Deep Deterministic Policy Gradient
for Urban Traffic Light Control

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Abstract

Traffic light timing optimization is still an active line of research despite the wealth of scientific literature on the topic, and the problem remains unsolved for any non-toy scenario. One of the key issues with traffic light optimization is the large scale of the input information that is available for the controlling agent, namely all the traffic data that is continually sampled by the traffic detectors that cover the urban network. This issue has in the past forced researchers to focus on agents that work on localized parts of the traffic network, typically on individual intersections, and to coordinate every individual agent in a multi-agent setup. In order to overcome the large scale of the available state information, we propose to rely on the ability of deep learning approaches to handle large input spaces, in the form of Deep Deterministic Policy Gradient (DDPG) algorithm. We performed several experiments with a range of models, from the very simple one (one intersection) to the more complex one (a big city section).

Keywords: deep learning, reinforcement learning, traffic light control, policy gradient

1. Introduction

Cities are characterized by the evolution of their transit dynamics. Originally meant solely for pedestrians, urban streets soon shared usage with carriages and then with cars. Traffic organization became soon an issue that led to the introduction of signaling, traffic lights and transit planning.
Nowadays, traffic lights either have fixed programs or are actuated. Fixed programs (also referred to as *pretimed control*) are those where the timings of the traffic lights are fixed, that is, the sequences of red, yellow and green phases have fixed duration. Actuated traffic lights change their phase to green or red depending on traffic detectors that are located near the intersection; this way, actuated traffic light are dynamic and adapt to the traffic conditions to some degree; however, they only take into account the conditions local to the intersection. This also leads to dis-coordination with the traffic light cycles of other nearby intersections and hence are not used in dense urban areas. Neither pretimed or actuated traffic lights take into account the current traffic flow conditions at the city level. Nevertheless, cities have large vehicle detector infrastructures that feed traffic volume forecasting tools used to predict congestion situations. Such information is normally only used to apply classic traffic management actions like sending police officers to divert part of the traffic.

This way, traffic light timings could be improved by means of machine learning algorithms that take advantage of the knowledge about traffic conditions by optimizing the flow of vehicles. This has been the subject of several lines of research in the past. For instance, Wiering proposed different variants of reinforcement learning to be applied to traffic light control (Wiering et al., 2004), and created the *Green Light District* (GLD) simulator to demonstrate them, which was further used in other works like (Prashanth and Bhatnagar, 2011). Several authors explored the feasibility of applying fuzzy logic, like (Favilla et al., 1993) and (Chiu and Chand, 1993). Multi-agent systems where also applied to this problem, like (Cai and Yang, 2007) and (Shen et al., 2011).

Most of the aforementioned approaches simplify the scenario to a single intersection or a reduced group of them. Other authors propose multi-agent systems where each agent controls a single intersection and where agents may communicate with each other to share information to improve coordination (e.g. in a *connected vehicle* setup (Feng et al., 2015)) or may receive a piece of shared information to be aware of the crossed effects on other agents’ performance ((El-Tantawy et al., 2013)). However, none of the aforementioned approaches fully profited from the availability of *all* the vehicle flow information, that is, the decisions taken by those agents were in all cases partially informed. The main justification for the lack of *holistic* traffic light control
algorithms is the poor scalability of most algorithms. In a big city there can be thousands of vehicle detectors and tenths of hundreds of traffic lights. Those numbers amount for huge space and action spaces, which are difficult to handle by classical approaches.

This way, the problem addressed in this works is the devisal of an agent that receives traffic data and, based on these, controls the traffic lights in order to improve the flow of traffic, doing it at a large scale.

2. Traffic Simulation

In order to evaluate the performance of our work, we make use of a traffic simulation. The base of a traffic simulation is the network, that is, the representation of roads and intersections where the vehicles are to move. Connected to some roads, there are centroids, that act as sources/sinks of vehicles. The amount of vehicles generated/absorbed by centroids is expressed in a traffic demand matrix, or origin-destination (OD) matrix, which contains one cell per each pair of origin and destination centroids. During a simulation, different OD matrices can be applied to different periods of time in order to mimic the dynamics of the real traffic through time. In the roads of the network, there can be traffic detectors, that mimic induction loops beneath the ground that are able to measure traffic data as vehicles go pass through them. Typical measurements that can be taken with traffic detectors include vehicle counts, average speed and percentage of occupancy. There can also be traffic lights. In many cases they are used to regulate the traffic at intersections. In those cases, all the traffic lights in an intersection are coordinated so that when one is red, another one is green, and vice versa (this way, the use of the intersection is regulated so that vehicles don’t block the intersection due to their intention to reach an exit of the intersection that is currently in use). All the traffic lights in the intersection change their state at the same time. This intersection-level configuration of the traffic lights is called a phase, and it is completely defined by the states of each traffic light in the intersection plus its duration. The different phases in an intersection form its control plan. The phases in the control plan are applied cyclically, so the phases are repeated after the cycle duration elapses. Normally, control plans of adjacent intersections are synchronized to maximize the flow of traffic avoiding unnecessary stops.
Urban traffic simulation software can keep models at different levels of abstraction. Microscopic simulators simulate vehicles individually computing their positions at every few milliseconds and the the dynamics of the vehicles are governed by a simplified model that drives the behaviour of the driver under different conditions, while macroscopic simulators work in an aggregated way, managing traffic like in a flow network in fluid dynamics. There are different variations between microscopic and macroscopic models, broadly referred to as mesoscopic simulators. To our interests, the proper simulation level would be microscopic, because we need information of individual vehicles and their responses to changes in the traffic lights, mimicking closely real world dynamics in terms of congestion. As third party simulator we chose Aimsun (Casas et al., 2010; Aimsun, 2012), a commercial microscopic, mesoscopic and macroscopic simulator widely used, both in the private consulting sector and in traffic organization institutions.

3. Preliminary Analysis

The main factor that has prevented further advance in the traffic light timing control problem is the large scale of any realistic experiment. On the other hand, there is a family of machine learning algorithms whose very strength is their ability of handle large input spaces, namely deep learning. Recently, deep learning has been successfully applied to reinforcement learning, gaining much attention due to the effectiveness of Deep Q-Networks (DQN) at playing Atari games using as input the raw pixels of the game (Mnih et al., 2013, 2015). Subsequent successes of a similar approach called Deep Deterministic Policy Gradient (DDPG) were achieved in (Lillicrap et al., 2015), which will be used in our work as reference articles, given the similarity of the nature of the problems addressed there, namely large continuous state and action spaces. This way, the theme of this work is the application of Deep Reinforcement Learning to the traffic light optimization problem with an holistic approach, by leveraging deep learning to cope with the large state and action spaces. Specifically, the hypothesis that drives this work is that Deep reinforcement learning can be successfully applied to urban traffic light control, having similar or better performance than other approaches.

