A Traffic Light Dynamic Control Algorithm with Deep Reinforcement Learning Based on GNN Prediction

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Abstract

Today’s intelligent traffic light control system is based on the current road traffic conditions for traffic regulation. However, these approaches cannot exploit the future traffic information in advance. In this paper, we propose GPlight, a deep reinforcement learning (DRL) algorithm integrated with graph neural network (GNN), to relieve the traffic congestion for multi-intersection intelligent traffic control system. In GPlight, the graph neural network (GNN) is first used to predict the future short-term traffic flow at the intersections. Then, the results of traffic flow prediction are used in traffic light control, and the agent combines the predicted results with the observed current traffic conditions to dynamically control the phase and duration of the traffic lights at the intersection. Experiments on both synthetic and two real-world data-sets of Hangzhou and New-York verify the effectiveness and rationality of the GPlight algorithm.

Introduction

With the rapid increase of vehicle quantity, traffic congestion has become an urgent problem to be solved in many places around the world, especially in big cities. In order to solve this problem, reduce the waiting time of vehicles on the road and increase the carrying capacity of urban road network. Intelligent Transportation System (ITS) has become one of the hot research issues in recent years, which aims to optimize the coordination and control of traffic flow.

Traffic light control is an important part of ITS. In recent years, reinforcement learning (RL) technology has become one of the most widely used approaches and has been extensively used for traffic light control problem (Wei et al. 2019c). Different from traditional approaches, RL control algorithm can dynamically adapt to the current traffic state according to the real-time road traffic environment. However, the traffic light control algorithm only based on the current traffic conditions may not be able to deal with the high complexity and high dynamics of the traffic system. Because it only assigns the green light source according to the current state, it ignores the congestion caused by the large traffic flow that may occur in the future for a period of time.

For the above reasons, we propose an algorithm named GPlight, which predicts the traffic flow in the future term before adopting the reinforcement learning algorithm to control the traffic lights. In GPlight algorithm, traffic forecast, which aims to estimate the urban traffic status of a period of time, is integrated with the traffic light control to reduce the possible future congestion, so as to improve control efficiency and avoid congestion. More specifically, in real-world intersection scenarios, each lane has a maximum vehicle capacity limit. Moreover, the green light duration is not infinite. During a limited period of green light, some vehicles are bound to be left in the incoming lanes of the intersection. If congestion is expected in the future, traffic prediction can help the traffic light control system reduce the number of vehicles left behind in the congestion direction, freeing up more space for future vehicles heading into intersections.

Traffic prediction algorithms fall into two main categories. The first one is the traditional approaches based on statistics, and the other one is the deep learning algorithms driven by big data, such as Convolutional Neural Networks (CNN) for spatial correlation learning and Recurrent Neural Networks (RNN) for temporal sequence learning. However, the traditional convolution approaches cannot capture the structural information of the road network. On the other hand, the road network can be conveniently represented as a graph, which preserves its structural information. A state-of-the-art approach combines the network structure modeling using graph theory algorithm with the convolution algorithm, and proposes a Graph neural Network (GNN), which is effective in traffic state prediction (Chengcheng, Bo, and Xiaoping 2019; Zhiyong et al. 2019; Shengnan et al. 2019; Guo et al. 2020; Zhang et al. 2019b; Diao et al. 2019; Chen et al. 2019).

In this paper, a new traffic light control algorithm named GPlight is proposed, which combines traffic prediction and reinforcement learning control. Our study considers the traffic light control problem of a complex traffic network with multiple intersections, aiming to increase the throughput of the road network. The proposed GPlight algorithm is divided into two stages. Firstly, the traffic flow information recorded in the previous period is used to predict the traffic flow in a short term. After that, the optimal green light direction and green light duration are selected for the intersection by comprehensively considering the traffic prediction results and the road traffic status obtained from real-time observation.
To summarize, the main contributions of this work are as follows:

- We emphasize the importance of the traffic prediction in ITS and integrate it with traffic light control to reduce the traffic congestion.
- We propose a GPlight algorithm, which the GNN algorithm is used to predict the traffic flow of road network in the future time, and an RL algorithm is used to control the traffic lights based on the predicted results. The duration of the green light is dynamically adjusted according to the predicted and current road congestion.
- We conduct experiments on both synthetic and two real-world data-sets of Hangzhou and New-York. Extensive results demonstrate the effectiveness and rationality of the proposed algorithm.

