Approximating Traffic Simulation using Neural Networks and its Application in Traffic Optimization

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Abstract

We present an idea for approximating outcomes of traffic simulation using neural networks, which might be especially useful in one of most difficult traffic optimization problems, the *traffic signal settings* problem. Results of initial experiments show that such approximation may have a very good accuracy, which may lead to important applications in advanced traffic management systems.

1 Introduction

Large traffic congestion is a serious civilizational and commercial issue, causing waste of fuel/energy, drivers' time and money, increasing noise and emission of fumes [1]. Thus, the problem of a proper traffic management is of utmost importance for our society. There exist many approaches for improving urban traffic, e.g.,

- reducing traffic density by introducing fees (or bans), car-sharing / carpooling, extending public transport, building new roads,
- advanced traveler information systems (e.g., variable message signs, Google Maps),
- adaptive traffic signal control.

In the presented research, the focus is on the last approach: adaptive traffic signal control. More precisely, we design algorithms for the *traffic signal setting* optimization problem, which was proven to be NP-hard for very simple cases ([2]) and seems to be at least that hard for a more advanced traffic models, e.g., microscopic traffic simulation model based on a cellular automaton, which is used in our work [3]. However, we expect that the presented methodology may go far beyond that problem and may found applications in many other optimization problems related to complex processes.

In our approach, we evaluate traffic control strategies using large-scale traffic simulation and use metaheuristics (e.g., genetic algorithms) to search through a large space of possible settings, to find the best one (or suboptimal). This approach alone may give quite good results ([4], [5]), but a large computational complexity prevents application of our method to a real-time traffic management (however, the approach may be still very useful). Thus, one of major goals of our recent research was to speed up conducted experiments, in particular, to reduce time required for evaluating traffic control strategies (i.e., computing values of the objective function).

We came up with an idea for applying neural networks to approximate outcomes of traffic simulation, which may significantly reduce time of computing values of the objective function. We implemented the idea and ran initial experiments, focusing on the traffic signal setting problem. Our experiments gave promising and potentially very important results.

In Section 2 we present state of the art of traffic optimization and identified issues of existing approaches. In Section 3 we describe the traffic optimization problem that we tackle and outline our idea for a simulation-based traffic management system. We also explain why the undertaken

research is so important and may have a significant impact on the future of traffic management. Section 4 summarizes our experiments related to approximation of simulation outcomes using neural networks. Finally, Section 5 concludes the paper.

2 Existing approaches to traffic signal control

Some cites have already installed traffic signal control systems such as SCATS ([6]), SCOOT ([7]), RHODES ([8]), OPAC ([9]), MARLIN ([10]). In many cases their quality is good and they are able to improve the traffic, at least in typical, recurrent and predictable conditions, and in case of low travel demand and low number of cars. The problem usually arises in case of a heavy demand or atypical conditions, such as sudden road blockage (e.g., caused by a car accident [11]), changes in traffic organization (e.g., because of mass events or roadworks), bad weather conditions.

We identified the following issues of existing traffic management systems:

- reactiveness, but not proactiveness: reacting to past and present traffic conditions (which might be sufficient for regular, smooth, recurrent traffic, but may not be sufficient when major changes happen - the reaction might be inappropriate or just too late to prevent occurrence of a large traffic jam), but not anticipating and preventing undesired traffic states,
- lack of accurate evaluation of changes introduced to the traffic control system,
- relatively small space of possible modifications to the traffic control system,
- lack of scalability, questionable efficiency in case of large road networks.

A comprehensive review of existing traffic management systems can be found in [12].

3 The idea for a simulation-based traffic optimization

To solve problems related to existing traffic management systems we develop a simulation-based traffic management system evaluating many different traffic control strategies using large-scale traffic simulation. Also, metaheuristics (e.g., genetic algorithms) are used as the main optimization method, neural networks are used to approximate values of the objective function obtained from the simulation to speed up computations, along with cluster computing (e.g., Apache Spark framework), GPU and a cloud computing infrastructure, which may also ensure robustness, scalability and location-independence.

