PROJECT PROPOSAL: AUTONOMOUS DRIVING USING DEEP DETERMINISTIC POLICY GRADIENTS

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ABSTRACT

Investigation of the application of deep reinforcement learning to autonomous driving. It is interesting because autonomous car driving is one of the biggest technological pursuits of the decade. Methods combining reinforcement learning and deep learning have tremendous potential in this regard.

1 INTRODUCTION

In the proposed project, we would be exploring the use of a generic algorithm like Deep Deterministic Policy Gradients in teaching a car to autonomously follow lanes.

2 RELATED WORK

Despite early interest for end-to-end driving [Pomerleau (1989)], current autonomous driving projects still use the perception-planning-control paradigm [Montemerlo et al. (2008)]. The slow development of end-to-end driving can be attributed to the computational and algorithmic limitations imposed by the recent developments in deep learning. There has been a number of deep learning approaches to solve end-to-end control (aka behavioral reflex) for robots [Muller et al. (2006)] but still very few were applied to end-to-end driving.

The only work related to end-to-end driving was performed by [Jaritz et al. (2018)] and [Kendall et al. (2018)].

3 IMPLEMENTATION

Though there are existing results [Kendall et al. (2018)], there are no implementations available. Our first task would be to implement and evaluate the findings of the aforementioned paper, and then move on to implementing changes as suggested below.

1. Kendall et al. (2018) use a reward function that is proportional to the distance traveled before an infraction is encountered. We plan to explore its limitations. Also, we would like to explore different rewards by incorporating factors such as navigation goal set-point and safety criteria.

2. Another goal would be to improve the state-space representation from the observations. More specifically, we would like to employ the use of Recurrent Neural Networks to take into account the sequential nature of our observations.

4 DATA

For the first phase, we would be employing the use of a driving simulator - Carla [Dosovitskiy et al. (2017)]. We chose Carla because of the following reasons:

1. Maturity of the code base
2. Support for diverse weather conditions
3. Randomizing vehicle start position per episode, thereby giving us a new segment of road to traverse (Even though Kendall et. al. build their own driving simulator with procedural map generation, the simulator is not open-source.)

If time permits, we would like to generalize our findings on a 1/10-scale RC car.

5 FINAL GOALS & EVALUATION

As per Kendall et al. (2018), we would start by replicating the results from their paper. The paper evaluates the performance of an algorithm by considering the distance traveled by the agent with respect to the number of episodes. There are 2 sets of algorithms, 1 each for simulation and real-world. Our first priority would be to implement in simulation, and if time permits, to a 1/10th model RC car.

Algorithm *ddpg-vae* distills the state-space (observations) by using a convolutional neural network coupled with a variational auto-encoder to get a compressed version of the monocular images viewed by the vehicle.

Algorithm *ddpg* only uses a convolutional neural network.

Both the algorithms use the Deterministic Policy Gradient method, with Prioritised Experience Replay.

Qualitatively, we would provide plots detailing metres travelled versus episodes. ALso, we would be providing videos to showcase the progress made by our agent.

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