B.Tech. Project Report

on

Deep Reinforcement Learning in Traffic

Submitted by

Ujwal Padam Tewari

(201551085)

under the supervision of

(Name of the Supervisor)

Mentor: Varsha Raveendran

Name (for off-campus BTP)

Mentor:Dr Naveen Kumar

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY VADODARA

2017

Declaration

I, Ujwal Padam Tewari, declare that this written submission represents my ideas in my own words and where other′s ideas or words have been included, I have adequately cited and referred the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not mispresented or fabricated any idea/data/fact/source in my submission. I fully understand that any violation of the above will cause for disciplinary action by the institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained.

(Signature)

Ujwal Padam Tewari (Name of the student)

Ujwal Padam Tewari Date: Roll no. 201551085

Abstract

Adaptive traffic signal control (ATSC) systems are key to efficient traffic management in smart cities. While RADAR or inductive loop based systems are regularly used for the task in the developed world, financial and infrastructure constraints precludes use of sophisticated and expensive sensors in the developing countries.

The on going project provides the techniques to minimize traffic in the city of Bangalore using the Reinforcement Learning. The project was aimed at successful deployment of RL model[9] using Feed Forward network and LSTM(Long Short Term Memory) on a single traffic junction and optimize the network. The current agent give a far lesser delay time than the FST -60(Fixed standard time of 60 seconds via round roubin technique to each section of the junction).

After the current optimization of a single juntion using RL model we plan to further expand to it to multiple junctions using Mulit agent Reinforcement Learning.

Contents

Chapter 1

Introduction

21st century is era of modern developments and scientific progress and with this progress there has been an ever increasing demand of intelligent traffic systems to minimize the unprecedented congestion of vehicles. It is therefore high time for conventional traffic systems to evolve to deal with the high volumes of traffic network in every day to day scenario. One such way is to encompass state of the art technologies and make the existing traffic signals more efficient and adaptive to the changing traffic patterns. The application of Reinforcement Learning(RL) in traffic signals has led to development of smart traffic signals that are self learning and optimal in terms of delay optimization. RL algorithms can find the optimal strategy using inputs like traffic density, vehicle speed, queue length of the vehicle and their position on the lane.

We propose the use of normalised queue length in designing our RL algorithm since we believe in a realistic approach queue length is more effective in comparison to density, speed and position of vehicles. This is due to the fact that queue length has least possible expected error for if traffic density or number of vehicles are being calculated by any vision technique, there are high chances that the pre-trained models may not recognize vehicles like rickshaw or animals blocking the pathway which is a typical Indian scenario. Over and above low light at night may hinder in providing correct numbers. One of the most widely used function approximation techniques are the Neural Networks which when used with RL state of the art techniques to give better and more efficient results. DNN's are ideal for processing high dimensional data and computations because of more layers and hence deeper structures. For our simulation and environment we have used Aimsun Live which is a simulation-based traffic forecasting solution, developed and marketed by Aimsun. Traffic control centres use Aimsun Live (formerly Aimsun Online) to make real-time decisions about the management of a road network. It is used to dynamically forecast future traffic conditions based on the current state of the network and to evaluate incident response or traffic management strategies.

Aimsun Live slots right into the traffic control centre and continuously processes live field data, simulating vehicle movement inside a road network of any size, from a single highway corridor to an entire major world city. By combining these live traffic data feeds and high-speed simulations with emulation of congestion mitigation strategies, Aimsun Live can accurately forecast the future network flow patterns that will result from a particular traffic management or information provision strategy.

Chapter 2

Literature Survey

Some similar and notable past works that are providing a great help in deciding the state and action spaces along with the networks to be deployed when using different reward functions-

- Deep Reinforcement Learning for Traffic Light Control in Vehicular Networks-
  Xiaoyuan Liang, Xusheng Du,Student Member, IEEE,Guiling Wang,Member, IEEE,and Zhu HanFellow, IEEE

- Using a Deep Reinforcement Learning Agent for Traffic Signal Control -
  Wade Gendersa, Saiedeh Razavib

- Multi-agent Reinforcement Learning for Traffic Signal Control -
  Prabuchandran K.J.1, Hemanth Kumar A.N1, Shalabh Bhatnagar1,Senior Member, IEEE

  have proposed to divide the road surface in equal sized cells, and then generate a state representation composed of three vectors. the first vector indicates the presence of a vehicle in each cell, the second records the speed of the vehicle in each cell (0 if vehicle not present) and the third represents the current phase. The representation requires gathering information from expensive sensors and division into cells implicitly assumes lane driving. Their work uses a deep Q-network traffic signal control agent (DQTSCA), with the action-value function modeled as a deep convolutional neural network trained using reinforcement learning in a traffic microsimulator, SUMO, on an isolated intersection. The DQN algorithm used by them suffers from known instability issues due to non sta-

tionary nature of the target. The network ends up chasing a non stationary value which leads to an unstable training process.