This is hence the main contribution of the present work, along with the different techniques applied to make this application possible and effective.
Taking into account the nature of the problem and the abundant literature on the subject, we know that some of the challenges of devising a traffic light timing control algorithm that acts at a large scale are:

- Define a sensible **state space**. This includes finding a suitable representation of the traffic information. Deep learning is normally used with input signals over which convolution is easily computable, like images (i.e. pixel matrices) or sounds (i.e. 1-D signals). Traffic information may not be easily represented as a matrix, but as a labelled graph. This is addressed in section 6.4.

- Define a proper **action space** that our agent is able to perform. The naive approach would be to let the controller simply control the traffic light timing directly (i.e. setting the color of each traffic light individually at each simulation step). This, however, may lead to breaking the normal routing rules, as the traffic lights in an intersection have to be synchronized so that the different intersection exit routes do not interfere with each other. Therefore a careful definition of the agent’s actions is needed. This is addressed in section 6.5.

- Study and ensure the **convergence** of the approach: despite the successes of Deep Q-Networks and DDPG, granted by their numerous contributions to the stability of reinforcement learning with value function approximation, convergence of such approaches is not guaranteed. Stability of the training is studied and measures for palliating divergence are put in place. This is addressed in section 6.9.

- Create a sensible **test bed**: a proper test bed should simulate relatively realistically the traffic of a big city, including a realistic design of the city itself. This is addressed in section 7.

4. Related Work

In this section we identify and explore other lines of research that also try to solve the traffic light control problem.

4.1. Offline Approaches

The most simple traffic light control approaches are those that define **fixed** timings for the different traffic light phases. These timings are normally
defined offline (i.e. not in closed loop). Several different approaches have been proposed in the literature for deriving the phase timings, which can be grouped into the following categories:

- **Model-based**: a mathematical model of the target urban area is prepared and then used to derive an optimal timing, either via derivative calculus, numerical optimization, integer linear programming, or any other method. An example of this approach is MAXBAND (Little, 1966), which defines a model for arterials and optimizes it for maximum bandwidth by means of linear programming. Another example is the TRANSYT system (Robertson, 1969), which uses an iterative process to minimize the average journey time in a network of intersections.

- **Simulation-based**: this case is analogous to the model-based, but the core of the validation of the timings is a traffic simulation engine, which is connected to a black box optimization computation that iteratively searches the traffic light timing space to find an optimal control plan. Some examples of this approach are (Rouphail et al., 2000), which make use of genetic algorithms together with the CORSIM simulator (Holm et al., 2007), or (Garcia-Nieto et al., 2013), which uses particle swarm optimization with the SUMO simulator (Krajzewicz et al., 2012).

The usual way of maximizing the success of this kind of methods is to analyze historical traffic data and identify time slots with different traffic volume characteristics; once defined, a different timing strategy is derived for each of these *time bands*. However, not even this partitioning scheme adapts to the dynamism of traffic demand or progressive changes in drivers’ behaviour.

### 4.2. Model-based Adaptive Approaches

The simplest of these approaches only one intersection into consideration. They define a model (e.g. based on queue theory) that is fed with real detector data (normally from the closest detectors to the intersection). Then, by using algorithmic logic based on thresholds and rules, like (Lin, 1989), or optimization techniques like (Shao, 2009), they try to minimize waiting times.

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1 The categorization focuses on both the adaptative nature (or lack thereof) of the approach and the type of algorithms used and their similarity to the approach proposed in this work.
More complex approaches are based on traffic network models of several intersections that are fed with the real time data from multiple traffic detectors. Some of these approaches are heuristically defined algorithms that tune their parameters by performing tests with variations on the aforementioned models. For example, the SCOOT system (Hunt et al., 1982) performs small reconfigurations (e.g. individual intersection cycle offsets or cycle splits) on a traffic network model. More recent approaches like (Tubaishat et al., 2007) make use of the information collected by Wireless Sensor Networks (WSN) to pursue the same goal. There are also approaches where more formal optimization methods are employed on the traffic network models fed with read time data, like the case of (Gartner, 1983), (Henry et al., 1983), (Boillot, 1992) or (Sen and Head, 1997), which compute in real time the switch times of the traffic lights within the next following minutes by solving dynamic optimization problems on realistic models fed with data from real traffic detectors.

4.3. Classic Reinforcement Learning

Reinforcement Learning has been applied in the past to urban traffic light control. Most of the instances from the literature consist of a classical algorithm like Q-Learning, SARSA or TD(λ) to control the timing of a single intersection. Rewards are typically based on the reduction of the travel time of the vehicles or the queue lengths at the traffic lights. (El-Tantawy et al., 2014) offers a thorough review of the different approaches followed by a subset of articles from the literature that apply reinforcement learning to traffic light timing control. As shown there, many studies use as state space information such as the length of the queues and the travel time delay; such type of measures are rarely available in a real-world setup and can therefore only be obtained in a simulated environment. Most of the approaches use discrete actions (or alternatively, discretize the continuous actions by means of tile coding, and use either ε-greedy selection (choose the action with highest Q value with $1 - \varepsilon$ probability, or random action otherwise) or softmax selection (turn Q values into probabilities by means of the softmax function and then choose stochastically accordingly). In most of the applications of reinforcement learning to traffic control, the validation scenario consists of a single intersection, like in (Thorpe, 1997). This is due to the scalability problems of classical RL tabular approaches: as the number of controlled intersections increases, so grows the state space, making the learning unfeasible due to the impossibility for the agent to apply every action under every pos-
sible state. This led some researchers to study multi-agent approaches, with varying degrees of complexity: some approaches like that from (Arel et al., 2010) train each agent separately, without notion that more agents even exist, despite the coordination problems that this approach poses. Others like (Wiering et al., 2000) train each agent separately, but only the intersection with maximum reward executes the action. More elaborated approaches, like in (Camponogara and Kraus Jr, 2003), train several agents together modeling their interaction as a competitive stochastic game. Alternatively, some lines of research like (Kuyer et al., 2008) and (Bakker et al., 2010) study cooperative interaction of agents by means of coordination mechanisms, like coordination graphs ((Guestrin et al., 2002)).

