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A Spatio-Temporal Multi Agent Reinforcement Learning For Traffic Data Prediction in Smart City Environment

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Abstract **-** *A multiagent-based reinforcement learning algorithm is proposed in this paper, in which the interactions between travelers and the environment are taken into account in order to simulate the temporal-spatial characteristics of activity-travel patterns in a smart city environment. As a medium for transmitting the influence of one traveler's decision to other travelers, the degree of road congestion is included in the reinforcement learning algorithm. During the simulation, both macroscopic activity-travel characteristics such as traffic flow spatial-temporal distribution and microscopic activity-travel characteristics such as activity-travel schedules of each agent are obtained, as well as both macroscopic and microscopic activity-travel characteristics. In this paper, we will discuss the most likely or "average" state of the system, rather than the most extreme state. However, it is also interesting to investigate how the agents would react to drastic changes in their environment and how they would interact with one another in such situation.*

Keywords: *Multi Agent Reinforcement Learnig (MARL), Intelligent Transportation System (ITS), Internet of Things (IoT)*

1. INTRODUCTION

This type of data refers to information that is both spatial and temporal in nature. The extraction of patterns and knowledge from spatial and temporal data is referred to as geospatial and temporal analysis. Use dynamic traffic information to control, monitor, and manage the flow of people and goods in the roadways. A nation's transportation planning, infrastructure development and smart city initiatives all benefited from real-time traffic information. It is impossible to study traffic patterns without considering time and space. Data from adjacent, upstream, and downstream links can be used to identify traffic flow's temporal characteristics. In order to predict traffic flow, the spatial and temporal aspects of traffic flow must be taken into account. Problem-solving techniques based on computational intelligence are at the heart of Artificial Intelligence (AI). CI is based on formal mathematical proofs, scientific methods, and measures. Data patterns that can be used to solve operational problems in dynamic systems can be retrieved by these researchers. Highway traffic flow prediction is one of the dynamic systems being studied in this research. Vehicle traffic flow in real-time transport scenarios can be affected by factors such as time and location. Both spatial and temporal traffic flow modelling is examined in the paper. On a traffic sequence mining framework for the prediction of traffic volume on highways, spatial-temporal traffic information sequences are formulated and put into practise. Intelligent transportation systems (ITS) and a variety of ITS services are discussed in the following section.

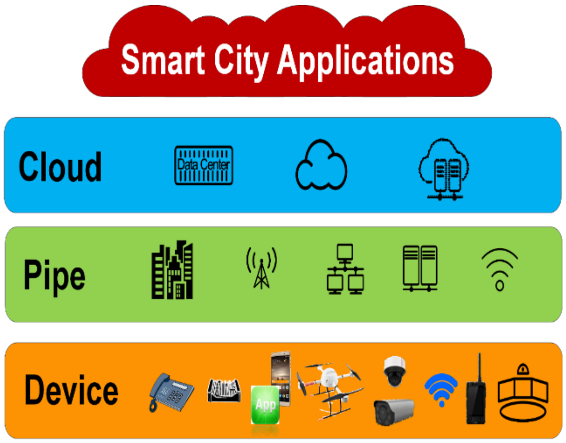

Figure 1: Smart City Applications

Reinforcement Learning: When you hear the term Reinforcement Learning, it refers to a class of algorithms that have the ability to learn through trial and error. An RL agent is deployed into an environment, usually with no prior knowledge of how to behave in order to achieve its objectives. In response to the agent's interactions with its environment, it receives a scalar reward signal r based on the outcomes of actions that it has previously selected. In either case, a negative or positive reward function is used, and a properly designed reward function allows the agent to iteratively learn an optimal or near-optimal control policy over time. In order to maximize the reward received during its lifetime, the agent must strike a balance between exploitation of known good actions and exploration of the consequences of new actions, among other things.

Parallel Reinforcement Learning: A new paradigm in robotics called Parallel Learning (PL) allows multiple agents to pool their experiences while learning simultaneously on a problem, improving performance and decreasing convergence times. A common application of PL is to accelerate the convergence of single agent reinforcement learning (RL) problems, rather than investigating competitive or cooperative strategies and emergent behaviour as is the case in mainstream Multi Agent Reinforcement Learning (MARL) research. It is more common for PL agents to influence each other's behaviour through information sharing than it is for MARL agents to interact directly with one another directly. This is due to the fact that PL agents learn in separate instances of the same problem, as opposed to multiple agents learning in a single problem instance, as is common in the literature on multi-agent reinforcement learning (MARL).

