Simulated Autonomous Driving on Realistic Road Networks using Deep Reinforcement Learning

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Abstract. Using Deep Reinforcement Learning (DRL) can be a promising approach to handle tasks in the field of (simulated) autonomous driving, whereby recent publications only consider learning in unusual driving environments. This paper outlines a developed software, which instead can be used for evaluating DRL algorithms based on realistic road networks and therefore in more usual driving environments. Furthermore, we identify difficulties when DRL algorithms are applied to tasks, in which it is not only important to reach a goal, but also how this goal is reached. We conclude this paper by presenting the results of an application of a new DRL algorithm, which can partly solve these problems.

Keywords. Artificial Intelligence, Machine Learning, Deep Reinforcement Learning, Autonomous Driving, Realistic Road Networks

1. Introduction

In the field of autonomous driving, a vehicle can be well thought of as an autonomous agent, acting in a complex environment. Hence, the particular machine learning paradigm called Reinforcement Learning (RL), which can be broadly defined as the \textit{computational approach to learning from interaction with an environment}, could be a promising idea to make progress in this field [1]. Indeed, some authors recently showed on the basis of simulations, that especially the field of Deep Reinforcement Learning (DRL; the combination of Deep Learning and RL), can be a promising approach to create autonomous agents, which are capable of learning to drive in yet simplified environments [2,3,4].

All the authors of the mentioned studies above validated their used DRL algorithms in a racing car simulator called \textit{The Open Racing Car Simulator (TORCS)} [5], which does not provide a usual driving environment. Since this drawback is precipitated through the software itself, it does not vanish, even if the algorithms are becoming more sophisticated. To make further progress in the application of RL to autonomous driving, we therefore developed a simulation software which we call \textit{Driving School for Autonomous Agents (DSA\textsuperscript{2})} and used it together with a new DRL algorithm to let autonomous agents learn to smoothly accelerate and brake while driving on realistic road networks.
2. Driving School for Autonomous Agents (DSA²)

DSA² provides a more usual driving environment based on realistic road networks for evaluating DRL algorithms in the context of (simulated) autonomous driving. The software mainly consists of four modules which are depicted in Figure 1.

![Figure 1. DSA² modules](image)

In the course of development, we decided to use Open Street Maps (OSM) as the provider of the realistic road networks, such that corresponding OSM-XML files can be imported. After such an import, an adjustable number of vehicles can be spawned and is going to be placed onto the road network by the DSA² backend module. While the simulation runs, this module continuously let the vehicles sense their driving environment as well as maintain and move them (according to their velocity and control) along their paths, which were defined using the street network. The current velocity of a vehicle is determined based on a physical model, where the learning module of the software (the DRL algorithm) controls the throttle and brake based on the vehicles’ current state. Furthermore, the learning module is also receiving rewards for its decisions from the backend module, which allows the complete system learn to fulfill a task, e.g., the task of smoothly driving the vehicles along their paths.

In the current version of DSA², the physical model is focusing on the longitudinal dynamics; this already poses significant challenges for driving safe, smooth and according to a varying setpoint. In the next step, we plan to generalize the software to also include the possibility of steering. Furthermore, DSA² is developed to evaluate DRL algorithms of a special kind, i.e., algorithms which are based on the actor-critic architecture, which usually can handle continuous state and action spaces.
3. Deep Reinforcement Learning

In the standard RL framework \[1\], an agent interacts with an environment \( E \) in discrete time steps and at each time step \( t \), the agent receives the representation of the environment's state \( s_t \) (further: state). Based on \( s_t \), the agent can choose from a set of possible actions in that state and which particular action is chosen, is controlled by the policy \( \pi \) of the agent. Now, let \( c_t \) be the action, which the agent has actually taken in \( s_t \). Then, she will receive in time step \( t + 1 \) a numerical reward \( r_{t+1} \in \mathbb{R} \) as a consequence of her decision about \( c_t \) in \( s_t \) and is transitioned into a new state \( s_{t+1} \).

