



A Study Based On Artificial Intelligence Of Smart Cities For On Demand Automation Of Vehicles System

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ABSTRACT

There are many ways in which automated vehicles (AVs) could improve smart city transportation. Autonomous vehicles (AVs) have the ability to improve vehicle platooning by decreasing the required space between vehicles. However, even bigger changes might be possible with well-developed autonomous cars. The present road and highway designs have to be changed if autonomous cars start to be used more often. Maximizing the potential of autonomous vehicles in smart public transportation networks calls for the kind of swift preparation that is essential. Researching and using the unique characteristics of AVs has the potential to lead to technological advancements and the development of AV systems with a plethora of extra benefits. This is due to "the underlying three main types of study subjects: Automotive information systems, including data pertaining to self-driving cars and roadways. "When driverless cars connect to the power grid, this is called a "V2G" scenario. Batteries are the power source for almost all driverless cars. Power generation costs can rise if smart grid supply and demand are out of sync. To keep power networks stable and balanced, one option would be to tap into the massive battery capability of autonomous cars. Charging the driverless cars is a potential option if our energy supply exceeds our needs. In the case that demand exceeds supply, they may decide to turn off the self-driving cars (AVs) so that more power may be sent into the grid.

Keyword: *Automated Vehicles, Smart Transportation Network, Traffic Forecasting*

Introduction

The human species has been continually creating new modes of movement over the course of millennia, beginning with carriages carried by animals, and progressing all the way up to high-speed trains and vehicles of recent times. The ultimate goal of the initiative has always been to cut down on travel times and expenses while simultaneously improving the efficiency and safety of transportation. The cabs, buses, and subways that are used in modern urban transportation are the essential components. various people have a tendency to prefer various modes of transportation due to the fact that every kind of transportation has both positives and negatives associated with it. A large number of passengers may be transported by public transit, such as buses and subways, for a nominal cost and in accordance with the schedule. However, in order to accommodate a large number of customers, the service provider was most likely only stop at the most popular sites. This is the case even if these sites are not necessarily the "beginning point" or "final destination" for any one client. However, if you take a cab, you won't have to worry about being crammed in with a bunch of people and you'll be able to go from point A to point B in luxury. It is not necessary for passengers to switch trains; they are free to continue with their journey from any terminal. Taxis are often more expensive than public transportation options like buses and subways, and passengers in densely populated areas may have to wait for a taxi to arrive. It's possible that the slowness of the cab service made the traffic jam much worse. The Transport on Demand (MoD) system is a relatively new method of transportation that provides the "passenger" with more agency (Chau,2017).

Predicting "traffic "flows is useful" for building AV-based intelligent transport "systems in a smart city, as they saw in Chapter 1. "Demand for transport services is a key component of traffic data. A number of requests for

transportation at a certain location and time. It can make it easier to send empty cars to regions with heavy traffic" in advance, cutting down on wait times and improving service for customers. In this chapter, they look into how geographical and temporal correlations in transport and related data might be used to forecast future travel demand. To do this, researchers "visualize" the travel needs in the city at a given time as a picture, with each tiny region representing a pixel and the trip demand for that area being the value of the pixel. A model dubbed the Multi-Scale Convolutional Long ShortTerm Memory network (Multiclinality) is presented for travel demand prediction, and it takes its cues from the deep learning approach used for image and video processing. Input demand data from the past may be processed using Multiclinality. It stores the derived features in a similar fashion to LSTM by performing convolution between the input and weights. To further improve the forecast accuracy, Multiclinality may leverage historical data with varying geographical resolutions and metadata, such as time and weather information. The proposed deep learning model is tested on around 400 million records from a subset of Manhattan, New York taxi records spanning six and a half years.

