Real-Time AI-Based Traffic Prediction for Autonomous Vehicles

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1. Introduction

As part of the core effort to make transportation safe, effective, and efficient, mild or fully self-driving vehicles are being developed and tested around the world. Autonomous transport systems in cities can potentially benefit from other technical areas, including integrated traffic management, greatly boosting their effectiveness and, by doing so, the quality of service and safety. AI is becoming one of the pillars of upcoming traffic systems. AI can be used to build predictive models of traffic, which are useful for the management strategies to maintain traffic within operational boundaries. The more timely such predictions are, the better traffic systems can adapt. It has, thus, become increasingly clear that real-time traffic prediction that can work effectively will be fundamental in a future world with ever-increasing levels of automation. For urban intelligent transport systems whose designs increasingly rely on AI-based methods, traffic analysis is one of—if not the—primary data sources used.

To ascertain useful temporal trends, traffic systems must be timed to respond accordingly. Good predictions of traffic volumes, speeds, and traffic state values will likely improve specific additional services in future urban areas, such as driver assistance and control, route planning, and the timely making of real-time journey services. When vehicular infrastructures approach their capacity limits, the ability to monitor and negotiate traffic in response to events in real time becomes increasingly vital. We consider the application of Deep Learning for real-time traffic prediction in an AI-based manner. We will start by distinguishing some of the differences between traditional concepts and AI-driven fabrication of these traffic predictors. We offer new insight into the nature of such states. Finally, we close by indicating the sorts of industrial and academic research sectors in which our research on such problematic questions might be of use.

2. Understanding Traffic Prediction in Autonomous Vehicles

Given that safety-critical decisions for driving must be made in fractions of a second, accurate and fast traffic forecasting is an essential aspect of autonomous vehicle safety and comfort. The increasing automation of vehicles has made the need to forecast traffic more urgent than ever. Consequently, forecasting methodologies that can generate accurate predictions well in advance have received special attention from the automotive industry.

Traffic prediction for autonomous vehicles involves the use of big real-time data from various sources to provide real-time traffic maps and analytics. It can be carried out by two forms of data, namely past data and future sensor data. Such predictions require models that forecast the future spatial occurrence of vehicles, speed of vehicles, as well as future states of the vehicles, such as road relevancy values. With real-time accurate forecasts, route planning and eco-driving can be carried out by onboard coaches and navigation applications. In summary, traffic prediction is the forecasting of all or key attributes of vehicles on an upcoming time frame horizon. Based on the time frame, there are always n outcomes that can be generated by any state-of-the-art prediction module, where n ranges from 1 to N: up to the complete prediction horizon.

The ability of such predictions can have far-reaching implications on the joined field of decision-making using prediction. The surveys reviewed decades of techniques and briefly touched upon the previously proposed classification of prediction techniques. These predictive methodologies were broadly based on the type of pattern to be modeled, and in particular, the datasets and attributes used, namely traffic speed, historical vehicle occurrence, events and incidents, traffic queues, and future sensor data. The survey also studied the use of features and clustering techniques. However, the most effective prediction methodologies were based on combined feature prediction. Generally, all of these surveyed methodologies showed lower predictive accuracy for longer forecast horizons and bursts in complete prediction horizon for future vehicle states, such as road relevancy, thresholds, etc. Most of the existing works also suffer from common issues such as computational overhead cost, real-time applications, and inability to scale to very large traffic networks.

2.1. Challenges in Traditional Traffic Prediction

The majority of traditional traffic prediction methods face several challenges when it comes to accurately predicting traffic conditions. One primary concern is data availability, as measuring and collecting traffic data from multiple sensors along all road segments at a high temporal resolution is costly and may not be feasible in every location. Furthermore, predictive algorithms need to be able to work in an online setting, where predictions of future traffic conditions are made in real time and more historical data is continuously made available. This includes the original algorithm runtime, as well as batch training and hyperparameter optimization. Traffic prediction also needs to be able to model the inherently non-linear traffic dynamics that are hard to replicate with simple rule-based systems or statistical models. Predictions need to be able to model both the traffic system as well as human decision making, which can be hard to accurately model due to its complexity and unpredictable nature.