- Deep Learning vs. Discrete Reinforcement Learning for Adaptive Traffic Signal Control-Soheil Mohamad Alizadeh Shabestary, Department of Civil Engineering, University of Toronto, Toronto, Abdulhai,Department of Civil Engineering, University of Toronto, Toronto,

- Reinforcement Learning for True Adaptive Traffic Signal Control
  -Baher Abdulhai and Rob Pringle and Grigoris J. Karakoulas
  have used positions and speeds of the vehicles in the at the intersection as inputs in the form of an image like structure wherein if there is a vehicle on the street, the specific cell corresponding to that part of the street is filled with 1, otherwise 0. By putting together these matrices for all the carriageways an image like representation of the position of the approaching vehicles at the intersection is formed.

Chapter 3

Chapters on the present investigation

A successful implementation of the RL model algorithm for a single traffic junction has been achieved and has been tested rigorously among varied state and action spaces and reward function so as to reduce the delay time as much as possible. As a result the agent is easily able to achive lesser delay time of the traffic when put against FST-60 (60 seconds to each section of the junction).

Following are the noteworthy aspects and achievements accomplished during the deployment of RL model on a single junction-

1. Establishing proper communication between the simulator Aimsun and external Python source.
2. Creation of an Environment class for Aimsun traffic simulation was necessary since Aimsun is not python simulated to controlled.
3. Fetching the data from the simulator like Density, Queue length and delay time of each section of the given junction.
4. Addition of real life models of Indian Vehicles like Auto rickshaw and motorbikes to make the traffic 3D rendering look more realistic.
5. Building the RL code around the Environment class to smoothen the training operation. Environment was created like OpenAI enviroments for the generalised testing and uses.

Figure 3.1: Moving from Left to right:
Leftmost image represents the map created for the Aimsun simulation which corresponds to the area around Siemens and the experiments have been carried out on the junction just outside Siemens
Middle iamge represents the 3D rendering of the simulation with autos and motorbiker along with busese and usual cars.
Right most image corresponds to the Enviroment created for the RL and Aimsun modulation.

6. Traing the RL model model on the juntion bu supplying the traffic from various other FST operated juntions.

7. Training different models on various state and action spaces for minimizing the delay in the traffic

Chapter 4

Results and Discussions

Up till now a proper framework has been established between the Aimsun api and the RL code along with the creation of a realistic simulation environment which replicates Indian traffic. Training and testing of the agent on a single junction has been carried out and the agent has achieved good results when put in comparison to naive round robin techniques

- Implemented RL model architecture on two running instances of Aimsun.
- Extend the architecture on multiple agents.
- Test the architecture on multiple traffic junctions.
- Training the model on real life data for 24 hours has been completed. Pyautogui has been used for automatic start and stop of the simulation for every episode reset.
- Lesser delay when competing against the FST 60
- Established a message passing interface between multiple junctions or agents training them.