As described throughout this section, there are several examples in the literature of the application of classical reinforcement learning to traffic light control. Many of them focus on a single intersection. Others apply multi-agent reinforcement learning techniques to address the problems derived from the high dimensionality of state and action spaces. Two characteristics of most of the explored approaches are that the information used to elaborate the state space is hardly available in a real-world environment and that there are no realistic testing environments used.

4.4. Deep Reinforcement Learning

There are some recent works that, like ours, study the applicability of deep reinforcement learning to traffic light control:

Li et al. studied in (Li et al., 2016) the application of deep learning to traffic light timing in a single intersection. Their testing setup consists of a single cross-shape intersection with two lanes per direction, where no turns are allowed at all (i.e. all traffic either flows North-South (and South-North) or East-West (and West-East), hence the traffic light set only has two phases. This scenario is therefore simpler than our simple network A presented in 7.2. For the traffic simulation, they use the proprietary software PARAllel MIcroscopic Simulation (Paramics) (Cameron and Duncan, 1996), which implements the model by Fritzsche (Fritzsche, 1994). Their approach consists of a Deep Q-Network ((Mnih et al., 2013, 2015)) comprised of a heap of stacked auto-encoders (Bengio et al., 2007; Vincent et al., 2010), with sigmoid activation functions where the input is the state of the network and the output is the Q function value for each action. The inputs to the deep Q
network are the queue lengths of each lane at time $t$ (measured in meters), totalling 8 inputs. The actions generated by the network are 2: remain in the current phase or switch to the other one. The reward is the absolute value of the difference between the maximum North-Source flow and the maximum East-West flow. The stacked autoencoders are pre-trained (i.e. trained using the state of the traffic as both input and output) layer-wise so that an internal representation of the traffic state is learned, which should improve the stability of the learning in further fine tuning to obtain the Q function as output ((Erhan et al., 2010)). The authors use an experience-replay memory to improve learning convergence. In order to balance exploration and exploitation, the authors use an $\epsilon$-greedy policy, choosing a random action with a small probability $p$. For evaluating the performance of the algorithm, the authors compare it with normal Q-learning ((Sutton and Barto, 1998)). For each algorithm, they show the queue lengths over time and perform a linear regression plot on the queue lengths for each direction (in order to check the balance of their queue length).

Van der Pol explores in (van der Pol, 2016) the application of deep learning to traffic light coordination, both in a single intersection and in a more complex configuration. Their testing setup consists of a single cross-shaped intersection with one lane per direction, where no turns are allowed. For the simulation software, the author uses SUMO (Simulation of Urban MOBility), a popular open-source microscopic traffic simulator. Given that SUMO teleports vehicles that have been stuck for a long time \(^2\), the author needs to take this into account in the reward function, in order to penalize traffic light configurations that favour vehicle teleportation. Their approach consists on a Deep Q-Network. The author experiments with two two alternative architectures, taken verbatim respectively from (Mnih et al., 2013) and (Mnih et al., 2015). Those convolutional networks were meant to play Atari games and receive as input the pixel matrix with bare preprocessing (downscaling and graying). In order to enable those architectures to be fed with the traffic data as input, an image is created by plotting a point on the location of each vehicle. The action space is comprised of the different legal traffic light configurations (i.e. those that do not lead to flow conflicts), among which the network chooses which to apply. The reward is a weighted sum of sev-

\(^2\)See http://sumo.dlr.de/wiki/Simulation/Why_Vehicles_are_teleporting
eral factors: vehicle delay (defined as the road maximum speed minus the vehicle speed, divided by the road maximum speed), vehicle waiting time, the number of times the vehicle stops, the number of times the traffic light switches and the number of teleportations. In order to improve convergence of the algorithm, the authors apply deep reinforcement learning techniques such as prioritized experience replay and keeping a shadow target network, but also experimented with double Q learning (Hasselt, 2010; Van Hasselt et al., 2015). They as well tested different optimization algorithms apart from the normal stochastic gradient optimization, such as the ADAM optimizer (Kingma and Ba, 2014), Adagrad (Duchi et al., 2011) or RMSProp (Tieleman and Hinton, 2012). The performance of the algorithm is evaluated visually by means of plots of the reward and average travel time during the training phase. The author also explores the behaviour of their algorithm in a scenario with multiple intersections (up to four) by means of a multi-agent approach. This is achieved by training two neighbouring intersections on their mutual influence and then the learned joint Q function is transferred for higher number of intersections.

Genders et al. explore in (Genders and Razavi, 2016) the application of deep convolutional learning to traffic light timing. Their test setup consists of a single cross-shaped intersection with four lanes in each direction, where the inner lane is meant only for turning left and the outer lane is meant only for turning right. As simulation software, the authors use SUMO, like the work by Van der Pol (van der Pol, 2016) (see previous bullet). However, Genders et al do not address the teleportation problem and do not take into account its effect on the results. Their approach consists of a Deep Convolutional Q-Network. Like in (van der Pol, 2016), Genders et al. transform the vehicle positions into a matrix so that it becomes a suitable input for the convolutional network. They, however, scale the value of the pixels with the local density of vehicles. The authors refer to this representation as discrete traffic state encoding (DTSE). The actions generated by the Q-Network are the different phase configurations of the traffic light set in the intersection. The reward defined as the variation in cumulative vehicle delay since the last action was applied. The network is fed using experience replay.
5. Theoretical Background

**Reinforcement Learning** (RL) aims at training an agent so that it applies actions optimally to an *environment* based on its state, with the downside that it is not known which actions are good or bad, but it is possible to evaluate the goodness of their effects after they are applied. Using RL terminology, the goal of the algorithm is to learn an optimal policy for the agent, based on the observable state of the environment and on a *reinforcement signal* that represents the reward (either positive or negative) obtained when an action has been applied. The underlying problem that reinforcement learning tries to solve is that of the *credit assignment*. For this, the algorithm normally tries to estimate the expected cumulative future reward to be obtained when applying certain action when in certain state of the environment. RL algorithms act at discrete points in time. At each time step $t$, the agent tries to maximize the expected total return $R_T$, that is, the accumulated rewards obtained after each performed action: $R_t = r_{t+1} + r_{t+2} + \cdots + r_T$, where $T$ is the number of time steps ahead until the problem finishes. However, as normally $T$ is dynamic or even infinite (i.e. the problem has no end), instead of the summation of the rewards, the discounted return is used:

$$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$$

(1)

