Traffic Light Control Using Deep Reinforcement Learning Agent

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Abstract and Figures

Recent advances in combination deep neural network architectures and reinforcement learning techniques have shown promising potential results in solving complex control problems with high dimensional state and action spaces. Inspired by these successes, in this study, we build a deep reinforcement learning agent which can predict the best possible traffic signal in each state of an isolated intersection. At each time step, our adaptive traffic light control agent receives a snapshot of the current state of a graphical traffic simulator and maps its observation directly to control signals. Our method shows promising results in a traffic network simulated in the SUMO traffic simulator, without suffering from instability issues during training process.

Deep reinforcement… | Average Cumulative delay | Average queue length

Traffic Light Control Using Deep Reinforcement Learning Agent

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Abstract

Recent advances in combination deep neural network architectures and reinforcement learning techniques have shown promising potential results in solving complex control problems with high dimensional state and action spaces. Inspired by these successes, in this study, we build a deep reinforcement learning agent which can predict the best possible traffic signal in each state of an isolated intersection. At each time step, our adaptive traffic light control agent receives a snapshot of the current state of a graphical traffic simulator and maps its observation directly to control signals. Our method shows promising results in a traffic network simulated in the SUMO traffic simulator, without suffering from instability issues during training process.

1. Introduction

With regard to fast growing population around the world, the urban population in the 21st century is expected to increase dramatically. Hence, having a set of facilities that can be responsible to provide efficiently services to growing demand of an urban environment is inevitable. Obviously, one of those possibilities that must be taken into account by modern cities is devolving smart traffic management systems. The main goal of a traffic management system is reducing traffic congestion which nowadays is one of the major issues of megacities. Efficiently urban traffic management results in saving money, time as well as most importantly, reduction CO2 emission into atmosphere. To address this issue, a lot of solutions have been proposed [1].

They can be classified, roughly, into three types. The first is pre-timed signal control, where a fixed time is determined for all green phases according to historical traffic demand. The second is vehicle-actuated signal control where, they use information of traffic demand provided by inductive loop detectors on an equipped intersection to decide to control the signals. The third is adaptive signal control, where the signal timing control is managed and updated automatically according to the current state of the intersection [2]. In this study, we are interested in the third approach and aim to propose a novel method for traffic signal control by leveraging recent advances in machine learning and artificial intelligence fields.

Reinforcement Learning as a machine learning perfect knowledge of the environment in adva example traffic flow. A reinforcement learnin learns based on trial and error. It receives a reward after taking each action in the environme obtained reward is based on how well the taken is and the agent's goal is to learn an optimal policy so as to discounted cumulative rev maximized via a repeated interaction w environment.

In recent years, some deep learning tec including supervised and unsupervised architectures have started to incorporate reinfo learning methods, as function approximato feature learners. The evaluation of the resulti algorithms and methods has shown that deep l techniques can also be used to learn representations for reinforcement learning p [4,7]. Inspired by the successes of co reinforcement learning with deep learning paradi with regard to the complex nature of environ traffic signal control problem, in this paper we use the effectiveness and power of deep reinfo learning to build an adaptive signal control me order to optimize the traffic flow.

2. Deep Q-learning

One of the main advantages of deep neural ne is the capability of automating feature extractio row input data. A deep Q-learning Network [4,8,9] uses this benefit of deep learning in represent the agent's observation as an representation in learning an optimal control The DQN method aggregates a deep neural function approximator with Q-learning to learn value function and as a result a policy π, the b of the agent which tells the agent what action sh selected for each input state. Applying no function approximators such as neural networ model-free reinforcement learning algorithms i dimensional continuous state and action spac some convergence problems. Usually, policy methods are used, because of their better conv properties [5].

3. System Description

State Representation we represent the state system as an image $s_t \in R^d$ or a snapshot of the state of a graphical simulator (e.g. SUMO-G camera on an intersection which enables it to view the whole intersection.

Fig. 1: Deep reinforcement learning agent of traffic signal control.

Action Set to control traffic signal phases, we define a set of possible actions A = {North/South Green (NSG), East/West Green (EWG)}. NSG allows vehicles to pass from North to South and vice versa, and also indicates the vehicles on East/West route should stop and not proceed through the intersection.

Reward Function typically an immediate reward $r_t \in R$ is a scalar value which the agent receives after taking the chosen action in the environment at each time step. We set the reward as the difference between the total cumulative delays of two consecutive actions [10].

4. Experimental Results

To evaluate the performance of the proposed method, we compared it against a baseline traffic controller, a controller that gives an equal fixed time to each phase of the intersection. We ran SUMO-GUI simulator for the suggested model and compared the average total cumulative delay and average queue length achieved to the baseline. Figures 2 and 3 illustrate the performance comparison of the leaning agent regarding average cumulative delay time and average queue length metrics, respectively, to the baseline, while the agent is following the learning policy over time.

Fig. 3: Average queue length

5. Conclusion

In this research, we applied a deep reinfor learning algorithm to traffic signal control pro order to find optimal control policies of signali by using raw visual input data of the traffic si snapshots. Our approach has led to promising and showed it can find more stable control compared to previous work of using deep reinfor learning in traffic light optimization. In our w developed and tested the proposed method in application, extending the work for more c traffic simulations, for instance considering intersections and multiple agents to contro intersection, using multi-agent learning techni handle coordination problem between agents w a direction for future research.

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April 2017 · IET Intelligent Transport Systems

Sajad Mousavi · Michael Schukat · Peter Corcoran · Enda Howley

Recent advances in combining deep neural network architectures with reinforcement learning techniques have shown promising potential results in solving complex control problems with high dimensional state and action spaces. Inspired by these successes, in this paper, we build two kinds of reinforcement learning algorithms: deep policy-gradient and value-function based agents which can predict the ... [Show full abstract]

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May 2017

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In order to accelerate the learning process in high dimensional reinforcement learning problems, TD methods such as Q-learning and Sarsa are usually combined with eligibility traces. The recently introduced DQN (Deep Q-Network) algorithm, which is a combination of Q-learning with a deep neural network, has achieved good performance on several games in the Atari 2600 domain. However, the DQN ... [Show full abstract]

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