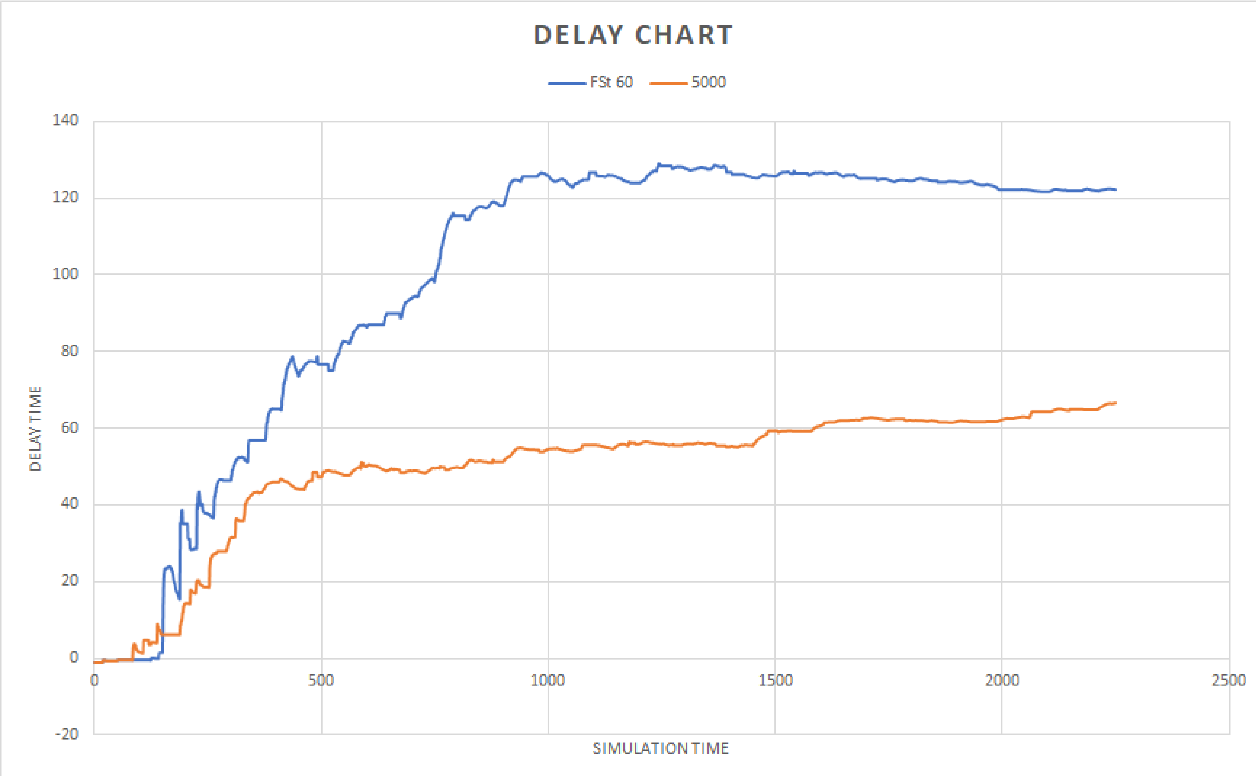

Figure 4.1: a

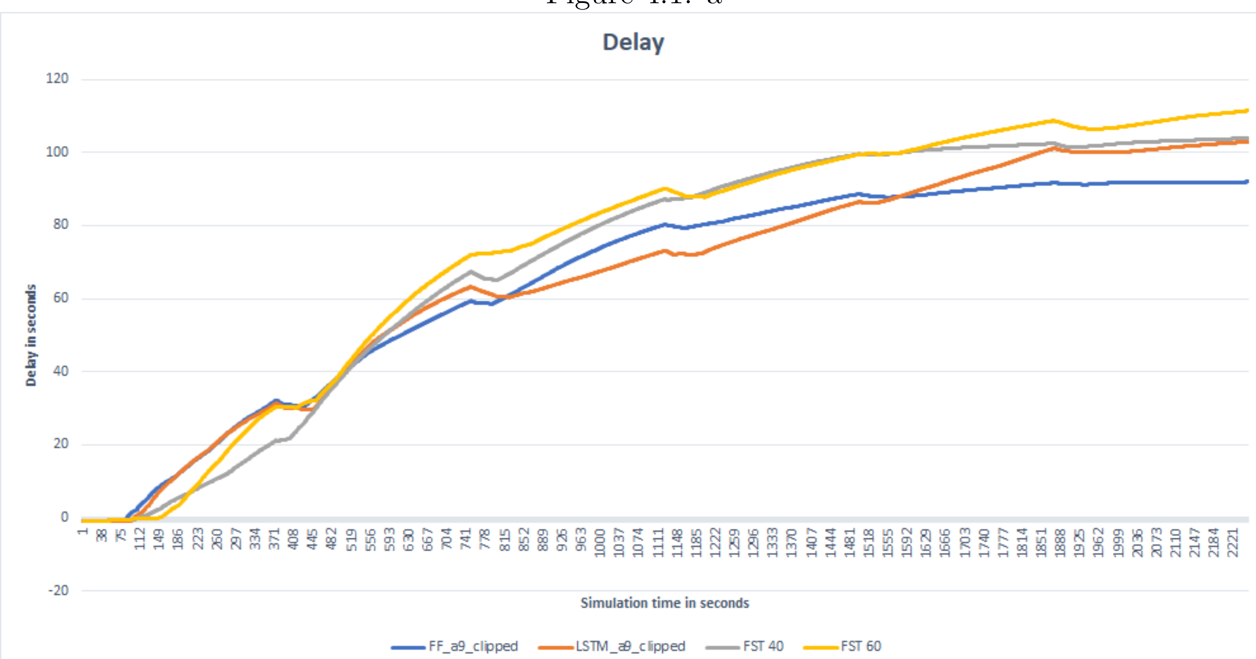

Figure 4.2: 1

Figure 4.3: Plots of Delay comparison:
a) The graphs represents the delay time against the simulation time for 60 minutes in simulator taken at a junction when FST 60 is used in comparison to the RL agent which gives much lesser delay time.
b) The graph represents the delay time against the simulation time for 60 minutes in simulator taken at a junction between LSTM and Feed Forward models along with FST 40 and FST 60