Related Work

There have been a lot of researches on intelligent traffic signal control problem using RL algorithm, which have achieved better performance than traditional approaches. Previous paper (Zheng et al. 2019) presents an algorithm of traffic light phase control in single intersection environment. Some other papers (Wei et al. 2019b) consider the interaction and influence between adjacent intersections, extending the traffic light control system to the multi-intersection environment, and using a real-world road network model for experiments. A novel approach (Wei et al. 2019a) has been introduced which combines RL algorithm with max pressure to get a more intuitive representation of the state and reward. However, all of these above algorithms rely only on the current state as the basis for action selection. An approach that considers not only the current state but also the future when making decisions may yield a better strategy.

Some studies (Kim and Jeong 2020) make traffic prediction of the next state according to the variables such as weather, date and time in the real world, and add the prediction results into the calculation of Q-function for traffic light control. However, this traditional approach basing on statistics cannot effectively reflect the urban traffic system with the characteristics of randomness and dynamic changes. Therefore, various deep learning algorithms, such as convolutional neural network (CNN) and recursive neural network (RNN), are increasingly used in traffic prediction problem, in which CNN is used to capture spatial dependency and RNN to temporal dynamic. However, these algorithms destroy the connectivity and structural relationship between the nodes in the complex traffic network and cannot capture the structural characteristic information in the network. State-of-the-art researches express the complex road network in the form of graph and combine it with neural network, proposing the graph neural network (GNN) algorithm (Chengcheng, Bo, and Xiaoping 2019; Zhiyong et al. 2019; Shengnan et al. 2019; Guo et al. 2020; Zhang et al. 2019; Diao et al. 2019; Chen et al. 2019). These studies use the directed or undirected graphs to define the nodes in the traffic network and the relations between them, constructing traffic prediction frameworks which use GNN to capture spatio-temporal characteristics of traffic flow data.

Because of its spatial characteristics, the traffic road network can be easily represented as a graph, in which a variety of node and edge definitions can be adopted. One way is to take each vehicle on the road as a node, and the connections between it and up to eight vehicles around as edges (Diehl et al. 2019). This model will cause high complexity in the road network with a large number of vehicles. Another approach is to use nodes to represent road sections, and adjacency matrix is used to represent whether roads are connected or not (Xu et al. 2019; Zhao et al. 2019; Wang et al. 2018). A more easily implemented approach is to take sensors installed in the road network as nodes, and the edges and weights indicate the connectivity between sensors (Ge et al. 2019; Zhou et al. 2020; Yu, Yin, and Zhu 2018). These approaches above are simple, but not suitable for traffic light control which get observations at intersections.

Problem Definition

In this section, we will describe traffic flow prediction and traffic signal control problems, introduce the details of scenario modeling, and define some relevant terms and notations.

Traffic Prediction Problem

We firstly describe traffic flow prediction and traffic signal control problems. For the traffic road network, we use a weighted undirected graph to represent it, which is noted as $G = (V, E, W)$. $V = \{v_1, v_2, \ldots, v_N\}$ represents $N$ nodes as intersections in the road network, and the traffic feature data collected at the intersections is used for the training and...
testing of the prediction model. $E$ represents the edges in the undirected graph $G$, represents the roads connecting the intersections, indicating the intersections’ connectivity. For intersections $v_x$ and $v_y$, $e(x,y)$ has values 1 and 0. When $v_x$ and $v_y$ are connected, the value is 1, otherwise 0. And $W \in \mathbb{R}^{N \times N}$ is the weighted adjacency matrix of graph $G$. Specifically, the edge weight from $v_x$ to $v_y$ is noted as $w(x,y)$.

In the traffic road network, we regard each intersection as a node of the weighted undirected graph $G$, and observe the traffic attribute characteristics of the road through sensors over a period of time. The observed data-set is expressed as $X \in \mathbb{R}^{T \times N \times D}$, where $T$ represents the sampling time, $N$ represents the number of nodes, and $D$ represents the dimension of observed traffic characteristics. Node attribute characteristics can be any traffic information, such as traffic flow, vehicle speed, etc. Specifically, we use $x_{t}^{d,i}$ to represent the information of the $d$-th feature in node $i$ observed at time $t$. Let the values of all the characteristics of node $i$ at time $t$ be expressed in terms of $x_{t}^{d,i}$, matrix $X_t = (x_{t}^{1,i}, x_{t}^{2,i}, \ldots, x_{t}^{N,i}) \in \mathbb{R}^{N \times D}$ records all the characteristic information of all nodes in the graph at time $t$, and for a period of time, matrix $X = (X_{t-T+1}, X_{t-T+2}, \ldots, X_t) \in \mathbb{R}^{N \times D \times T}$ is regarded as the feature matrix of the traffic network graph.