Challenges of IoT in Smart City Traffic Management

As far as the system into consideration, the measures taken by the intelligent transportation system, the following are the challenges that must be addressed in the deployment of IoT for traffic control:

1. Confidentiality and security When the Internet of Things (IoT) is incorporated into ITS VANET systems, there are concerns and issues related to privacy and system security. As reported by HP, approximately 70% of the Internet of Things devices present in a smart city are at risk of being compromised due to bugs and vulnerabilities such as a poor authorization system, a lack of a firewall, or a lack of a detection prevention system. Given the limited power of sensors, security features such as weak encrypted communication protocols must be sacrificed in order to maintain operational efficiency and reliability of sensors (Botta, 2016).

2. Reliability Particularly in adverse weather conditions, during periods of heavy traffic, in the

event of a collision, or in the event of a technical failure, sensors can be prone to providing inaccurate data.

3. Overburdening the network and data integration It is difficult for an ATMS system to provide a complete overview of traffic to a single driver, which may cause the network to become overburdened and eventually fail. Another significant issue in IOT-based traffic management systems is data integration, because each detector has its own unique measurement, which necessitates the standardisation of information.

2. LITERATURE REVIEW

Liao, H., et al (2019). Since, the early days of electronic circuit design, global routing has been a particularly difficult problem to solve because it requires connecting an enormous number of circuit components with wires while adhering to printed circuit board and integrated circuit designs. Complex hydraulic systems, pipe systems, and logistics networks face similar routing issues. Gluttonous algorithms and hard-coded heuristics typically make up existing solutions. As a result, current approaches lack model flexibility and frequently fail to address sub-problems simultaneously. An alternative method for solving the global routing problem in a simulated environment is presented in this work. With deep reinforcement learning, an agent is able to create an optimal route for a given problem, and this method is presented with a conjoint optimization mechanism that can be used to achieve this.

Wang, Y., et al (2020). An intelligent traffic light control system must be developed in order to implement smart transportation. There have been various attempts to optimize individual traffic lights, but they have neglected to take into account the spatial and temporal influences on the use of multi-intersection traffic lights, which have a greater impact. Here, a new STMARL framework is put forth to better capture the interdependence of multiple related traffic lights and control them in a coordinated manner, taking into account their spatial and temporal interdependencies. Adjacency graphs for traffic lights are first created using the current spatial arrangement of those lights. Recurrent Neural Networks (RNNs) are used to combine historical traffic data with current traffic conditions. The deep Q-learning method will be used to make the decision for each traffic light in a distributed manner based on the temporally dependent traffic information. In addition, we develop a graph neural network model to represent the relationships between multiple traffic lights. "By analyzing synthetic and real-world data, our STMARL framework has proven to be effective and has allowed us to better understand the influence mechanism among multi-intersection traffic lights.

Bazzan, A. L. (2009) Due to our society's growing dependence on mobility comes new challenges for traffic engineering, computer science, artificial intelligence, and multiagent systems. A better use of transportation infrastructure is needed here because additional capacity cannot be provided. Multiagent systems have a strong connection to many traffic management and control issues because of their distributed nature.

Buşoniu, L (2010) The advantages and difficulties of multi-agent reinforcement learning are discussed. Multiagent learning goals are a central problem in the field; this chapter reviews the goals proposed in the literature. Multi-agent reinforcement learning techniques have been used in a variety of problem domains.. For an illustration of the use of multi-agent reinforcement learning algorithms, two cooperative robots are shown to be moving something together. For the multi-agent reinforcement learning field, there are a number of important open issues that need to be addressed, and promising research avenues that can help.

Marc Lanctot et al (2017) The challenge of multiagent reinforcement learning is to teach agents how to interact with each other in a shared environment in order to achieve general intelligence (MARL). Independent reinforcement learning (InRL) is the simplest form, in which each agent treats its experience as part of its (non-stationary) surroundings. Overfitting to other agents' policies during training can cause InRL policies to not be sufficiently generalised when they are used in real-world situations. Joint-policy correlation is the new metric we use to measure this effect. Based on approximate best responses to mixtures of policies generated by deep reinforcement learning and empirical game-theoretic analysis, we describe an algorithm for general MARL.

Reinforcement learning is a hot topic right now. Using deep learning methods, researchers have been able to perform complex control tasks, such as in robotics and video games (Mnih et al. 2015; Silver et al. 2016). Learning techniques that use neural networks as function approximators are at the heart of these findings. However, despite these accomplishments, the vast majority of studies have focused on single-agent settings, which is contrary to the nature of many real-world applications. Autonomous vehicles, multi-robot control, communication networks, and financial markets are just a few examples of how this technology can be put to use. As each agent discovers a strategy in tandem with other entities in a shared environment, they adjust their policies in response. There has been an uptick in interest in the multi-agent reinforcement learning (MARL) community since the recent advances of single-agent deep RL. When using deep learning methods, the community was able to tackle problems that were more complex than those that had been studied in the past using only tabular data.