One reason why it is so difficult to model traffic in general is that traffic conditions and driver behaviors can be highly irregular and non-deterministic. Furthermore, traffic signals vary based on geographic location and can have traffic light timings and road rules that change based on time and location. Lastly, although some prediction methods also use real-time data to predict traffic conditions, the integration of these two data points can be challenging given their inconsistent and perhaps incompatible nature. This means that methods need to be developed in order to normalize metadata and use them in a joint framework. One main worry is also related to the temporal aspect. Traffic conditions can change rapidly and abruptly, and the method that is developed needs to account for this with either short forecast times or the ability to quickly adapt to changes in traffic conditions. Overall, traditional traffic prediction methods can be broken down into two categories, namely rule-based systems and three-step benchmark methods, neither of which are suited to accurately model and predict such complex and varying situations in a smaller geographic region on a high-resolution time scale. Given all of these limitations, a new method for traffic prediction needed to be proposed that could overcome these challenges.

2.2. Benefits of AI-Based Real-Time Traffic Prediction

II. Literature Review

2. Computational Traffic Prediction 2.2. Benefits of AI-Based Real-Time Traffic Prediction Numerous benefits are achievable by integrating modern AI-based methods in data-driven and real-time traffic prediction systems. AI algorithms can handle vast amounts of data

quicker to achieve instantaneous predictions, with no need for a specific update interval, and update the predictions in a timely manner whenever input data are received from the surveillance systems and vehicle fleet. It can yield accurate predictions even of traffic states located more than half an hour ahead, with instant resolution.

Unlike traditional time-series approaches, where an explicit model structure has to be designed, deep learning-based traffic models can learn from new data while making predictions. This improved adaptability makes traffic predictions more accurate, useful, and informative, even if traffic management strategies and policies change over time in some areas of urban mobility or transport systems. Other benefits, such as the execution of proactive and real-time traffic management and transport services, contribute to a more timely, sustainable, efficient, and reliable transportation experience; improving the performance of automated and autonomous vehicles and enhancing their safety features, such as advanced driver-assistance systems, are also feasible. Furthermore, AI systems that drive knowledge and management information reports can be inherited from such data streams in order to take crucial, incisive, and efficient operational management decisions that enhance the performance, safety, and security of transport networks and systems. Overall, all such AI-based benefits are crucial for the autonomous operation of vehicles and fleets in urban areas. Many researchers have considered the application of AI techniques for traffic prediction to improve the performance of existing and future traffic control systems. The integration of viable and reliable prediction systems that seamlessly interact with real-time vehicle systems is an essential first step.

3. Machine Learning Techniques for Traffic Prediction

Machine learning has been presented as one of the most effective data-driven techniques applicable to the domain of traffic prediction. Being capable of effectively capturing the non-linear spatial and temporal patterns embedded within traffic data, machine learning techniques have been shown to offer a broad scope for predictive modeling through various algorithmic strategies such as neural networks, support vector machines, and an ensemble of these algorithms. Within the machine learning application to predictive modeling, the ensemble techniques, which integrate the predictive capability of multiple base models, have been recognized to improve prediction performance and overcome the issues related to single results or methods by averaging various predictions. Moreover, the strength of ensemble models has also proven effective in traffic prediction through enhanced prediction accuracy and generalization. In line with this, the machine learning methods occupy prominent positions in the traffic prediction domain due to their promising ability to capture high-dimensional patterns and deep relationships within traffic data.

Applications of machine learning techniques have been widely explored for traffic prediction at different temporal horizons. A variety of machine learning approaches have been examined in this respect, with the primary distinction being made based on the algorithm type. One of the cornerstones of categorizing machine learning techniques in traffic prediction is based on the character (static or dynamic) of the model that is used to capture the relationships within traffic data. Further, machine learning techniques differ with regard to the quality of data inputs, as some methods require points and the complete time series as input data for the prediction model. Another distinctive feature with regard to machine learning techniques, and one of the topics of this paper, is prediction horizon-based categorization. From this perspective, a variety of machine learning techniques have been examined, including DNN, CNN, and DeepAR-LSTM, which are capable of predicting several steps into the future. Despite the apparent benefits of using machine learning techniques for traffic prediction, a certain degree of uncertainty still exists with respect to the potential of these models for different predictive horizons. Each of the studies summarized in this section identifies a particular machine learning model for long-term traffic prediction and provides insights into its potential benefits and limitations.

Traffic predictions can either be short-term, medium-term, or long-term, which relates to the nature of the prediction horizon. There are three main types of techniques explored in traffic prediction. A coarse-grained traffic flow prediction is designed to forecast the traffic situation and can categorize the situation into typical states. A traffic speed prediction aims to estimate traffic speeds for roads, lanes, or vehicles consisting of continuous speeds. Finally, congestion duration or downstream/backward queue length and propagation distance can depict detailed congestion information including queue length and congestion location. Estimating detailed congestion was also a function of the congestion prediction models related to long-term prediction.