The state of the environment is observable, either totally or partially. The definition of the state is specific to each problem. One example of state of the environment is the position $x$ of a vehicle that moves in one dimension. Note that the state can certainly contain information that condenses pasts states of the environment. For instance, apart from the position $x$ from the previous example, we could also include the speed $\dot{x}$ and acceleration $\ddot{x}$ in the state vector. Reinforcement Learning problems that depend only on the current state of the environment are said to comply with the *Markov property* and are referred to as *Markov Decision Processes*. Their dynamics are therefore defined by the probability of reaching from a state $s$ to a state $s'$ by means of action $a$:

$$p(s'|s,a) = P(S_{t+1} = s'|S_t = s, A_t = a)$$

(2)

This way, we can define the reward obtained when transitioning from state $s$ to $s'$ by means of action $a$:

$$r(s,a,s') = \mathbb{E} [R_{t+1}|S_t = s, A_t = a, S_{t+1} = s']$$

(3)
Deep Reinforcement Learning refers to reinforcement learning algorithms that use a deep neural network as value function approximator. The first success of reinforcement learning with neural networks as function approximation was TD-Gammon (Tesauro, 1995). Despite the initial enthusiasm in the scientific community, the approach did not succeed when applied to other problems, which led to its abandonment ((Pollack and Blair, 1997)). The main reason for its failure was lack of stability derived from:

- The neural network was trained with the values that were generated on the go, therefore such values were sequential in nature and thus were auto-correlated (i.e. not independently and identically distributed).
- Oscillation of the policy with small changes to Q-values that change the data distribution.
- Too large optimization steps upon large rewards.

Their recent rise in popularity is due to the success of Deep Q-Networks (DQN) at playing Atari games using as input the raw pixels of the game (Mnih et al., 2013, 2015).

\[
L(\theta) = \mathbb{E} \left[ (y - Q(s,a;\theta))^2 \right]
\] (4)

In DQNs, there is a neural network that receives the environment state as input and generates as output the Q-values for each of the possible actions, using the loss function (4), which implies following the direction of the gradient (5):

\[
\nabla_{\theta} L(\theta) = \mathbb{E} \left[ \left( r + \gamma \max_{a'} Q(s',a';\theta) - Q(s,a;\theta) \right) \nabla_{\theta} Q(s,a;\theta) \right]
\] (5)

In order to mitigate the stability problems inherent to reinforcement learning with value function approximation, in (Mnih et al., 2013, 2015), the authors applied the following measures:

- **Experience replay**: keep a memory of past action-rewards and train the neural network with random samples from it instead of using the real time data, therefore eliminating the temporal autocorrelation problem.
- **Reward clipping**: scale and clip the values of the rewards to the range \([-1, +1]\) so that the weights do not boost when backpropagating.
• **Target network**: keep a separate DQN so that one is used to compute the target values and the other one accumulates the weight updates, which are periodically loaded onto the first one. This avoids oscillations in the policy upon small changes to Q-values.

However, DQNs are meant for problems with a few possible actions, and are therefore not appropriate for continuous space actions, like in our case. Nevertheless, a recently proposed Deep RL algorithm referred to as **Deep Deterministic Policy Gradient** or DDPG (Lillicrap et al., 2015) naturally accommodates this kind of problems. It combines the actor-critic classical RL approach (Sutton and Barto, 1998) with Deterministic Policy Gradient (Silver et al., 2014). The original formulation of the policy gradient algorithm was proposed in (Sutton et al., 1999), which proved the policy gradient theorem for a stochastic policy $\pi(s,a;\theta)$:

**Theorem 1. (Policy Gradient theorem from (Sutton et al., 1999))**
For any MDP, if the parameters $\theta$ of the policy are updated proportionally to the gradient of its performance $\rho$ then $\theta$ can be assured to converge to a locally optimal policy in $\rho$, being the gradient computed as

$$\Delta \theta \approx \alpha \frac{\partial \rho}{\partial \theta} = \alpha \sum_s d^\pi(s) \sum_a \frac{\partial \pi(s,a)}{\partial \theta} Q^\pi(s,a)$$

with $\alpha$ being a positive step size and where $d^\pi$ is defined as the discounted weighting of states encountered starting at $s_0$ and then following $\pi$: $d^\pi(s) = \sum_{t=0}^{\infty} \gamma^t P(s_t = s|s_0, \pi)$

This theorem was further extended in the same article for the case where an approximation function $f$ is used in place of the policy $\pi$. In this conditions the theorem holds valid as long as the weights of the approximation tend to zero upon convergence. In our reference articles (Silver et al., 2014) and (Lillicrap et al., 2015), the authors propose to use a deterministic policy (as opposed to stochastic) approximated by a neural network actor $\pi(s;\theta^\pi)$ that depends on the state of the environment $s$ and has weights $\theta^\pi$, and another separate network $Q(s,a;\theta^Q)$ implementing the critic, which is updated by means of the Bellman equation like DQN (5):

$$Q(s_t,a_t) = E_{r_t,s_{t+1}} [r(s_t,a_t) + \gamma Q(s_{t+1},\pi(s_{t+1}))]$$ (6)
And the actor is updated by applying the chain rule to the loss function (4) and updating the weights $\theta^\pi$ by following the gradient of the loss with respect to them:

$$\nabla_{\theta^\pi} L \approx \mathbb{E}_s \left[ \nabla_{\theta^\pi} Q(s, \pi(s|\theta^\pi)|\theta^Q) \right]$$

$$= \mathbb{E}_s \left[ \nabla_a Q(s, a|\theta^Q)|a=\pi(s|\theta^\pi) \nabla_{\theta^\pi} \pi(s|\theta^\pi) \right]$$

(7)

In order to introduce exploration behaviour, thanks to the DDPG algorithm being off-policy, we can add random noise $N$ to the policy. This enables the algorithm to try unexplored areas from the action space to discover improvement opportunities, much like the role of $\varepsilon$ in $\varepsilon$-greedy policies in Q-learning.

In order to improve stability, DDPG also can be applied the same measures as DQNs, namely reward clipping, experience replay (by means of a replay buffer referred to as $R$ in algorithm 1) and separate target network. In order to implement this last measure for DDPG, two extra target actor and critic networks (referred to as $\pi'$ and $Q'$ in algorithm 1) to compute the target Q values, separated from the normal actor and critic (referred to as $\pi$ and $Q$ in algorithm 1) that are updated at every step and which weights are used to compute small updates to the target networks. The complete DDPG, as proposed in (Lillicrap et al., 2015), is summarized in algorithm 1.