In this way, the graph-based traffic prediction problem is regarded as measuring the traffic feature information of $N$ nodes in the past $T$ time steps, and using the recorded observation information $X$ to predict the traffic features of nodes in the next $H$ time steps, which is denoted as $Y = (Y_{t+1}, Y_{t+2}, \ldots, Y_{t+H}) \in \mathbb{R}^{N \times D \times H}$, as shown in Eq. 1:

$$
(Y_{t+1}, Y_{t+2}, \ldots, Y_{t+H}) = \arg \max_{P} \{Y_{t+1}, Y_{t+2}, \ldots, Y_{t+H} \mid X_{t-T}, X_{t-T+1}, \ldots, X_t\}. \tag{1}
$$

**GPlight Algorithm**

In this section, we first describe the algorithm of traffic prediction using GNN. Then, the framework of GPlight algorithm using RL algorithm to control the traffic flow at the intersection with the predicted results is presented.

**Traffic Prediction on Road Graph**

The structure of the traffic prediction section at GPlight, as shown in Figure 2, consists of two spatial-temporal convolution blocks and a fully-connected layer, which are cascaded together. Each convolution block contains two gated temporal convolutional layers and a spatial graph convolutional layer in the middle of them. The spatio-temporal correlation information of traffic flow is extracted by convolution blocks, and the features obtained are integrated and processed by the fully-connected output layer to generate prediction.

**Spatial graph convolutional layer.** GPlight uses GNN to extract spatial information from previous traffic flow observations. The convolution is carried out directly on the data with graph structure, which preserves the spatial structure features of the traffic network. In order to apply the standard convolution to the graph structure, the Fourier transform is used to apply the convolution to the spectral domain, commonly known as the spectral graph convolution. In the concept of spectral convolution, the graph convolution operator is defined as follows, such as the convolution between the convolution kernel $\Theta$ and an input signal $x$:

$$
\Theta *_G x = U\Theta(L)U^T x = \Theta(U\Lambda U^T)x = \Theta(L)x, \tag{2}
$$

where $L = I_n - D^{-\frac{1}{2}}W D^{-\frac{1}{2}} \in \mathbb{R}^{N \times N}$ is the normalized Laplacian matrix, in which $I_n \in \mathbb{R}^{N \times N}$ is an identity matrix and $D \in \mathbb{R}^{N \times N}$ is the diagonal degree matrix with $D_{ii} = \sum_j W_{ij}$; $U \in \mathbb{R}^{N \times N}$ is the Fourier basis matrix of eigenvectors of $L$, and $\Lambda \in \mathbb{R}^{N \times N}$ is the diagonal matrix of the eigenvalues of $L$.

The convolution computation in large graph networks has high complexity, and Chebyshev polynomial approximation can be used to reduce the computational complexity of Eq. [2]. In Chebyshev polynomial $T_k(x)$, the graph convolution kernel $\Theta$ can be approximately written as a polynomial: $\Theta(L) = \sum_{k=0}^{K-1} \theta_k T_k(\Lambda)$, where $\theta$ is the coefficient of the polynomial, and $K$ is the size of the convolution kernel. The diagonal matrix $\Lambda$ is scaled as $\Lambda = 2\Lambda/\lambda_{\text{max}} - I_n$, where $\lambda_{\text{max}}$ is the largest eigenvalue of $L$. In this way, the definition of convolution in Eq. 2 can be approximately written as:

$$
\Theta *_G x = \sum_{k=0}^{K-1} \theta_k T_k(\tilde{L})x, \tag{3}
$$

where $\tilde{L} = 2L/\lambda_{\text{max}} - I_n$ denotes the scaled Laplace matrix.

