Literature Review on Reinforcement Learning in Traffic Signal Control

Bachelor‘s Thesis of Viktor Zajic

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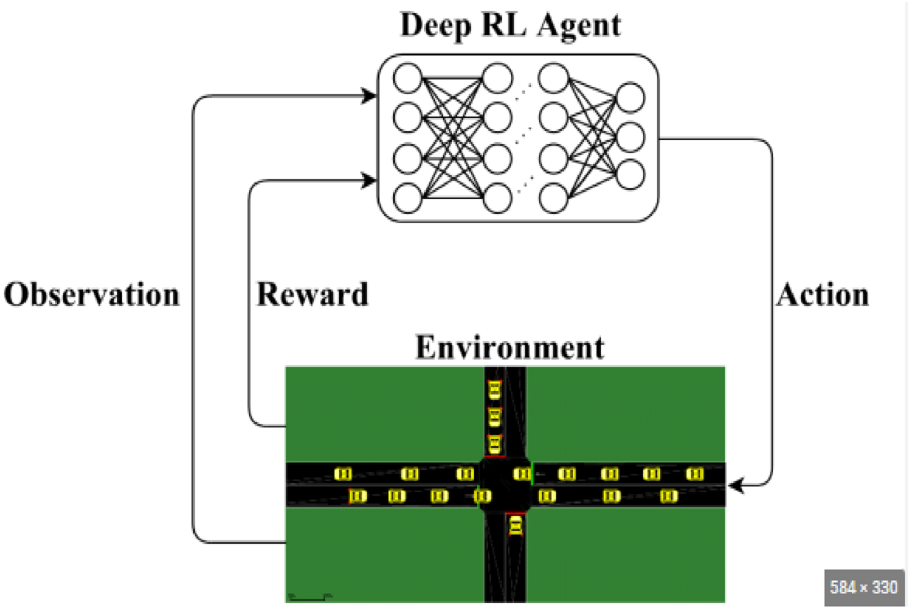

Figure 1: Reinforcement Learning in Traffic Signal Control, Mousavi et al., 2017. (Source: doi.org, 2017, retrieved from https://doi.org/10.1049/iet-its.2017.0153)

Reinforcement learning (RL) is a type of machine learning, that involves an agent who makes sequential decisions and learns from the consequences of those decisions to shape future decisions. The agent operates in an environment, and receives a subset of information from this environment, known as the state. Using this state as input, the agent takes an action, that affects the environment and receives a reward signal based on that action. The agent then observes a new state, takes a new action, and receives a new reward. This process is repeated until the agent learns the best action to take to maximize the reward. Reinforcement Learning techniques are not able to handle the large and continuous state spaces, represented in the traffic signal control (TSC) problem, alone. Because of that, they are combined with Deep Learning techniques (DL) that incorporate neural networks into the algorithm, making use of their advances to abstract the high-level representations of raw input data.