3.1. Supervised Learning Algorithms

The basic supervised learning algorithm starts by constructing a set of labeled data to train a model for predicting the outcome. The trained model starts receiving queries after training so the observed output can be compared and the predictions are evaluated. Sometimes, feedback may also be needed to continuously upgrade the operational model. The output from the model reflects the traffic parameters; traffic forecasts and traffic predictions are performed by the model. The advantage of using supervised learning algorithms is a structured forecast that relies on structured statistics and the flexibility to predict the outcomes of the algorithm.

Several standard algorithms used in studying supervised learning include regression algorithms, which enable you to foresee indefinite numerical distribution values for future traffic trajectories. For numerical metric patterns that consist of more than one price label, classification works well. This is meant mostly for aligned data, and indicators and multiples are used considerably to assist in the creation of traffic estimations. The assorted variety of parameters communicated in the title, considering the results of the prediction, provides five different solutions at the entrance that are viable in different areas.

Challenges concerning overfitting and information irregularities are discovered in employing supervised prediction programs and may result in unpredictable outcomes due to focusing on creating daily occurrences extremely perfectly while overlooking regulations with the forecast. Model flexibility and forecasting depend strongly on correctly identifying indicators and related adjustments formulated in the theory of modeling in commercial prediction. Furthermore, models depend on structured outcomes as well as ongoing process configurations.

3.2. Unsupervised Learning Algorithms

Given the challenges with survey data for labeled traffic prediction, unsupervised learning provides an alternative. Unsupervised learning, also known as self-organization or self-discovery, is essentially pattern recognition without the luxury of labeled outputs. Instead, unsupervised learning identifies relationships and elements within the data. Pattern recognition can be meaningful or unstructured. In the first, "clustering" or "classification" techniques are used. Clustering groups items into clusters so similar items belong to the same cluster. The results of a well-designed clustering algorithm reflect the functional similarity between items. In the latter, "anomaly detection" is conducted. Detecting anomalies in traffic can be crucial as they compromise safety, and anomaly detection can shed light on the hidden patterns of traffic flow.

Traffic clustering and anomaly detection naturally fit into traffic state revealing issues, such as identifying spatial-temporal patterns that define traffic congestion hotspots, stop-and-go traffic wave front patterns at signalized intersections, and the boundaries of these patterns, all detectable via the use of single loop detectors and signal phase time data. Unlike supervised learning, unsupervised learning methods identify new phenomena as they become evident in the data using either clustering techniques to see how typical clusters shift or change in reaction to perturbations or anomaly detection techniques to systematically record when "typical" traffic starts to show up in new and unusual parts of the road. A major challenge in applying clustering and anomaly detection strategies is the sheer dimensionality of the data and the difficulty humans face in understanding either the results or the calculated relationships within the clustering. Alternatively, the clustering may be clear, but the complex task faces the system of deciding if the clustering information is sufficient for meaningfully understanding significant traffic features. While it is beyond the current effort to address these challenges, they suggest future research topics that may be integrated with the overall predictive problem. They discuss how unsupervised traffic analysis can find trends and information previously unknown. In a very real sense, this link on unsupervised traffic behavior analysis concerns the determination of the global state-space evolution over a time interval. A similar definition is presented by those who also present a system that uses unsupervised processing to determine flow rates and upstream queue length with an echeloned approach to intersection control.

Transportation networks generate large amounts of traffic-related data, such as driver behavior, traffic management, and mobility information. Unsupervised learning is appropriate in cases where labeled output data is missing. The system could infer previously hidden trends and information that can give insights about the underlying dynamics. In computational science, traffic prediction is an active research area. A system can learn from the information stored in the database. Then, the system will replicate the knowledge after being trained with the input data and the corresponding output. A model will be replenished by the training features from the input data. AI training uses class division, regression, and constraint-solving methodologies. This survey focuses on unconventional methods for detecting and predicting anomalies in the event of a sudden outbreak of incidents, such as traffic jams, accidents, and breakdowns. The data could be higher dimensional. Moreover, a well-prepared clustering algorithm can identify the functional similarity among data. Grounded on spatial-temporal correlation, the unsupervised learning algorithms can reveal the underlying state-space of traffic. Based on state-space information, we integrate unsupervised learning with real-time traffic management, real-time routing algorithms, and traffic models.