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**Figure 1: Road network structure and intersection setting**
**Temporal gated convolutional layer.** The temporal convolutional layer is used to capture the temporal characteristics of the traffic flow, which consists of a one-dimensional causal convolution and a gated unit. Let $Y \in \mathbb{R}^{m \times c_{in}}$ represents the input to the convolutional layer, where $m$ represents the size of temporal, and $c_{in}$ represents channel dimensions. The temporal gated convolution can be defined as:

$$
\Gamma(S \circ Y) = Y_1 \odot \sigma(Y_2),
$$

(4)

where $\tau \in \mathbb{R}^{K \times c_{in} \times 2c_{out}}$ is the width-$K$ convolutional kernel, and $Y_1, Y_2 \in \mathbb{R}^{(m-K+1) \times c_{out}}$ are the input of GLU. $\odot$ is the element-wise Hadamard product, and $\sigma(Q)$ is the sigmoid gate which controls input $Y_1$ of the current states.

**DQN Algorithm Setting**

Deep Q-Network (DQN) is used for traffic light control, which combines Q-learning with deep neural network. In our scene, an DQN agent is set at each intersection in the road network, and trains its own model separately. Considering that the traffic flow between intersections and the action selections of traffic lights will influence each other, and closer intersections have a bigger impact, the agents obtain the information of the adjacent intersections through the attention mechanism, and use these information to realize the collaborative control of multiple intersections.

A Markov Decision Process (MDP) is used to represent the process of agents making decisions in its interaction with the environment. This MDP can be represented by $< S, A, p, R, \gamma >$, in which there is a set of states $s_t \in S$, a set of actions $a_t \in A$, a transfer probability $p$, a reward function $R$, and a discount factor $\gamma$.

In GPlight algorithm, the state represents the observation of the situation at intersections. The action space includes the choice of both green phase direction and green phase duration. Inspired by the pressure algorithm in Presslight [Wei et al., 2019a], this paper uses an improved pressure algorithm to define the rewards for actions. The improved pressure algorithm takes into account the maximum carrying capacity of the lane, and is determined by the number of vehicles on the incoming and outgoing lanes, which is calculated by the following equation:

$$
P_t = N_{in} \times (1 - \frac{N_{out}}{N_{max}}),
$$

(5)

where $P_t$ is the pressure of traffic movement $i$. $N_{in}$ and $N_{out}$ is the number of vehicles on incoming and outgoing lane, respectively. $N_{max}$ is the maximum number of vehicles that can fit in a lane.

The reward for traffic movement $i$ is set according to the pressure in Eq. 5, which is defined as:

$$
r_t = -P_t.
$$

(6)

Since there are 12 traffic movements at one intersection, the total reward $R$ for an action is:

$$
R = \sum_{i=0}^{11} r_i = - \sum_{i=0}^{11} P_i.
$$

(7)

At each intersection, the agent takes the phase information and vehicle queue length on incoming and outgoing lanes at time $t$ as the current state $s_t$, estimates Q-value of all actions according to $s_t$, and selects the green light phase and duration as action $a_t$. Then the agent observes the state $s_{t+1}$ at time $t + 1$ and gets feedback to update the parameters of Q-network by gradient descent. The Q-function is defined as:

$$
Q(s_t, a_t) = R(s_t, a_t) + \gamma \max_{a_{t+1}} \{Q(s_{t+1}, a_{t+1})\},
$$

(8)

where $\gamma$ is the discount factor. And the loss function is expressed as follow:

$$
J = \sum_{i=0}^{1} \frac{1}{B}(R_i + \gamma \max \hat{Q}(s_{t+1}, a_{t+1}; \theta) - Q(s_t, a_t; \theta))^2,
$$

(9)

where $Q$ is the target function, and $\hat{Q}$ is the primary function. $B$ is the batch size in DQN.

**Framework of GPlight**

The GPlight framework is divided into two parts: traffic flow prediction and traffic light control using RL algorithm, as shown in Figure 2. In GPlight, GNN algorithm introduced in Section 4.1 is used to predict the traffic flow in a short term. This prediction is used to determine the expected green light duration $t_{exp}$ at the intersection. Specifically, the number of vehicles coming in the future is used to determine the duration of the green light that will allow all future vehicles
Algorithm 1 GPlight: Traffic Light Control based on GNN Prediction

