch size of 100 and epochs equivalent to the number of samples batches.

The episode duration \(T\) (seconds) is a function of complexity, \(T = \min(\max(c_i, 10), 40)\). Short episodes for low complexity prevents exploration of unwanted states and early optimization of the policy. While clamping \(T\) for larger complexity helps in optimizing the speed it also prevents unwanted wiggling, thus attaining the best policy. As optimizer we use Adam with a learning rate of 1e-5, and step-wise decay with step size of 5000 and \(\gamma = 0.96\). The trajectories collected for each episode are trained for 15 epochs with a policy and value clip of 0.1. The discount factor used is 0.99.

B. Performance

We evaluate our method proposal in threefold, first briefly evaluating the perception module to ensure effectiveness of our world model, second evaluating the policy performance on train tracks, and third studying the generalization capacity of our world model and policies.

Policy. To evaluate policy, Fig. 6b shows the goal distances in meters – i.e. curriculum complexity – for all three policies trained in parallel. The turn left policy (LP) and turn right policy (RP) evolve concurrently with visible effect of our curriculum revert strategy since the goal partly decrease locally. Conversely, we denote that the straight policy (SP) requires significantly more episodes to optimize. We conjecture that it relates to the overcompensation problem of RL agents [19]. Ultimately, all policies converged in less than 600 episodes, with agents driving at an average speed of 10.5kmph. Since sparse reward does not enforce speed, the velocity in fact relates to the minimum acceptable speed to complete episodes being 9kmph (i.e. the episode duration \(T\) forces the agent to complete 100m in less than 40sec). We conjecture that decreasing the episode duration could further speed up the driving.

On driving style, Fig. 7 top shows 100 runs when driving either policy (left, straight, right) on training tracks, with markers color evolwing from high speed (red) to low speed (white). On train tracks, despite the absence of any dense reward, we denote the agents successfully learned to drive in the safe drivable area. Even more, the car naturally stays close to the track center although wiggling is visible as often mentioned in the literature [61], [19]. Finally, on Left/Right Policy we observe that the agents learned to turn from the inside by shifting on the right or left first. While this lead to driving rules infringement we highlight that such time-optimized driving is impossible with dense rewards that penalize distance from the lane center [19].

Generalization. Qualitative driving on unseen test tracks, Fig. 7 bottom, also demonstrates generalization of the learned policies and the world model. Despite the small domain gap of our navigation views, notice that test tracks include unseen road layout which both the world model and policy have
to cope with. This is visible on test tracks for example in straight policy (SP) and right policy (RP), Fig. 7 bottom.

To further study generalization, Tab. I reports the success rate for different goal distances on unseen test tracks (for 100 runs). From the latter, ours simultaneous completes 20m goal with 100% success rate, and 100m goal – the highest trained complexity – with 82% success rate. Of interest, we demonstrate that despite that agents only train with up to 100m goals, the policy scales to long driving goals like 200m (66%) and 300m (41%). Training perception and policy pipeline in a sequential manner (ours sequential), we denote few percent better success rates. However, this comes at the cost of more complex and twice longer training (~18 hours), which is why we prefer simultaneous training. In the supplementary video we show our agent – although only trained up to 100m – is able to generalize to unseen tracks and maneuvers much longer distance (~1.2kms).

### C. Ablation

We now discuss ablation of our contributions, and report quantitative performance in Tab. I and Fig. 8.

### TABLE I: Driving test tracks performance. Success rate of goal completion on unseen test tracks for different goal distances. The first two lines denote our pipeline with perception and policy either trained simultaneous or sequential, while bottom lines are ablations of our contributions. Even if training does not exceed 100m, policy is able to drive longer.

| Method                  | 20m | 50m | 100m | 200m | 300m |
|-------------------------|-----|-----|------|------|------|
| Ours - simultaneous     | 1.0 | 0.85| 0.82 | 0.66 | 0.41 |
| Ours - sequential       | 0.91| 0.90| 0.90 | 0.69 | 0.51 |
| w/o revert              | 0.51| 0.08| 0.02 | 0    | 0    |
| w/ curr. +2             | 0.99| 0.89| 0.91 | 0.54 | 0.07 |
| w/ fixed episode dur.   | 0.36| 0.04| 0    | 0    | 0    |
| w/o constraints         | 0.87| 0.44| 0.11 | 0    | 0    |

**Individual policies vs Multiple policies.** To study the effect of learning multiple task simultaneously, using sparse rewards, we compare in Fig. 8a the performance of our pipeline when training either individual policies (left, straight, right) separately or all together in a single policy. From the plot, it is clearly inefficient to learn all policies ('All') in comparison to individual policies (‘LP’, ‘SP’, ‘RP’). Specifically, when learning all policies grouped, it optimizes slowly and reaches a plateau (around 40m complexity), while our individual policies all reaches max goal complexity (100m).

**Goal constraints.** We evaluate the benefit of our goal constraints described in Sec. III-B. From Fig. 8b it is clear that without constraints (‘w/o C’, dotted) the policy still manages to achieve similar curriculum complexity, though speed graph shows that without constraints the agent tend to drive slower. Also, from Tab. I without constraints the success rate is in fact significantly slower, and is even unable to generalize for long distance goals (over 100m). In the sparse reward settings, these constraints are indeed useful when an agent needs to perform a sub task along with the main goal (like driving following the traffic rules). The addition of constraints prevents the agent from exploring different actions leading to sub-optimal performance. The agent without constraints tends to deviate a lot initially in the training phase even for lesser complexity goal but learns the optimal actions with time.

**Curriculum strategies.** We also evaluate the benefit of our curriculum strategy in Tab. I. Performance without our revert strategy (‘w/o revert’) demonstrate the significant benefit of our yet simple strategy, as it avoids remaining stuck in a local minimum. Increasing complexity twice faster (‘w/ curr +2’) show acceptable but worse performance.

### V. Conclusion

We propose the first sparse reward dependent reinforcement learning agent for end to end driving. Instead of front view images, we rely on navigation maps to learn individual policies in parallel and simultaneously train perception and world model. Our results demonstrate exciting generalization capacity and natural emergence of driving styles. We also believe RL driving with constrained sparse rewards open doors to new perspective such as the inclusion of driving rules – a major RL challenge especially when accounting for other road users.
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