Background of the study

Self-directing autonomous "vehicles" (AVs) are seen as a game-changer for the transportation industry. "When there is no human driver present, "autonomous vehicles" (AVs) are able to drive themselves on public roads without the need for human intervention. Using a network of sensor and communication devices, they are able to gather and transmit information about their physical surroundings. This enables them to operate in a completely autonomous manner, which includes the ability to change lanes and merge with other vehicles. The current trend in the industry indicates that batteries that run on electricity are the main source of power for the majority of autonomous vehicles. Since the beginning of the Defense Advanced Research Projects Agency's (DARPA) Urban Challenge in 2007, there has been a significant amount of attention and curiosity over it. Google had collected more than three million kilometers of autonomous driving by the time May of this year rolled around. This was a continuation of the company's demonstration in 2015 that its driverless vehicles could operate freely on public roads. Tesla's Autopilot, a self-driving system, is now being considered for use in corporate vehicles. All of these applications make it abundantly evident that AV is a technology that was see a meteoric rise in prominence over the course of the next "years. "When it comes to the process of creating and deploying individual autonomous vehicles (AVs), collective control has the ability to expand the benefits and possibilities that already exist with completely automated control. "Autonomous MoD" (AMoD) is the name of a new mode of transportation that is currently under consideration. It integrates the Ministry of Defense with autonomous driving, making it possible for autonomous vehicles to provide transportation services. This would result in an increase in the number of different services that are provided. A commercial autonomous car service known as "Waymo One" was introduced in Phoenix, Arizona, in the United States of America in the year 2018. A smartphone app may be used by customers to make arrangements for a pickup. The Autonomous Vehicle Public transit System (AVPTS) is one project that wants to expedite the financialization of ridesharing. However, it is also one of the initiatives that aims to incorporate autonomous vehicles into public transit. Monitoring and regulating a fleet of autonomous cars allows for the most effective routes and times to transport "passengers" to be determined by a single, centralized location. Not only does it have the ability to maximize revenues, but it also provides valid requests with the highest attention (Tesla,2020).

The purpose of the research

Technology for smart cities are based on the Worldwide Web of Things (IoT), which enables the conversion of urban surroundings into sustainable and intelligent ecosystems. The Internet of Things (IoT) enables the utilization of seamless connectivity, data collecting, and real-time analytics to achieve optimum resource management, improved public services, more citizen involvement, and more livable ecosystems. The Internet of Things (IoT) could develop further in the future, leading to smart cities that are quite different from what they are now. Smart cities are communities that are sustainable, linked, and operate efficiently (Kim,2018).

Literature Review

The length of time that passengers are required to wait at different stations has a major impact not just on the overall health of the train system but also on mental health concerns such as stress and anxiety. There is a possibility that passengers might benefit by being aware of the wait times at various sites beforehand. As a result of this, suppliers of services may have an easier time designing a transportation system that is more intelligent, which in turn minimizes the amount of time that individuals spend trapped in traffic (Bengio,2019). However, it may be expensive to continually gather all of the necessary data at each and every point within a public transit system to meet the requirements. Because of this, it is encouraging to see that researchers are focusing their efforts on developing techniques for measuring wait times by making use of other data that is more readily accessible (proxy data). The purpose of this chapter is to offer a deep learning strategy that makes use of just preliminary data and a little quantity of labeled data in order to determine the length of time that individuals wait at stops for public transit. A technique known as semi-supervised learning (SSL) was used in

order to ascertain the average wait times at each station. A look at the graph revealed the public transportation system's interconnectedness. The input data are vectors of feature vectors that show the movements of passengers over the course of time, and the data being provided are waiting time levels that correspond to a selection of stations. Our deep learning model has the capability of classifying the various waiting times that are experienced at the stations. Utilizing Graph Convolutional Networks (GCNs), which are able to function directly on graph-structured data, allows for the dynamic nature of transportation networks to be taken into account. Certain stations' travel data and waiting times are used for the purpose of performing testing on the actual Hong Kong subway system. These tests are intended to be conducted in Hong Kong. Almost every time they run the algorithm through it, they are able to get the appropriate categorization for the various degrees of waiting time at the stations.

Research Questions

1. How the "traffic data and travel demand are" related?
2. What is the "procedure for AVs to avail dynamic lane reversal-traffic" scheduling management?

Research Methodology

In this part, the algorithm that was used to find a solution to the problem is described in depth. Both the MPC and GA components, as well as the solvers, are included in it. An illustration of the algorithm's flow may be seen in Figure. Within the framework of an MPC-based optimization process, the first step involves optimizing a restricted time horizon by using both past and future data. Subsequently, they iterate and enhance the outcome by including new data from the subsequent time period. In accordance with this MPC paradigm, forecasters of travel demand have the potential to enhance the precision of their predictions by making use of the most recent data that is accessible for each time period. The first thing that they do is make sure that the necessary information R and \bar{R} are up to date at the beginning of each time period t . The GA and solver components are both provided with the most recent information.