6. Proposed Approach

In this section we explain the approach we are proposing to address the control of urban traffic lights, along with the rationale that led to it. We begin with section 6.1 by defining which information shall be used as input to our algorithm among all the data that is available from our simulation environment. We proceed by choosing a problem representation for such information to be fed into our algorithm in section 6.4 for the traffic state and section 6.6 for the rewards.

6.1. Input Information

The fact that we are using a simulator to evaluate the performance of our proposed application of deep learning to traffic control, makes the traffic state fully observable to us. However, in order for our system to be applied to the real world, it must be possible for our input information to be derived from data that is available in a typical urban traffic setup. The most remarkable
Algorithm 1 Deep Deterministic Policy Gradient algorithm

Randomly initialize weights of $Q(s, a|\theta^Q)$ and $\pi(s|\theta^\pi)$.
Initialize target net weights $\theta^Q' \leftarrow \theta^Q$, $\theta^\pi' \leftarrow \theta^\pi$.
Initialize replay buffer $R$.

for each episode do
    Initialize random process $N$ for action exploration.
    Receive initial observation state $s_1$.
    for each step $t$ of episode do
        Select action $a_t = \pi(s_t|\theta^\pi) + N_t$.
        Execute $a_t$ and observe reward $r_t$ and state $s_{t+1}$.
        Store transition $(s_t, a_t, r_t, s_{t+1})$ in $R$.
        Sample from $R$ a minibatch of $N$ transitions.
        Set $y_i = r_i + \gamma Q'(s_{i+1}, \pi'(s_i+1|\theta^\pi)|\theta^Q')$.
        Update critic by minimizing the loss:
        $$\mathcal{L} = \frac{1}{N} \sum_i (y_i - Q(s_i, a_i|\theta^Q))^2.$$ 
        Update the actor using the sampled policy gradient:
        $$\nabla_{\theta^\pi} \mathcal{L} \approx \frac{1}{N} \sum_i \nabla_a Q(s, a|\theta^Q) \nabla_{\theta^\pi} \pi(s|\theta^\pi)|s_i.$$ 
        Update the target networks:
        $\theta^Q' \leftarrow \tau \theta^Q + (1 - \tau) \theta^Q'$
        $\theta^\pi' \leftarrow \tau \theta^\pi + (1 - \tau) \theta^\pi'$.
    end for
end for

Examples of readily available data are the ones sourced by traffic detectors. They are sensors located throughout the traffic network that provide measurements about the traffic passing through them. Although there are different types of traffic detectors, the most usual ones are induction loops placed under the pavement that send real time information about the vehicles going over them. The information that can normally be taken from such type of detectors comprise vehicle count (number of vehicles that went over the detector during the sampling period), vehicle average speed during the sampling period and occupancy (the percentage of time in which there was a vehicle located over the detector). This way, we decide to constrain the information received about the state of the network to vehicle counts, average speed and occupancy of every detector in our traffic networks, along with the description of the network itself, comprising the location of all roads, their
connections, etc.

6.2. Congestion Measurement

Following the self-imposed constraint to use only data that is actually available in a real scenario, we shall elaborate a summary of the state of the traffic based on vehicle counts, average speeds and occupancy. This way, we defined a measured called speed score, that is defined for detector \( i \) as:

\[
speed\_score_i = \min \left( \frac{\text{avg}\_\text{speed}_i}{\text{max}\_\text{speed}_i}, 1.0 \right)
\]  

(8)

where \( \text{avg}\_\text{speed}_i \) refers to the average of the speeds measured by traffic detector \( i \) and \( \text{max}\_\text{speed}_i \) refers to the maximum speed in the road where detector \( i \) is located. Note that the speed score hence ranges in \([0, 1]\). This measure will be the base to elaborate the representation of both the state of the environment (section 6.4) and the rewards for our reinforcement learning algorithm (section 6.6).

6.3. Data Aggregation Period

The microscopic traffic simulator used for our experiments divides the simulation into steps. At each step, a small fixed amount of time is simulated and the state of the vehicles (e.g. position, speed, acceleration) is updated according to the dynamics of the system. This amount of time is configured to be 0.75 seconds by default, and we have kept this parameter. However, such an amount of time is too short to imply a change in the vehicle counts of the detectors. Therefore, it is needed to have a larger period over which the data is aggregated; we refer to this period as episode step, or simply ”step” when there is no risk of confusion. This way, the data is collected at each simulation step and then it is aggregated every episode step for the DDPG algorithm to receive it as input. In order to properly combine the speed scores of several simulation steps, we take their weighted average, using the proportion of vehicle counts. In an analogous way, the traffic light timings generated by the DDPG algorithm are used during the following episode step. The duration of the episode step was chosen by means of grid search, determining an optimum value of 120 seconds.

6.4. State Space

In order to keep a state vector of the environment, we make direct use of the speed score described in section 6.2, as it not only summarizes properly
the congestion of the network, but also incorporates the notion of maximum speed of each road. This way, the state vector has one component per detector, each one defined as shown in (9).

\[ state_i = speed\_score_i \quad (9) \]

The rationale for choosing the speed score is that, the higher the speed score, the higher the speed of the vehicles relative to the maximum speed of the road, and hence the higher the traffic flow.

6.5. Action Space

In the real world there are several instruments to dynamically regulate traffic: traffic lights, police agents, traffic information displays, temporal traffic signs (e.g. to block a road where there is an accident), etc. Although it is possible to apply many of these alternatives in traffic simulation software, we opted to keep the problem at a manageable level and constrain the actions to be applied only to traffic lights. The naive approach would be to let our agent simply control the traffic lights directly by setting the color of each traffic light individually at every simulation step, that is, the actions generated by our agent would be a list with the color (red, green or yellow) for each traffic light. However, traffic lights in an intersection are synchronized: when one of the traffic lights of the intersection is green, the traffic in the perpendicular direction is forbidden by setting the traffic lights of such a direction to red. This allows to multiplex the usage of the intersection. Therefore, letting our agent freely control the colors of the traffic lights would probably lead to chaotic situations. In order to avoid that, we should keep the phases of the traffic lights in each intersection. With that premise, we shall only control the phase duration, hence the dynamics are kept the same, only being accelerated or decelerated. This way, if the network has \( N \) different phases, the action vector has \( N \) components, each of them being a real number that has a scaling effect on the duration of the phase. However, for each intersection, the total duration of the cycle (i.e. the sum of all phases in the intersection) should be kept unchanged. This is important because in most cases, the cycles of nearby intersections are synchronized so that vehicles travelling from one intersection to the other can catch the proper phase, thus improving the traffic flow. In order to ensure that the intersection cycle is kept, the scaling factor of the phases from the same intersection are passed through a softmax function (also known as normalized exponential function). The result is the
ratio of the phase duration over the total cycle duration. In order to ensure a minimum phase duration, the scaling factor is only applied to 80% of the duration.