The proposed system is composed of 4 main modules:

1. module for collecting real-world traffic data,
2. module for building virtual traffic model,
3. module for finding (sub)optimal traffic management settings,
4. module for applying (sub)optimal settings to the real-world traffic control.

We don't go into technical details of the system, because it is beyond the scope of the paper (details can be found in the appended slides [13] and poster [14]), instead, we focus on the crucial component of the system, which is a **module for finding (sub)optimal traffic management settings for a given traffic situation**, represented as a virtual traffic model (built based on collected traffic data: positions, speeds and routes of all cars). Among possible traffic control settings, which values could be altered to find the optimum, we can distinguish, for example: traffic signal settings, route assignments, parameters of algorithms of drive of self-driving cars. The focus of the presented research is on traffic signal settings, namely, so called *traffic signal setting* optimization problem:

Definition 3.1 *Traffic signal setting problem*

- *Given is a directed graph of a road network with traffic signals located in some vertices. Traffic signals are objects with attributes: duration of a red signal phase (T_R), duration of a green signal phase (T_G), offset (T_S) - values of these attributes may be modified.*

- ***Traffic Signal Setting** (TSS) - set of values (T_G, T_R, T_S) for all signals in a road network.*

- *Given is a virtual traffic model: cars with initial speeds, positions in some vertices of the road network graph, static routes, rules of drive on edges.*

- *Given is an objective function **F** which calculates the quality of a traffic signal setting.*

- **Goal:** *Find a traffic signal setting for which value of F is (sub)optimal.*

The presented optimization problem is nonconvex and in some cases was proven to be NP-hard ([2]).

3.1 The objective function

What should be the objective function F? How its values should be calculated? Ideally, we would like to have a function which for a given TSS (and initial traffic conditions) returns some values related to traffic efficiency, e.g., the total waiting time (times spent with a speed $0\frac{km}{h}$, summed up over all cars), time spent with a low speed (e.g., below $20\frac{km}{h}$), average speed of all cars, delay (wasted time, in comparison to the free flow case), emission of fumes, fuel consumption, length of queues at crossroads, number of stops. In case of a real-world traffic, existing in an open environment, there is no such computable function (having such a computable function would mean that we can deterministically simulate and predict the future). The only solution is to make approximations, such as microscopic traffic simulation models describing dynamics of cars. They can simulate the traffic, starting from a certain initial conditions, and compute positions and speeds of all cars in each second, as well as values of the objective function (e.g., waiting times) of the optimization problem. However, finding an optimal traffic control setting in a simulation scenario may not necessarily mean that this setting will be also optimal in a real-world scenario, but there are reasonable chances that it will be sufficiently good, e.g., it will prevent occurrences of traffic jams and will be usually better than most of other settings. To make it happen, it is important to have traffic models and traffic simulators that have very good consistency with a real-world traffic, at least with regard to values of the objective function.

In the presented research, the authors chose to use the Traffic Simulation Framework software (TSF, [3]), which employs realistic road network data of Warsaw, originating from the OpenStreetMap service [15], and implements a microscopic simulation model based on a cellular automaton. To make simulations realistic, the software was calibrated using population density data, origin-destination (OD) matrices and results of traffic flow measurements for Warsaw.

3.2 Traffic optimization using genetic algorithms

For the presented optimization problem, since 2010 we have been running series of experiments with a genetic algorithm (GA) encoding set of traffic offsets (values from the set $\{0, 1, 2, \ldots, 119\}$) for the whole road network in Warsaw as genotypes (so far, we have been assuming that T_R and T_G were constant: $T_R = 62, T_G = 58$). In the first try, in 2010, we achieved 3.11% reduction of waiting times (comparing to the best known setting in a randomly generated initial set) after only 10 iterations of the GA algorithm (details are described in [4]), but one of drawbacks was a significant computational complexity - running a single traffic signal setting evaluation (simulating 10 minutes of traffic) took a few minutes on a standard machine. The consequence is that the method can't be applied to the real-time adaptive traffic management responding to dynamically changing traffic conditions (however, it might be used to determine default optimal settings for each hour, based on historic data and patterns, and estimated OD matrices, but still it is important to compute values of the objective function relatively fast).

