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Survey on Autonomous Vehicle Control Using Reinforcement Learning

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ABSTRACT

In this paper we study the demonstration of the application of deep reinforcement learning to autonomous driving. From randomly initialised parameters, the model is able to learn a policy for lane following in a handful of training episodes using a single monocular image as input. The paper provides a general and easy to obtain reward: the distance travelled by the vehicle without going of the lane. Model use a continuous, model free deep reinforcement learning algorithm, with all exploration and optimisation performed on-vehicle.This demonstrates a new framework for autonomous driving which moves away from reliance on pre determined logical rules, mapping, and direct supervision. The paper discusses the challenges and opportunities to scale this approach to a broader range of autonomous driving tasks.

Keywords : Reinforcement Learning, Deep Learning, Self-Driving Cars, Imitation Learning, Autonomous cars and Lane Detection.

I. INTRODUCTION

Now-a-days self driving cars are more and more popular for quick transportation, safety and economic advantages but these cars would only follow orders about destination and route, and may only adopt some lane-keeping or car-following guidance whereas in order to make autonomous driving a truly ubiquitous technology, paper advocates for robotic systems which address the ability to drive and navigate in absence of maps and explicit rules, relying-just like humans - on a comprehensive understanding of the immediate environment and the various objects in the environment, predict their possible future behaviors and interactions, and then plan how to control it in order to safely move closer to their desired destination while obeying the rules of the environment. This is a difficult robotics challenge that humans solve well, making reinforcement learning a promising approach. Reinforcement learning is one of the strongest paradigms in AI domain, which can be used to teach machines how to behave through environment interaction. The concept of deep reinforcement learning was introduced recently and was tested with success in games like Go or Atari 2600, proving the capability to learn and understand a good representation of the environment. Reinforcement Learning allows the agent to learn its behaviour based on feedback that is received from the environment. This behaviour can be learnt at the beginning once and for all, or keep on adapting as time goes by. If the problem is modelled with care, some Reinforcement Learning algorithms can perform remarkably well and converge to the global optimum; this is the ideal behaviour that maximises the reward. This automated learning scheme implies that there is no or little need for a human. The time spent designing a solution will be less, since there is no need for hand-crafting complex sets of rules as with *Expert Systems*, and all that is required is someone familiar with Reinforcement Learning. The motive of these paper is about getting insights reinforcement learning to the level where it has a shot at driving a real vehicle; although the same insights may apply to other domains as well.

II. LITERATURE SURVEY

Here we discuss the literature review of existing techniques:

Alex Kendall, Jeffrey Hawke, David Janz, Przemyslaw Mazur, Daniele Reda, John-Mark, Allen Vinh-Dieu Lam, Alex Bewley, Amar Shah [1], they demonstrate the first application of deep reinforcement learning to autonomous driving. It has been previously demonstrated that it is possible to drive a fully autonomous car on rural country roads, using GPS for coarse localisation and LIDAR to understand the local scene proposed system is developed in MATLAB which uses state and action sets. They suggest that the generality of reinforcement learning makes it a useful framework to apply to autonomous driving. Most importantly, it provides a corrective mechanism to improve learned autonomous driving behaviour. The main task they use to showcase the vehicle is that of lane-following however done on a real vehicle as well as on simulation, and done from image input, without knowledge of lane position. For both simulation and real-world experiments they use a small convolutional neural network. The model has four convolutional layers, with 3×3 kernels, stride of 2 and 16 feature dimensions, shared between the actor and critic models. The testing is done on the 3D simulator developed using Unreal Engine 4. The car understands the environment and quickly learn through interactions, The autonomous driving capabilities of the real car is quite remarkable.