3.3. Reinforcement Learning in Traffic Prediction

Reinforcement learning (RL) can complement traditional modeling techniques in enhancing the prediction capabilities of traffic systems. At its core, RL focuses on decision-making in a dynamic environment, effectively serving to enable the autonomous selection of optimal actions in complex systems. In this type of framework, intelligent agents learn to interact with their environment towards achieving specific goals, which in traffic equate to collective objectives such as reducing total system delays. During these interactions, the agents "visit" various states with the possibilities to initiate actions that may elicit change in the environment—in this instance, the agents can be viewed as affecting traffic state transitions. Subsequently, the environment presents the decision-maker with reward or punishment signals reflecting the quality of their elected decisions. The object of the RL exercise then becomes to find the optimal strategy of actions that maximize the cumulative rewards obtained from the environment over time.

Agents learn optimal strategies through trial-and-error interactions with the system, performing thousands, millions, or even billions of simulations that allow the exploration of diverse system conditions and—ultimately—the identification of preferred solutions. A growing area of RL research focuses on enhancing the real-time adaptability and learning potential of these algorithms. RL is regularly applied to problems related to traffic signal control, such as traffic light timing optimization and expanded signal modules. One of the main challenges of implementing Q-learning is the design of the system's reward function, while the convergence of the network can also present an issue, especially in sparse reward environments. The application of RL techniques has the potential to revolutionize traffic light optimization and the management of autonomous vehicles. Mobile resources can navigate through traffic lights to arrive on time rather than waiting at intersections. Control systems for autonomous vehicles often use predictive modeling for guiding decision-making and path planning.

4. Real-Time Data Collection and Processing

Real-time data collection and processing are essential for traffic data, especially when the prediction methods are deployed in an autonomous vehicle. In general, traffic data can be collected from traffic sensors on roads, roadside cameras, GPS-equipped vehicles, mobile phones, and sensor networks, as well as from the available crowd-sourced data and spatio-temporal databases. Based on the information gathering, traffic data can be categorized into multiple sources, such as fixed sensors, cameras, and meta-sources based on collective data induced from mobile devices and location-based services. Moreover, data quality is crucial for further processing and prediction. In the real world, traffic is subject to increasing dynamics during peak hours and real-time emergencies. In addition, metadata descriptions of the data are also essential for providing data analytics in real time. In the process of prediction model training and evaluation, real-time preprocessing techniques should also be considered, such as the detection of outliers and noise patterns, and data integration for handling missing values. Recent tools and technologies have the capability of handling and analyzing large datasets in a real-time manner.

Data privacy and security issues should also be considered for the processing of traffic big data in real time. Moreover, the variation of prediction performance for different timestamps associated with real-time traffic information can affect decision-making processes, especially with respect to route planning, developing congestion control measures, and identifying emergency events and abnormal behavior on the roads. Nowadays, among the crowd-sourced data, it is widely used and dynamically updated by volunteered users and can be employed to foster the development of multiple applications, including traffic analysis and environmental assessment. New data collection is a trend, and data collection methodologies are extensively discussed.

5. Case Studies and Applications

Investing in AI-based prediction systems serves to enhance the driving experience and help catch the time of connectivity. In this section, we present some case studies that show the application of traffic prediction in real-world implementation and provide evidence of effective outcomes. In the following, we will introduce two AI-related traffic prediction practical applications for urban and highway systems.

These real-world case studies have demonstrated that AI-based traffic prediction can provide benefits by improving traffic management, making planning and decision-making tasks optimal, and enhancing traffic safety. However, the right stakeholders need to collaborate.

For urban environments, we present a case study in a traffic video surveillance system that integrates the traffic behavior prediction method into the traffic management strategy. This case study is set in the context of an implementation. The fully integrated system has been designed to connect several services to offer an adaptive and intelligent user-centered system. The user will receive personalized and historical information in order to improve the visitors' touristic experience. The whole system will allow for observing users as well as their patterns and habits. It will predict entities' trajectories and driving behavior to adapt the driving style and routes as a proactive action before the user generates them. In short, this case study applies traffic prediction as a technique to assist in adjusting driving style instead of only giving route information to help improve driving safety and the driving experience.