The later research on this topic was focused on speeding up computations of the objective function and the whole optimization process. The most significant progress was achieved in 2015, when computations were run in a high-performance computing cluster and a microscopic simulation model was replaced by a mesoscopic model, in which travel times (and waiting times) of vehicles are just estimated based on default speeds of drive for each road segment - times of computing values of the objective function were significantly reduced giving opportunity to evaluate much more traffic signal settings. As a consequence, GA was able to find settings reducing waiting times up to 18.12% on the whole road network of Warsaw, and even more (up to 51%) on a smaller region (*Stara Ochota* district - 15 crossroads with traffic signals). Details can be found in [5].

4 Approximating values of the objective function using neural networks

In order to achieve greater speed up of computing values of the objective function, we trained neural networks to approximate outcomes of simulations in a microscopic model. In case of a sufficiently good accuracy of approximations, it would be possible to compute (approximate) values of the objective function using neural networks a few orders of magnitude faster than by using simulations.

4.1 Setup

We developed TensorTraffic - a TensorFlow-based software for training neural networks to approximate outcomes of traffic simulations. Using this software, we ran many experiments aiming to approximate values of the objective function - the total time spent with a speed $0\frac{km}{h}$ during 10 minutes of simulation, summed up over all vehicles travelling through a subregion of a Warsaw's road network (*Stara Ochota* district - 15 crossroads with traffic signals). In the paper we focus only on the most recent and valid results, but many initial experiments led us to useful conclusions which we took into account while designing next experiments.

We performed our experiments on the data from the TSF's microscopic model, running in a setting with 30000 cars initially and 20 new cars starting drive in each second. We randomly selected 117033 traffic signal settings with a value of the objective function computed by the simulation. Each traffic signal setting can be represented as a vector of 15 offsets - random integers between 0 and 119, which were the features of our model.

Then, we ran in TensorTraffic a very small grid search (12 configurations) to optimize the network. Each time we randomly divided obtained set into a training set (80% of all settings) and a test set (20% of all settings) and applied a 5-fold cross validation on the train set. We trained the network using Adam optimizer [16] with a batch size of 100. The loss function was a mean square error. We considered 3 different values of a learning rate (0.001, 0.01, 0.1) and 4 different configurations of neurons: $[100, 100]$ (2 layers with 100 neurons each), $[100, 100, 100]$ (3 layers with 100 neurons), $[200, 200]$ (2 layers with 200 neurons), $[200]$ (1 layer with 200 neurons).

4.2 Results

In the best scenario, for $learning\_rate = 0.01$, $neurons = [100, 100, 100]$, we achieved an average relative error 1.56% and a maximal relative error 9.18%. A similar result was achieved for $learning\_rate = 0.1$, $neurons = [100, 100, 100]$: an average relative error 1.74% and a maximal relative error 8.47%. We also found out that approximations are better for larger networks (more layers, more neurons). Details can be found in the appended slides.

5 Conclusions and future work

Generally, training neural networks (or other machine learning algorithms) to approximate outcomes of simulations of complex processes might have many important applications. Usually such simulations are time-consuming and it is not easy to speed them up or estimate their results, because complex systems are usually computationally irreducible [17].

The conducted research is preliminary, but results are very promising. We have started working on next experiments, in which we introduce additional parameters (and NN's features) related to the number of cars and urban area on which the objective function is computed and initial results show that we can achieve even better approximation accuracy for a microscopic model.

From a practical point of view, it is important to train the neural network as fast as possible, so an interesting research question is how this process can be optimized. Another interesting question is how the accuracy of approximations depend on the size of the training set and how to design neural networks to minimize required size (in order to minimize the number of required simulations). We are planning to investigate these topics and employ cloud computing infrastructure and cluster computing frameworks (e.g., Apache Spark) to speed up required experiments.

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