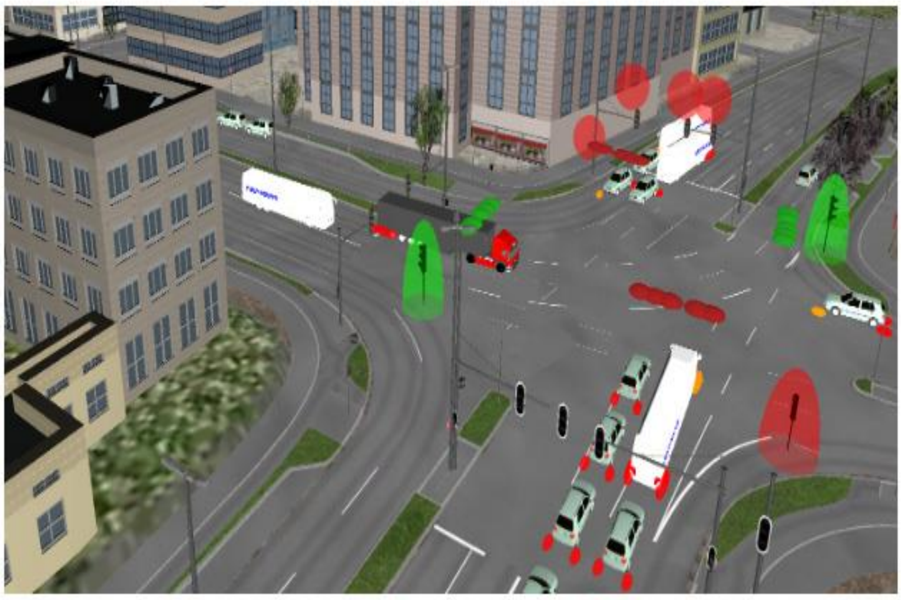

Figure 3: SUMO Traffic Simulation, 2020. (Source: eclipse.org, 2019, retrieved from https://www.eclipse.org/community/eclipse_newsletter/2019/december/3.php)

As urban and rural populations continue to grow exponentially, transportation systems in cities are struggling to efficiently handle the increasing number of vehicles on the road. The limited availability of space and resources poses significant challenges in enhancing existing infrastructure to accommodate the expanding urban population. Consequently, congestion becomes a pressing issue, leading to various problems such as heightened pollution resulting from vehicles idling in traffic jams, frequent traffic delays, and an increase in accidents. These challenges not only impact the environment and public safety but also result in economic losses and an overall decrease in the quality of life for residents. Therefore, the urgent need arises to improve traffic-flow and optimize traffic signal control within the constraints of the current infrastructure.

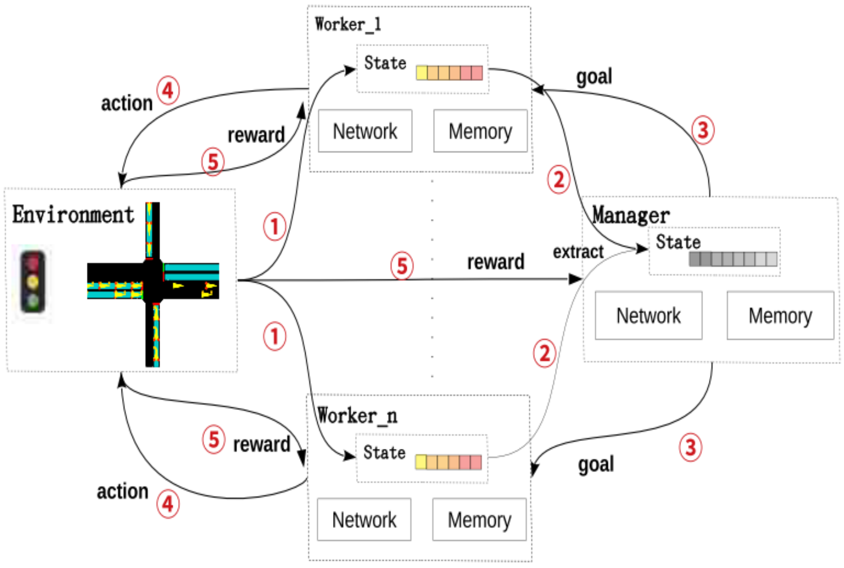

Figure 2: Framework of a hierarchical RL approach for a multi-agent scenario, 2020. (Source: ifaamas.org, 2020, retrieved from https://ifaamas.org/Proceedings/aamas2020/pdfs/p816.pdf)

To avoid the high costs and labor associated with deploying and testing traffic signal control strategies in the real world, simulations can serve as a useful alternative before actual implementation. In these microscopic simulations, traffic signal control strategies are tested on large, heterogeneous scenarios and vehicle-level information, that provide a detailed representation of traffic flow by modeling the behavior of each individual vehicle and its interaction with the environment. However, discrepancies between simulation and reality limit the application of learned policies in real-world scenarios. It seems, that there is insufficient collaboration between transportation engineers and researchers who are exploring the utilization of RL in TSC. This creates a significant gap between simulation and the real world. Although RL presents a hopeful strategy for TSC, allowing controllers to learn and adjust to varying traffic patterns in real time, a realistic real-world deployment is necessary to validate the effectiveness and practicality of deep RL-based automated traffic signal control.