Chapter 5

Summary and Conclusions

Vehicle density in the cities, especially in the developing world, is increasing exponentially. This is both due to the population growth accompanied by increasing urbanization, as well as rise in the car ownership with improving economic prosperity. However, the road infrastructure is often not able to keep pace with this increase due to financial as well as space constraints. In such a situation adaptive traffic signal control becomes the key to achieving maximum utilization of the existing road infrastructure.

A traffic controller is a system designed to regulate traffic at a single or a set of traffic intersections using static or adaptive rules. While the former creates a fixed phase switching routine based upon the historical traffic data, the adaptive controllers measure the traffic density and vehicle delays at each approach, and then generate an optimal green time for various phases so as to maximize the vehicle throughput at the junction.

The project aims to provide the techniques to minimize traffic congestion on Indian traffic scenarios and is being tested on the data collected in the city of Bangalore; using the Reinforcement Learning.

Our focus is on designing a practical and robust adaptive traffic signal control system specifically tailored to the conditions and requirements of the developing countries. Project indeed aims on creating a smart traffic signal and then actually put the research work into production.

References-

1) Adaptive traffic signal control with actor-critic methods in a real-world traffic network with different traffic disruption eventsMohammad Aslania,, Mohammad Saadi Mesgaria, Marco Wiering

2) Adaptive Traffic Signal Control : Exploring Reward Definition ForReinforcement LearningSaad Touhbia,b,c,, Mohamed Ait Babrama,b, Tri Nguyen-Huub, Nicolas Marilleaub,Moulay L. Hbida,b, Christophe Cambierb,c, Serge Stinckwich

3) Using a Deep Reinforcement Learning Agent forTraffic Signal Control Wade Gendersa, Saiedeh Razavib

4) Multi-agent Reinforcement Learning for Traffic Signal ControlPrabuchandran K.J.1, Hemanth Kumar A.N1, Shalabh Bhatnagar1,Senior Member, IEEE

5) Reinforcement Learning with FunctionApproximation for Traffic Signal ControlPrashanth L Aand Shalabh Bhatnagar

6) The Study of Reinforcement Learning for Traffic Self-AdaptiveControl under Multiagent Markov Game EnvironmentLun-Hui Xu,1,2Xin-Hai Xia,1,3and Qiang Luo

7) Flow: Architecture and Benchmarking forReinforcement Learning in Traffic ControlCathy Wu, Aboudy Kreidieh, Kanaad Parvate, Eugene Vinitsky, Alexandre M BayenUC Berkeley, Electrical Engineering and Computer ScienceUC Berkeley, Department of Civil and Environmental EngineeringUC Berkeley, Department of Mechanical EngineeringUC Berkeley, Institute for Transportation Studies

8)Framework for Control and Deep ReinforcementLearning in TrafficCathy Wu, Kanaad Parvate, Nishant Kheterpal, Leah Dickstein,Ankur Mehta, Eugene Vinitsky, Alexandre M BayenUC Berkeley, Electrical Engineering and Computer ScienceUCLA, Electrical EngineeringUC Berkeley, Mechanical EngineeringUC Berkeley, Institute for Transportation Studies

9) Asynchronous Methods for Deep Reinforcement Learning Volodymyr Mnih, Adri Puigdomnech Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, Koray Kavukcuoglu

10) Reinforcement Learning for True Adaptive Traffic Signal Control -Baher Abdulhai and Rob Pringle and Grigoris J. Karakoulas

11) Deep Learning vs. Discrete Reinforcement Learning for Adaptive Traffic Signal Control-Soheil Mohamad Alizadeh Shabestary, Department of Civil Engineering, University of Toronto, Toronto, Abdulhai,Department of Civil Engineering, University of Toronto, Toronto,

12) http://richardhenry.github.io/hotqueue/apireference.html
Hot Queue documentation