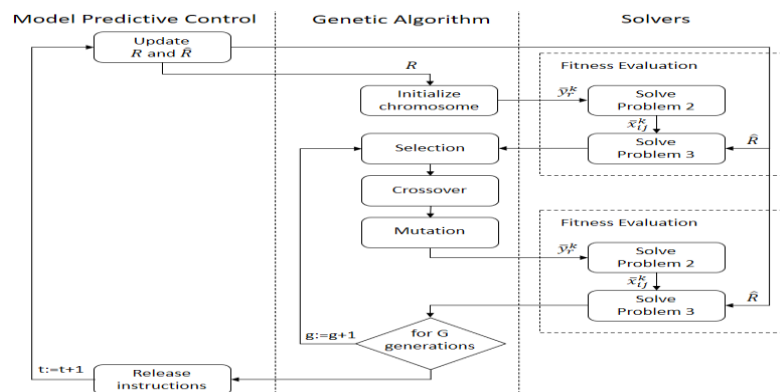
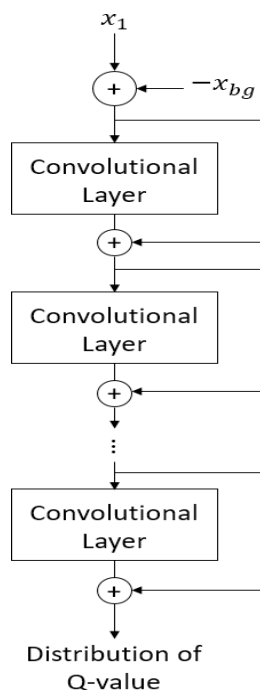


Figure 1: Algorithm Flow Chart

Conceptual Framework



Research Design

The new yellow cab trip data from "York City Open Data" was used to evaluate both the system and the strategy it employs. The information that is gathered during journeys was used to generate a pool of requests for transportation. Figure demonstrates that New York City is the most accurate representation of the road network due to the high density of its vertices and edges. A road segment that has the same length is represented by a collection of vertices that are four by six pixels in size. Assuming that the speeds of all vehicles stay the same, any edge that is the same distance away was a c_{ij} that is equal to one time slot. It is anticipated that the amount of time necessary to run over each edge was consistently be the same. Furthermore, they entirely disregard flashing red and green lights as well as stop signs. This is not even a consideration. The allowed vehicle capacity (Q_k) and the passenger capacity (q_r) both have a value of 5, which is the value in this case.

A random selection is made from the pool of transport requests to choose the set of transport requests R and the predicted trip demand R during the first time period. The construction of a relationship is accomplished by randomly picking requests from R_2 to build R_J . This is done in light of the fact that R_2 represents the predicted R_J in the future time period.

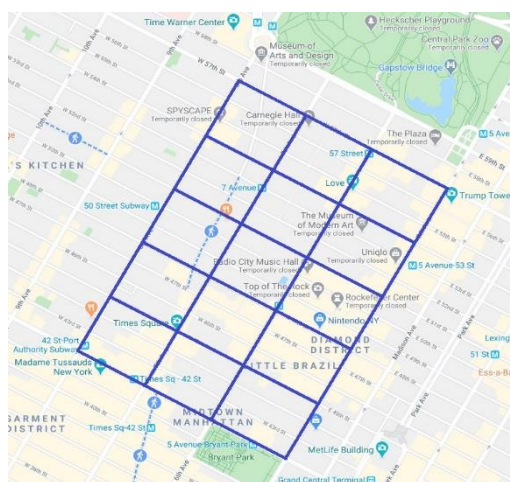


Figure 2 The selected road network

Data Analysis

When it comes to the process of updating the Q-parameters, the TSC approach that they have provided calls for a considerable amount of time spent on training. the internet-based During the training process, the convergence rate is an important consideration. Using technologies such as TensorFlow and Python, the deep reinforcement learning algorithms that were built by TSC are put into action. The OpenAI Gym provides you with the opportunity to practice in either the SUMO or Sumo-web3d virtual environments. If they are talking about testing, the GeForce GTX 1080 Ti is the one they are looking for.

Result

Table : Travel demand prediction errors with and without time information for" $\tau = 1$.

Model	With time info?	RMSE	MAE	SMAPE
RNN-LSTM	No	1.7439	1.0224	0.1911
	Yes	1.6243	0.9682	0.1766
ConvLSTM	No	1.6616	0.9980	0.1811
	Yes	1.6485	0.9825	0.1776
MulitConvLSTM	No	1.6107	0.9723	0.1789
	Yes	1.5405	0.9255	0.1663

Weekday rush hour traffic is particularly bad since people are rushing to and from work at this time. Worst case scenario: they don't want to brave the elements. The researcher examine the responses of deep learning models that are trained to forecast demand for travel based on time series data. Table shows the errors produced by several deep learning models while trying to forecast demand for travel, both with and without the data. Typically, the precision of demand forecasts for travel is enhanced when relevant information is available. Ignoring weather data in this study is for clarity's sake. It has been shown in that taking the weather into account may improve the precision of traffic flow projections. Therefore, the deep learning system may be trained with additional data to provide more precise "traveler" demand estimates.