6.6. Rewards

The role of the rewards is to provide feedback to the reinforcement learning algorithm about the performance of the actions taken previously. As commented in previous section, it would be possible for us to define a reward scheme that makes use of information about the travel times of the vehicles. However, as we are self-constraining to the information that is available in real world scenarios, we can not rely on other measures apart from detector data, e.g. vehicle counts, speeds. This way, we shall use the speed score described in section 6.2. But the speed score alone does not tell whether the actions taken by our agent actually improve the situation or make it worse. Therefore, in order to capture such information, we shall introduce the concept of baseline, defined as the speed score for a detector during a hypothetical simulation that is exactly like the one under evaluation but with no intervention by the agent, recorded at the same time step. This way, our reward is the difference between the speed score and the baseline, scaled by the vehicle counts passing through each detector (in order to give more weight to scores where the number of vehicles is higher), and further scaled by a factor $\alpha$ to keep the reward in a narrow range, as shown in (10).

$$\text{reward}_i = \alpha \cdot \text{count}_i \cdot (\text{speed\_score}_i - \text{baseline}_i)$$

(10)

Note that we may want to normalize the weights by dividing by the total vehicles traversing all the detectors. This would restrain the rewards in the range $[-1, +1]$. This, however, would make the rewards obtained in different simulation steps not comparable (i.e. a lower total number of vehicles in the simulation at instant $t$ would lead to higher rewards). The factor $\alpha$ was chosen to be $1/50$ empirically, by observing the unscaled values of different networks and choosing a value in an order of magnitude that leaves the scaled value around 1.0. This is important in order to control the scale of the resulting gradients. Another alternative used in (Mnih et al., 2013, 2015) with this very purpose is reward clipping; this, however, implies losing information about the scale of the rewards. Therefore, we chose to apply a proper scaling instead. There is a reward computed for each detector at each simulation time step. Such rewards are not combined in any way, but are
all used for the DDPG optimization, as described in section 6.8. Given the stochastic nature of the microsimulator used, the results obtained depend on the random seed set for the simulation. This way, when computing the reward, the baseline is taken from a simulation with the same seed as the one under evaluation.

6.7. Deep Network Architecture

Our neural architecture consists in a Deep Deterministic Actor-Critic Policy Gradient approach. It is comprised of two networks: the actor network $\pi$ and the critic network $Q$. The actor network receives the current state of the simulation (as described in section 6.4) and outputs the actions, as described in 6.5. As shown in figure 1, the network is comprised of several layers. It starts with several fully connected layers (also known as dense layers) with Leaky ReLU activations (Maas et al., 2013), where the number of units is indicated in brackets, with $nd$ being the number of detectors in the traffic network and $np$ is the number of phases of the traffic network. Across those many layers, the width of the network increases and then decreases, up to having as many units as actions, that is, the last mentioned dense layer has as many units as traffic light phases in the network. At that point, we introduce a batch normalization layer and another fully connected layer with ReLU activation. The output of the last mentioned layer are real numbers in the range $[0, +\infty]$, so we should apply some kind of transformation that allows us to use them as scaling factors for the phase durations (e.g. clipping to the range $[0.2, 3.0]$). However, as mentioned in section 6.5, we want to keep the traffic light cycles constant. Therefore, we shall apply an element-wise scaling computed on the summation of the actions of the phases in the same traffic light cycle, that is, for each scaling factory we divide by the sum of all the factors for phases belonging to the same group (hence obtaining the new ratios of each phase over the cycle duration) and then multiply by the original duration of the cycle. In order to keep a minimum duration for each phase, such computation is only applied to the 80% of the duration of the cycle. Such a computation can be pre-calculated into a matrix, which we call the phase adjustment matrix, which is applied in the layer labeled as ”Phase adjustment” in figure 1, and which finally gives the scaling factors to be applied to phase durations. This careful scaling meant to keep the total cycle duration can be ruined by the exploration component of the algorithm, as described in 1, which consists of adding noise to the actions (and therefore likely breaking the total cycle duration). This
way, we implement the injection of noise as another layer prior to the phase adjustment. The critic network receives the current state of the simulation plus the action generated by the actor, and outputs the Q-values associated to them. Like the actor, it is comprised of several fully connected layers with leaky ReLU activations, plus a final dense layer with linear activation.

Figure 1: Critic and Actor networks

6.8. Disaggregated Rewards

In our reference article (Lillicrap et al., 2015), as well as all landmark ones like (Mnih et al., 2013) and (Mnih et al., 2015), the reward is a single scalar value. However, in our case we build a reward value for each detector in the network. One option to use such a vector of rewards could be to scalarize them into a single value. This, however, would imply losing valuable information regarding the location of the effects of the actions taken by the actor. Instead, we will keep them disaggregated, leveraging the structure
of the DDPG algorithm, which climbs in the direction of the gradient of the critic. This is partially analogous to a regression problem on the Q-value and hence does not impose constraints on the dimensionality of the rewards. This way, we will have a \( N \)-dimensional reward vector, where \( N \) is the number of detectors in the network. This extends the policy gradient theorem from (Silver et al., 2014) so that the reward function is no longer defined as \( r : S \times A \rightarrow \mathbb{R} \) but as \( r : S \times A \rightarrow \mathbb{R}^N \). This is analogous to having \( N \) agents sharing the same actor and critic networks (i.e. sharing weights \( \theta^{\pi} \) and \( \theta^{Q} \)) and being trained simultaneously over \( N \) different unidimensional reward functions. This, effectively, implements multiobjective reinforcement learning. To the best of our knowledge, the use of **disaggregated rewards** has not been used before in the reinforcement learning literature. Despite having proved useful in our experiments, further study is needed in order to fully characterize the effect of disaggregated rewards on benchmark problems. This is one of the future lines of research that can be spawned from this work. Such an approach could be further refined by weighting rewards according to traffic control expert knowledge, which will then be incorporated in the computation of the policy gradients.