Input: Graph $G = (V, E, W)$, episode length $T$, greedy $\epsilon$, update rate $\alpha$, target network replacement frequency $C$
Initialize $Q$ with parameters $\theta$, $Q$ with parameters $\tilde{\theta}$

for each episode do
  Initialize step number $t$ and total time $t_{sum}$ to be 0
  while $t_{sum} < T$ do
    /* Traffic prediction */
    Capture spatial features by Eq. [3]
    Capture temporal features by Eq. [4]
    Get prediction: $(Y_{t+1}, Y_{t+2}, \cdots, Y_{t+H}) \leftarrow (X_{t-T}, X_{t-T+1}, \cdots, X_{t})$
    Get expected green phase duration $t_{exp} \leftarrow (Y_{t+1}, Y_{t+2}, \cdots, Y_{t+H})$
    /* Traffic light control */
    Select a random phase $pha$ with probability $\epsilon$
    Otherwise $pha \leftarrow \arg \max_{pha} Q(s_t, pha; \theta)$
    Get required green phase duration $t_{req}$ by current observation
    $t_{green} = \min(t_{exp}, t_{req})$
    $a_t \leftarrow \{pha, t_{green}\}$
    Execute $a_t$, observe new state $s_{t+1}$, get reward $R$
    $t_{sum} \leftarrow t_{sum} + t_{green}$, $t \leftarrow t + 1$
    Calculate the loss $J$ by Eq. [9]
    Update $\theta$ with $\nabla J$
    Every $C$ steps update $\tilde{Q}$: $\tilde{Q} \leftarrow Q$
  end while
end for

in chosen direction to pass. Then, DQN agent chooses the required duration of green light $t_{req}$ at intersection based on the road surface observation information at current time, which represents the duration of green time required to allow all vehicles currently waiting on the incoming lane to pass. Both the values of $t_{exp}$ and $t_{req}$ can be calculated by the number of vehicles, the average speed and acceleration of vehicles, and the length of intersections. The actual green light duration is determined by the minimum of $t_{exp}$ and $t_{req}$. In this way, the agents are able to determine the current green light duration based on the number of vehicles that will arrive in the future, choose a longer green light duration when the congestion is coming, so that the traffic flow in this direction can be cleared in advance and more space for the coming vehicles will be made. On the other hand, the choice of the minimum value in $t_{exp}$ and $t_{req}$ also avoids the waste of green light resources caused by too long duration. Finally, the agents select the optimal green phase and duration as the action based on the current observation and the prediction of the future traffic flow, and executes it in the next time step.

The pseudocode of GPlight algorithm is shown in Algorithm 1.

Experiment and Analysis

In this section, based on CityFlow (Zhang et al. 2019a) simulator, the simulation results are shown to verify the effectiveness of the proposed GPlight algorithm, which is compared with several state-of-the-art algorithms.

Data-sets and Experiment Setting

Three data-sets are used in traffic light control: Single, New-York and Hangzhou. For the Single data-set, there is only one intersection and the traffic flow is generated manually. Except for the flow going straight from west to east and from east to west, all other have an interval of 20 seconds. The interval of the W-E and E-W traffic flow is 1 second from 900-th second to 2700-th second and 20 seconds in other time. New-York and Hangzhou data-sets are based on collected vehicle trajectories from practice. There are 48 intersections in New-York, the lane length for the WE and NS direction is 350m and 100m respectively; and there are 16 intersections in Hangzhou, the distance between adjacent intersections is set at 300m, which are the same setup as in Colight (Wei et al. 2019b).

The GNN module for traffic flow prediction is trained by using traffic flow data completely consistent with the topology of traffic light control scene, and then is integrated into the traffic light control part. The distance between each node is calculated according to the respective road network. The data of past 10 minutes is utilized to predict the traffic volume of next 5 minutes. For the history data, the maximum number of vehicles of each lane is calculated for every minute and is then input to the GNN module. The output of GNN is regarded as the maximum number of vehicles of next 5 minutes and is used to get the maximum duration of the green light.

In the experiment, the greedy $\epsilon$ in Algorithm 1 is decreasing from 0.8 to 0.2. The discount factor $\gamma$ for calculating the accumulated reward is set as 0.8. The learning rate of the Q-network is set as 0.001.

Baseline

- **FixedTime.** Set green light for all phases with a predetermined order.
- **MaxPressure** (Varaiya 2013). Set green light for the phase with the max pressure
- **CoLight** (Wei et al. 2019b). An RL traffic light control algorithm for large-scale road networks. We consider two traffic light settings: Fixed and Dynamic. In Fixed, the traffic light duration is constant while in Dynamic the traffic light duration changes according to the real time traffic conditions.
- **PressLight** (Wei et al. 2019a). An RL traffic light control algorithm with pressure as the reward. Both Fixed and Dynamic are performed.