Now, let \((r_t, r_{t+1}, ..., r_T)\) be a particular reward sequence from time step \( t \) to time step \( T \) and we assume that in the case of an episodic task, \( T = \infty \) holds \[1\]. The return \( R_t \) is then defined as a function over this reward sequence, i.e., \( R_t := f(r_t, r_{t+1}, ..., r_T) \) and the formal goal of many RL algorithms is to find a \( \pi^* \) defined as \[1\] \[\pi^* := \arg \max_\pi \mathbb{E}_{s_i \geq 0, r_j \geq 1 \sim \delta, c_k \geq 0 \sim \pi}(R_1), \] where we have adapted the notation of \[6\] and \( \delta \) is the environment function. To find an optimal policy \( \pi^* \), many of these algorithms try to approximate an action-value function \( Q_\pi(s_t, c_t) \), which represents the value of taking action \( c_t \) in \( s_t \) and following thereafter policy \( \pi \) as well as try to simultaneously adjusting the policy towards \( \pi^* \) \[1\].

However, the standard RL framework implicitly assumes that the state and action space are both finite, which can be – focusing on real world applications – difficult to fulfill \[1\]. Therefore, some of the RL algorithms instead assume both spaces to be continuous and represent \( \pi \) as well as \( Q_\pi(s_t, c_t) \) by function approximators, which together usually leads to an architecture called actor-critic, where the policy \( \pi \) is the actor (chooses actions based on states) and where the action-value function \( Q_\pi(s_t, c_t) \) is the critic (represents values of taking particular actions in states under \( \pi \)) \[1\]. One popular algorithm based on this setting is known as the Deep Deterministic Policy Gradient (DDPG) algorithm, which uses two neural networks as the function approximators, justifying the association with Deep Reinforcement Learning \[6\].

4. Application

In the course of using DRL in the context of (simulated) autonomous driving, we started by using DSA\(^2\) together with the DDPG algorithm to solve the task of smoothly driving a vehicle along its path. Beside the fact that this algorithm exhibits a fair stability and was already successfully applied to real world tasks (e.g. \[3\]), we found that it is very difficult (if not impossible) to solve our task with it \[6\]. We identified the algorithms’ way of using reward signals as one of the most important factors, why it showed these difficulties. This is because, to let an agent learn to simultaneously care about desired (e.g. driving) and undesired behavior (e.g. abrupt accelerations), there usually has to be at least one additional cost term in her reward function, which will shrink her reward if she decides on undesired behavior. However, the problem with this procedure is that it is often not clear, how severe the cost term compared to the usual reward term should be, such that the agent is willing to execute the desired, but is also willing to avoid the undesired behavior. This is so, because the critic (which is used to optimize the actor)
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represents (approximative) returns over the long-run and it is nearly impossible to unfold the complex entangled character of actions and returns.

We therefore developed a new DRL algorithm for which we refer to as the Deep Deterministic Policy Gradient with a Modular Reward-Cost Memory (DDPG-MRCM) algorithm. This algorithm and respective its underlying architecture mainly extends the DDPG algorithm by the possibility to specify consequences to the agent and let her sense these. With this architecture, the agent can learn which actions have which consequences in which states and how long-lasting each consequence is, such that she can learn to meaningful react in the space of possibly contradictory behavioral goals to ultimately find an optimal policy, which may fulfill the task.

![Figure 2. DSA² statistics about a vehicle](image)

An application of this algorithm showed that the stated task was sufficiently solved after about 430,000 simulation steps (about 4h on a Core i5 without GPU acceleration). Figure 2 provides a snapshot of the corresponding statistics and it can be seen that the vehicle under consideration used its throttle and brake very smoothly (first row; ranging from -1 to 1), to adapt its velocity (second row) to new setpoints, which were given by the maximum speed allowed on its current street.

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