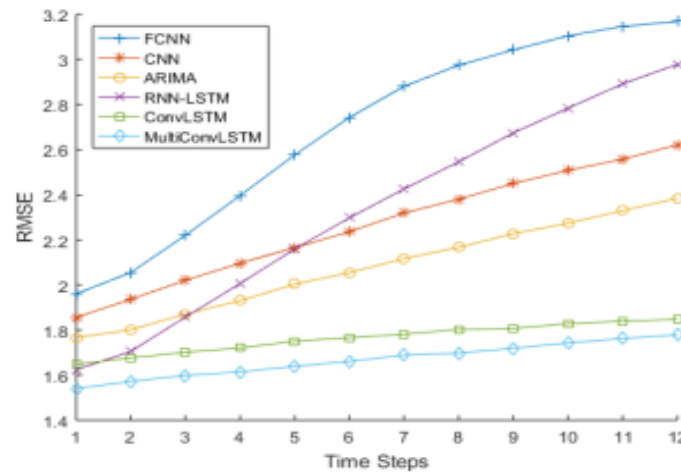


Figure : Multi-step error of travel demand prediction

Discussion

This chapter presents Multiclinality, a unique deep learning model. Its goal is to project future travel demand and reserve vacant automobiles in advance for possible customers' sources of travel. Utilizing preexisting data and metadata to extract temporal and geographical aspects, multiclinality—which is based on the multi-scale network and Comvest—has the ability to estimate future demand 43. In this study, they tackle the problem of trip demand prediction and provide many different pre-processing strategies that may be used with the given data. In a comprehensive experimental investigation, Multiclinality surpasses the latest algorithms for predicting in both single-step and multi-step predictions on a real-world transportation dataset from New York with over 400 million records. While the major focus of this chapter is travel demand forecasting, the built deep learning system is structured in a way that allows it to be extended to other domains. Some probable applications of this theory include analyzing images and videos due to its strong relationship to ordered information in visual media. To pre-allocate AVs, more precise passenger origin-destination (OD) flows prediction is necessary in addition to travel demand analysis. This is because AV stations are often placed in close proximity to passengers' ultimate destinations. The reason the OD matrix is often used to illustrate OD flows is because they have more dimensions than trip demand. Even if it may not be the optimal choice, our proposed Multiclinality might prove to be useful for predicting OD matrix data. The researcher was discuss the several approaches to controlling OD fluxes and the corresponding forecasting mechanism in the next chapter(Waymo LLC,2020).

Conclusion

The researcher propose a novel technology, which they abbreviate as Avoid (autonomous vehicle),for future smart cities. This thesis describes this system. Avoid primarily focuses on artificial intelligence-based transportation technologies, such include driverless cars. There's a chance that transportation and society may improve as autonomous vehicles (AVs) become more reliant on their own abilities. The supervision of autonomous cars, traffic data forecasting, and road infrastructure change are three of the most crucial tactics. The main goal of this project is to use artificial intelligence to enhance the transportation system for autonomous vehicles. Apart from their speed and independence, which make them quite desired, they provide Avoid solutions that was further enhance their usefulness. Three of the most important contributions to transportation networks have been the building, maintenance, and extension of road networks. This data is necessary in order to predict traffic patterns, keep an eye on the rollout of autonomous cars, and prepare for and react to changing conditions (Waymo,2020).

References

1. K.-F. Chu, E. R. Magsino, I. W.-H. Ho, and C.-K. Chau, "Index coding of point cloud-based road map data for autonomous driving," in Proceedings of the 2017 IEEE 85th Vehicular Technology Conference, Jun. 2017.
2. Tesla. (2020). Model S, [Online]. Available: <https://www.tesla.com/models>.
3. Waymo LLC. (2020). Waymo one, [Online]. Available: <https://waymo.com/waymo-one/>.
4. Waymo. (2020). Journey, [Online]. Available: <http://waymo.com/journey/>.
5. Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, et al., "Gradient-based learning applied to document recognition," Proceedings of the IEEE, vol. 86, no. 11, pp. 2278–2324, 2019.
6. S. Kim, S. Shekhar, and M. Min, "Contraflow transportation network reconfiguration for evacuation route planning," IEEE Transactions on Knowledge and Data Engineering, vol. 20, no. 8, pp. 1115–1129, Aug. 2018.