Result and Analysis

In Table 1, we list both the average travel time and the throughput for the three data-sets in one hour. As has been stated, with the prediction of future traffic flow, GPlight has the potential to increase the throughput of the traffic network and decrease the travel time by adjusting the maximum of green light duration. It seems that the FixedTime algorithm achieves the lowest travel time in table 1. However,
|                  | Average Travel Time | Throughput |
|------------------|---------------------|------------|
|                  | Single   | Hangzhou | New-York | Single   | Hangzhou | New-York |
| FixedTime        | 135.79   | 249.72   | 120.94   | 1250     | 3410     | 200      |
| MaxPressure      | 212.66   | 346.33   | 397.62   | 2082     | 4394     | 2373     |
| CoLight-Fixed    | 151.01   | 365.54   | 187.20   | 2178     | 4473     | 2716     |
| CoLight-Dynamic  | 130.38   | 355.87   | 183.72   | 2076     | 4383     | 2713     |
| PressLight-Fixed | 105.46   | 374.62   | 454.90   | 2210     | 4359     | 1312     |
| PressLight-Dynamic | 124.04  | 381.28   | 363.04   | 2096     | 4397     | 1206     |
| GPlight          | 91.54    | 336.78   | 181.81   | 2288     | 4575     | 2718     |

Table 1: Average Travel Time and Throughput in one hour

Figure 3: Gap of number of passed vehicles in one hour

development of green light. The GPlight controls the traffic flow by deciding the phase and duration of the green light. A detailed survey into the choice of GPlight can be therefore helpful and instructive. Figure 5 gives the accumulated duration of four phases over time. Each dot on the curves represents a change of choice to its corresponding phase. Note that the algorithm may choose one phase repetitively and such repetitive choice is not dotted to present a more clear result. ‘WE’ and ‘NS’ represent the green light is set for the west-east and north-south straight direction respectively. ‘WL’ means turning left from west to north and from east to south is allowed. ‘NL’ means turning left from north to east and from south to west is allowed. From all the figures, it can be seen that after the manual vehicle flow drives into the traffic network, green light for the “WE” direction in Single and Hangzhou data-sets and for the “NS” direction in New-York data-set is set more frequently and longer.

Recall that the curve in Figure 3 first drops before rises. The choice of green light in Figure 5 can serve as a rea-
sonable explanation. The expected rise can be explained by the long duration of the ‘WE’ green light. Since the heavy manual flow is added to the west-east straight direction, the green light in this direction can encourage more vehicles to pass. As for the drop of the curve in Figure 3, take a look at the choice of green lights around the 900-th second. For the Hangzhou data-set, before the arrival of heavy traffic, more green lights are given to the other three directions, especially the “NS” one. Considering that a large number of vehicles will arrive on the “WE” direction and the green light will set to that direction for a relatively long period, it seems wise to set green lights for other directions to clear vehicles on those directions. Otherwise, vehicles that have already been on the lane of the other three directions would have to wait for a long time, which is unsatisfactory in practice. On the other hand, for the Single data-set, during the first 900 seconds, the four curves are approximately the same, which is reasonable as the intervals of the flow in the four directions are the same. Before the manual flow arrives, no preference is given to the other three directions and after the manual arrives, “WE” phase gets selected more frequently. As a result, the negative gap in Figure 3(a) is larger.

Conclusion

In this paper, we propose GPlight, a reinforcement learning algorithm that combines traffic prediction and traffic light control for intelligent traffic control problem. The algorithm proposed first uses GNN, which combines graph theory with convolutional neural network algorithm, to predict the traffic flow in the short-term in future. After that, the prediction information and the real-time observation are used in the traffic light control using DQN algorithm. Experiments on both simulated and real-world data-sets show that the proposed GPlight algorithm improves the throughput and delay of the
traffic network compared to the baseline algorithm.

**Broader Impact**

This paper combines traffic prediction with intelligent traffic light control. The proposed algorithm uses the results of traffic prediction to clear the road which is going to become congested in advance. This algorithm can alleviate traffic congestion, reduce vehicle travel time, and thus reduce energy consumption and pollution.

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