### 6.9. Convergence

There are different aspects that needed to be properly tuned in order for the learning to achieve convergence:

- **Weight Initialization** has been a key issue in the results cast by deep learning algorithms. The early architectures could only achieve acceptable results if they were pre-trained by means of unsupervised learning so that they could have learned the input data structure (Erhan et al., 2010). The use of sigmoid or hyperbolic tangent activations makes it difficult to optimize neural networks due to the numerous local minima in the function loss defined over the parameter space. With pre-training, the exploration of the parameter space does not begin in a random point, but in a point that hopefully is not too far from a good local minimum. Pretraining became no longer necessary to achieve convergence thanks to the use of rectified linear activation units (ReLUs) (Nair and Hinton, 2010) and sensible weight initialization strategies. In our case, different random weight initializations (i.e. Glorot’s (Glorot and Bengio, 2010) and He’s (He et al., 2015)) gave the best results, finally selecting He’s approach.
Updates to the Critic: after our first experiments it became evident the divergence of the learning of the network. Careful inspection of the algorithm byproducts revealed that the cause of the divergence was that the critic network $Q'$ predicted higher outcomes at every iteration, as trained according to equation (11) extracted from algorithm 1.

$$y_i = r_i + \gamma Q'(s_{i+1}, \pi'(s_{i+1} | \theta^\pi') | \theta^Q')$$

(11)

As DDPG learning -like any other reinforcement learning with value function approximation approach- is a closed loop system in which the target value at step $t+1$ is biased by the training at steps $t$, drifts can be amplified, thus ruining the learning, as the distance between the desired value for $Q$ and the obtained one differ more and more. In order to mitigate this divergence problem, our proposal consists in reducing the coupling by means of the application of a schedule on the value of the discount factor $\gamma$ from Bellman’s equation, which is shown in figure 2. The schedule of $\gamma$ is applied at the level of the experiment, not within the episode. The oscillation in $\gamma$ shown in figure 2 is meant to enable the critic network not to enter in the regime where the feedback leads to divergence. Discount Factor scheduling has been proposed before in (Harrington et al., 2013) with positive results, although in that case the schedule consisted in a decaying rate.

Gradient evolution: the convergence of the algorithm can be evaluated thanks to the norm of the gradient used to update the actor network $\pi$. If such a norm decreases over time and stagnates around a low value, it is a sign that the algorithm has reached a stable point and that the results might not further improve. This way, in the experiments described in subsequent sections, monitoring of the gradient norm is used to track progress. The gradient norm can also be controlled in
order to avoid too large updates that make the algorithm diverge, e.g. (Mnih et al., 2013). This mechanism is called gradient norm clipping and consists of scaling the gradient so that its norm is not over a certain value. Such a value was empirically established as 0.5 in our case.

6.10. Summary

Our proposal is to apply Deep Deterministic Policy Gradient, as formulated in (Lillicrap et al., 2015), to the traffic optimization problem by controlling the traffic lights timing. We make use of a multilayer perceptron type of architecture, both for the actor and the critic networks. The actor is designed so that the modifications to the traffic light timings keep the cycle duration. In order to optimize the networks we make use of stochastic gradient descent. In order to improve convergence, we make use of a replay memory, gradient norm clipping and a schedule for the discount rate $\gamma$. The input state used to feed the network consists of traffic detector information, namely vehicle counts and average speeds, which are combined in a single speed score. The rewards used as reinforcement signal are the improvements over the measurements without any control action being performed (i.e. baseline). Such rewards are not aggregated but fed directly as expected values of the critic network.

7. Experiments

In this section we describe the experiments conducted in order to evaluate the performance of the proposed approach. In section 7.1 we show the different traffic scenarios used while in section 7.5 we describe the results obtained in each one, along with lessons learned from the problems found, plus hints for future research.

7.1. Design of the Experiments

In order to evaluate our deep RL algorithm, we devised increasing complexity traffic networks. For each one, we applied our DDPG algorithm to control the traffic light timing, but also applied multi-agent Q-Learning and random timing in order to have a reference to properly assess the performance of our approach. At each experiment, the DDPG algorithm receives as input the information of all detectors in the network, and generates the timings of all traffic light phases. In the multi-agent Q-learning implementation, there is one agent managing each intersection phase. It receives
the information from the closest few detectors and generates the timings for the aforementioned phase. Given the tabular nature of Q-learning, both the state space and the action space need to be categorical. For this, tile coding is used. Regarding the state space, the tiles are defined based on the same state space values as DDPG (see section 6.4), clustered in one the following 4 ranges \([-1.0, -0.2], [-0.2, -0.001], [-0.001, 0.02], [0.02, 1.0]\), which were chosen empirically. As one Q-learning agent controls the \(N_i\) phases of the traffic lights of an intersection \(i\), the number of states for an agent is \(4^{N_i}\). The action space is analogous, being the generated timings one of the values 0.2, 0.5, 1.0, 2.0 or 3.5. The selected ratio (i.e. ratio over the original phase duration) is applied to the duration of the phase controlled by the Q-learning agent. As there is one agent per phase, this is a multi-agent reinforcement learning setup, where agents do not communicate with each other. They do have overlapping inputs, though, as the data from a detector can be fed to the agents of several phases. In order to keep the cycle times constant, we apply the same phase adjustment used for the DDPG agent, described in section 6.5. The random agent generates random timings in the range [0, 1], and then the previously mentioned phase adjustment is applied to keep the cycle durations constant (see section 6.5).

Given the stochastic nature of the microscopic traffic simulator used, the results obtained at the experiments depend on the random seed set for the simulation. In order to address the implications of this, we do as follows:

- In order for the algorithms not to overfit to the dynamics of a single simulation, we randomize the seed of each simulation. We take into account this also for the computation of the baseline, as described in section 6.6.

- We repeat the experiments several times, and present the results over all of them (showing the average, maximum or minimum data depending on the case).

7.2. Network A

This network, shown in figure 3 consists only of an intersection of two 2-lane roads. At the intersection vehicles can either go straight or turn to their right. It is forbidden to turn left, therefore simplifying the traffic dynamics and traffic light phases. There are 8 detectors (in each road there is one
detector before the intersection and another one after it). There are two phases in the traffic light group: phase 1 allows horizontal traffic while phase 2 allows vertical circulation. Phase 1 lasts 15 seconds and phase 2 lasts 70 seconds, with a 5-seconds inter-phase. Phases 1 and 2 have unbalanced duration on purpose, to have the horizontal road accumulate vehicles for long time. This gives our algorithm room to easily improve the traffic flow with phase duration changes. The simulation comprises 1 hour and the vehicle demand is constant: for each pair of centroids, there are 150 vehicles.

![Urban network A](image)

Figure 3: Urban network A

The traffic demand is defined by hand, with the proper order of magnitude to ensure congestion. The definition and duration of the phases were computed by means of the classical cycle length determination and green time allocation formulas from (Webster, 1958).