3. PROPOSED METHODOLOGY

Transportation network is a dynamic (time-varying) network. Traffic flow through the network is influenced by spatial and temporal traffic characteristics of adjacent links. Urban transport faces unprecedented, robust and highly fluctuating traffic condition, especially during peak hours. Thus it is essential to analyse peak hour traffic behaviour and spatial-temporal aspects of real-time traffic conditions in travel decisions. Prediction of traffic flow at target link becomes more accurate when spatial-temporal dependence of adjacent links is considered. In this view, this chapter presents a survey on time series analysis of traffic variables in the perspective of deterministic and non-deterministic modelling of traffic flow. Artificial intelligence based traffic flow forecasting methods are presented. Traffic forecasting based on spatial-temporal dependence analysis is presented. Research challenges that need to be addressed are enumerated Traffic forecasting with missing data Short-term traffic forecasting has limited ability when even a small portion of traffic data is missing. This problem of missing data arises due to faulty sensing system, error due to communication noise in network, and incorrect interpretation made by software. However, these errors could be rectified using data imputation techniques but with cost of increasing complexity. The inconsistencies present in observed values affect the forecast accuracy,. Conventionally, historical average method is used but this method penalizes the forecast accuracy with prediction error. Data sampling and normalization is performed to convert raw facts and this data mining technique involves traffic data pre-processing, where quality of traffic data is screened for missing and erroneous values. In a data source with large variations, patterns close to those to be predicted can be inherently identified without classifying the data set. Therefore, when data is distributed irregularly, local regression is preferred. However, when data is distributed regularly away from any boundary, both kernel and local regression methods work well equally,. In short term prediction missing values are replaced with zero in some studies. Missing data computation is made to prepare complete data set by interpolating the arrival time based on traffic information at adjacent links with an assumption that travel time does not vary between two immediate time points consecutively. Hence, the need for rich historical datasets is thus evident from these studies. The strength of forecasting models can be assessed well when working with missing data. reported the influence of missing data using multivariate models. Vector auto-regressive model (VAR) is highly sensitive towards missing data, while generalized regression NN (GRNN) is robust and achieved reliable forecast. Spatial correlation between adjacent links helps not only in path selection but elimination of missing data as well.

4. PATTERN MINING TECHNIQUES ARE USED TO PREDICT TRAFFIC FLOW

Intelligent Transportation Systems include traffic management as an essential component (ITS).

To accurately forecast traffic conditions in the near future, these systems rely on input that is precise and accurate. Using this perspective, traffic information is divided into two components: (1) spatial data from upstream and downstream links, and (2) time-series traffic data from the target link in time series. According to traffic forecasting, spatial dependence between traffic links also provides valuable information. Data-driven approaches have dominated conventional traffic operations research in the majority of studies. Only a handful of researchers have expressed an interest in using sequential pattern mining techniques to study traffic patterns. When spatial information is incorporated into the k-nn model, researchers have found that their forecasts are more accurate, according to a study published in the Journal of Machine Learning Research. Multistep, multi-task learning model using fine- and coarse-grain correlation analysis was proposed to consider traffic data's spatial and temporal aspects. Traffic studies can benefit greatly from data-driven methods. In order to forecast traffic, we used three different models, which were then fed into a neural network to evaluate the aggregated results. A traffic flow model and a traffic density assessment were used to make the report. In order to better understand the flow dynamics, a neural network was used to do so. Additionally, traffic patterns were extracted using classification and clustering techniques to assess traffic density using neural network generated fuzzy c-means cluster based traffic flow patterns on historical data and were found to show significant results.

5. CONCLUSION

For reducing travel delay, the research outcome presented in this thesis can be further investigated so that the traffic sequence mining framework can be augmented with travel time index based traffic congestion management. Further, steps to deploy TT-PrefixSpan and STAR as software components in ITS have to be continued as the future research work to enable better route guidance on highways. Augmenting traffic network with travel time based traffic sequences would help in capturing traffic conditions during peak hours of the day. Hence, the traffic sequence mining framework can be extended to evaluate outlier traffic sequences considering both spatial and temporal components. This would result in better route guidance by clustering road segments based on the prediction of traffic volume by mining travel time based traffic sequences. Besides, outlier traffic patterns would significantly help the commuters in their travel to the destination, thereby, enabling useful decisions, especially during peak hour travel.

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