Mayank Bansal, Alex Krizhevsky and Abhijit Ogale [2] they propose imitation learning technique that is robust enough to drive a real vehicle. They built their system based on leveraging the training data (30 million real-world expert driving examples, corresponding to about 60 days of continual driving) as effectively as possible. They use a perception system that processes raw sensor information and produces our input: a top-down representation of the environment and intended route, where objects such as vehicles are drawn as oriented 2D boxes along with a rendering of the road information and traffic light states. They present this mid-level input to a recurrent neural network (RNN), named ChauffeurNet, which then outputs a driving trajectory that is consumed by a controller which translates it to steering and acceleration. The further advantage of these mid-level representations is that the net can be trained on real or simulated data, and can be easily tested and validated in closed-loop simulations before running on a real car. The first finding of this paper is that even with 30 million examples, and even with mid-level input and output representations that remove the burden of perception and control, pure imitation learning is not sufficient. The key challenge is that we need to run the system closed loop, where errors accumulate and induce a shift from the training distribution. They find that this challenge is surmountable if they augment the imitation loss with losses that discourage bad behavior and encourage progress, and, importantly, augment our data with synthesized perturbations in the driving trajectory. These expose the model to nonexpert behavior such as collisions and off-road driving, and inform the added losses, teaching the model to avoid these behaviors. They evaluated their system, as well as the relative importance of both loss augmentation and data augmentation, first in simulation. they then show how their final model successfully drives a car in the real world and is able to negotiate situations involving other agents, turns, stop signs, and traffic lights. Finally, it is important to note that there are highly interactive situations such as merging which may require a significant degree of exploration within a reinforcement learning (RL) framework. This will demand simulating other (human) traffic participants, a rich area of ongoing research.

Nihal ALTUNTAS, Erkan IMAL, Nahit EMANET, Ceyda Nur OZTURK [3], they propose a system to solve mobile robot navigation by opting for the most popular two RL algorithms, Sarsa(λ) and Q(λ). The proposed system is developed in MATLAB which uses state and action sets. It is defined in a novel way, to increase performance as much as possible. The system can avoid obstacles and guide the mobile robot to a desired goal. The success rate in both simulated and real environments is remarkable. In addition to that, it is possible to observe the effects of the initial parameters used by the RL methods, e.g., on learning, and also to make comparisons between the performances of Sarsa(λ) and Q(λ) algorithms. While implementing this proposed system, they found out it was essential to define the state and action sets in order to perform successful learning, since continuous environments have infinite possible states and actions. Thus, discretizing the continuous space determines the performance of the implemented RL algorithms. Their proposed system defines a state set using dynamic variables so that after the system learns how to behave in an environment, it can be successful in different environments where the target and obstacles are located in different points. An additional decision criterion is how to describe the reward function, which is the response of the environment to the actions of the intelligent agent. Although their implemented system gives promising results, it can be enhanced to increase its learning speed and performance. For instance, Q-values in the algorithms used by these systems are represented in tabular form, which requires a large space in the memory and complex mathematical calculations. As a substitute for the tabular form, it is possible to integrate a supervised learning algorithm to represent Q-values in order to reduce memory requirements and provide faster convergence to optimal policy.

III. TAXONOMY CHART

Algorithms	Learning to drive in a day(2018)	Learning to Drive by Imitating the Best and Synthesizing the Worst (2018)	Reinforcement learning-based mobile robot navigation(2016)
Training Dataset	✗	✓	✗
Real World Driving	✓	✗	✗

Simulations	✓	✓	✓
MDP-Markov Decision Process	✓	✗	✓
Deep Deterministic Policy Gradients	✓	✗	✗
Sarsa(λ) and Q(λ) - learning	✗	✗	✓
Monte Carlo	✗	✗	✓

IV.CONCLUSION

We study various techniques such as MDP, Monte Carlo, Sarsa(λ) and Q(λ) learning. Some of these algorithms are robust enough to drive a real vehicle such as Wayve from the paper Learning to Drive in a Day[5]. Whereas some of these papers propose methods to drive a car in a virtual environment. Through this paper we understand to attain truly ubiquitous technology in self driving cars the need of reinforcement learning is significant. Also, this paper helps us to understand the advantages and challenges using various algorithms.

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