7.3. Network B

This network, shown in figure 4 consists of a grid layout of 3 vertical roads and 2 horizontal ones, crossing in 6 intersections that all have traffic lights.
Traffic in an intersection can either go straight, left or right, that is, all turns are allowed, complicating the traffic light phases, which have been generated algorithmically by the software with the optimal timing, totalling 30 phases. There are detectors before and after each intersection, totalling 17 detectors. The traffic demand is defined by hand, ensuring congestion. The traffic light phases were defined, like network A, with the classical approach from (Webster, 1958). Four out of six junctions have 5 phases, while the remaining two junctions have 4 and 6 phases each. The traffic demand has been created in a random manner, but ensuring enough vehicles are present and trying to collapse some of the sections of the network.

7.4. Network C

This network, shown in figure 5 is a replica of the Sants area in the city of Barcelona (Spain). There are 43 junctions, totalling 102 traffic light phases, and 29 traffic detectors. The locations of the detectors matches the real world. The traffic demand matches that of the peak hour in Barcelona, and it presents high degree of congestion.
The number of controlled phases per junction \(^3\) ranges from 1 to 6, having most of them only two phases.

\(^3\)Note that phases from the network that have a very small duration (i.e. 2 seconds or less) are excluded from the control of the agent
7.5. Results

In order to evaluate the performance of our DDPG approach compared to both normal Q-learning and random timings on each of our test networks, our main reference measure shall be the episode average reward (note that, as described in section 6.6 there is actually a vector of rewards, with one element per detector in the network, that is why we compute the average reward) of the best experiment trial, understanding "best" experiment as the one where the maximum episode average reward was obtained.

![Figure 6: Algorithm performance comparison on network A](image)

In figure 6 we can find the performance comparison for network A. Both the DDPG approach and the classical Q-learning reach the same levels of reward. On the other hand, it is noticeable the differences in the convergence of both approaches: while Q-learning is unstable, DDPG remains remarkably stable once it reached its peak performance.
In figure 7 we can find the performance comparison for network B. While Q-learning maintains the same band of variations along the simulations, DDPG starts to converge. Given the great computational costs of running the full set of simulations for one network, it was not affordable to let it run indefinitely, despite the promising trend.

Figure 7: Algorithm performance comparison on network B

Figure 8: Algorithm performance comparison on network C
Figure 8 shows the performance comparison for network C, from which we can appreciate that both DDPG and Q-learning perform at the same level, and that such a level is beneath zero, from which we know that they are actually worse than doing nothing. This way, the performance of DDPG is clearly superior to Q-learning for the simplest scenario (network A), slightly better for scenarios with a few intersections (network B) and at the same level for real world networks. From the evolution of the gradient for medium and large networks, we observed that convergence was not achieved, as it remains always at the maximum value induced by the gradient norm clipping. This suggests that the algorithm needs more training time to converge (probable for network B) or that it diverges (probable for network C). In any case, further study would be needed in order to assess the needed training times and the needed convergence improvement techniques.

8. Conclusions

We studied the application of Deep Deterministic Policy Gradient (DDPG) to increasingly complex scenarios. We obtained good results in network A, which is analogous to most of the scenarios used to test reinforcement learning applied to traffic light control (see section 4 for details on this); nevertheless, for such a small network, vanilla Q-learning performs on par, but with less stability, though. However, when the complexity of the network increases, Q-learning can no longer scale, while DDPG still can improve consistently the obtained rewards. With a real world scenario, our DDPG approach is not able to properly control the traffic better than doing nothing. The good trend for network B shown in figure 7, suggests that longer training time may lead to better results. This might be also true for network C, but the extremely high computational costs could not be handled without large scale hardware infrastructure. Our results show that DDPG is able to better scale to larger networks than classical tabular approaches like Q-learning. Therefore, DDPG is able to address the curse of dimensionality (Goodfellow et al., 2016) regarding the traffic light control domain, at least partially. However, it is not clear that the chosen reward scheme (described in section 6.6) is appropriate. One of its many weaknesses is its fairness for judging the performance of the algorithm based on the individual detector information. In real life traffic optimization it is common to favour some areas so that traffic flow in arterials or large roads is improved, at the cost of worsening side small roads. The same principle could be applied to engineer a more realistic
reward function from the point of view of traffic control theory.

In order to properly assess the applicability of the proposed approach to real world setups, it would also be needed to provide a wide degree of variations in the conditions of the simulation, from changes in the traffic demand to having road incidents in the simulation. Another aspect that needs further study is the effect of the amount and location of traffic detectors on the performance of the algorithm. In our networks A and B, there were detectors at every section of the network, while in network C their placement was scattered, which is the norm in real world scenarios. We appreciate a loose relation between the degree of observability of the state of the network and the performance of our proposed traffic light timing control algorithm. Further assessment about the influence of observability of the state of the network would help characterize the performance of the DDPG algorithm and even turn it into a means for choosing potential locations for new detector in the real world. Also, the relevance of the provided information is not the same for all detectors; some of them may provide almost irrelevant information while others are key for understanding the traffic state. This is another aspect that should be further studied, along with the effect of the noise present in data delivered by real traffic detectors. An issue regarding the performance of our approach is the sudden drops in the rewards obtained through the training process. This suggests that the landscape of the reward function with respect to the actor and critic network parameters is very irregular, which leads the optimization to fall into bad regions when climbing in the direction of the gradient. A possible future line of research that addressed this problem could be applying Trusted Region Policy Optimization (Schulman et al., 2015), that is, leveraging the simulated nature of our setup to explore more efficiently the solution space. This would allow it to be more data efficient, achieving comparable results with less training.

We have introduced a concept that, to the best of our knowledge, has not been used before in the deep reinforcement learning literature, namely the use of disaggregated rewards (described in section 6.8). This technique needs to be studied in isolation from other factors on benchmark problems in order to properly assess its effect and contribution to the performance of the algorithms. This is another possible line of research to be spawned from this work.
On the other hand, we have failed to profit from the geometric information about the traffic network. This is clearly a possible future line of research, that can leverage recent advances in the application of convolutional networks to arbitrary graphs, similar to (Defferrard et al., 2016).

Finally, we have verified the applicability of simple deep learning architectures to the problem of traffic flow optimization by traffic light timing control on small and medium-sized traffic networks. However, for larger-sized networks further study is needed, probably in the lines of exploring the results with significantly larger training times, using the geometric information of the network and devising data efficiency improvements.
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