5.1. Urban Traffic Management Systems

The challenge is significant in cities. In fact, traffic prediction is also a part of an urban traffic management system seeking to optimize mobility at no cost. To do so, vehicles can be rerouted and signal timings can be adjusted based on real-time predictions. Smart traffic signals adjust their timings based on prediction simulations. Related adaptive traffic management applications, called adaptive or dynamic routing systems, point drivers toward the best option to face traffic and avoid congestion. However, their performance decreases due to excessive usage by drivers. Thanks to its unpredictability, the dynamic case is indispensable, realizing the performance of a signal system operating in the real world.

City planners also benefit from adaptive routing systems relying on the exchange of anonymized mobility provider data. This data is used to give drivers multimodal alternative routing options. Data from buses were used to help predict the effect of traffic jams. When forecasts predict a traffic jam, bus signal timings temporarily allow the bus to be given the highest priority, forcing buses to use the same infrastructure to reduce the impact on overall mobility. It is for these reasons that ways of sharing details are also crucial for other urban stakeholders, such as city planners. Their views are, however, shaped by many variables, with a particular schism existing between the views of technical stakeholders versus those of citizens and their elected representatives.

5.2. Highway Traffic Flow Optimization

Because of their dynamic traffic composition, highways face unique challenges in traffic flow management. Vehicles flow at a speed significantly higher than on city streets. The position of a vehicle becomes less deterministic with increased velocity. Flow volumes are commonly non-uniform, with more vehicles during rush hours. While access control could be a viable strategy to limit flow, managing the traffic flow after the on-ramp merging becomes a more challenging task. The prediction model can be utilized to optimize the traffic flow of a highway system by controlling ramp entry. Predictive analytics could also help in minimizing the impacts of traffic disruptions or accidents. Highways are also critical assets since they connect large cities and are part of long travel routes, providing logistical support to commuters and freight. Timely information regarding an incident and real-time optimization can help improve travel time reliability. Consequently, some benefits associated with acceptable travel time reliability include reduced vehicle emissions, as well as reduced stress for drivers. This wealth of information can be used by agencies to manage traffic. In terms of physical infrastructure, technology could also be used to automate lane management to efficiently accommodate traffic. The model could also inform the Advanced Traveler Information System about real-time traffic information, which can affect travel decisions. An AI-based traffic prediction model could be integrated with the current traffic management strategies to reap benefits. These strategies include traffic signals, speed control, ramp metering, and variable message signs. However, the integration of AI tools comes with several research needs and system adaptation challenges.

6. Future Direction

Future traffic prediction for autonomous vehicles is likely to be influenced by emerging tech trends such as AI, big data, machine learning, and mathematical computing. In the future, the advance in predictive regulation that utilizes mathematical computing for distributed control will be developed to formulate a regulator bank for the improvement of acceleration. Traffic systems will get a similar regulation performance to state-based acceleration systems. Local controllers will be integrated with distributed controllers without increasing much integration cost. Automotive technology and the deployment of autonomous vehicles and smart infrastructures are likely to be continually developed and integrated with ever more intelligent systems to improve road and highway systems. Digital twins are likely to arise in the Interoperable Creation of Digital Twins program, combining AI and ML techniques that implement behavioral algorithms along with state-space models. State-of-the-art algorithms for vehicle behavior will be developed, including machine learning and mean-field game theory. In future research and in the implementation of traffic simulation models, planners and policymakers are likely to design regulations that accommodate these representational models. Legal and regulatory frameworks will be developed alongside smart cameras to make this technology efficient and acceptable in society. Future developments and research are heading towards concepts of smart cities and connected vehicle networks. With readily accessible data streams and advances in ML and artificial intelligence, these predictive methods for traffic are likely to be refined and developed to create more accurate traffic prediction and traffic regulation systems. Regulatory processes will be further developed and sophisticated to predict changing patterns in road velocity and density. This may account for individual drivers' behavior and choices and susceptibility to trips such as weather and the likelihood of breakdowns and effects on the communities around them. Conversely, research has identified several key challenges and potential directions in future research for this topic. These include potential ethical and data privacy challenges in using real-time predictive algorithms, specifically with self-driving cars. This may also extend to predictive driving insurance policies and the like, where competitors can access private individuals' locations and personal habits. Further potential issues are the assurances of AI systems and security for self-driving cars intended to be connected or partially dependent on this network. These issues may be addressed through interdisciplinary training and ensuring open dialogue on the applications of real-time AI networks to autonomous vehicles.

7. Conclusion

In this paper, we presented an overview of real-time traffic prediction techniques in the context of autonomous vehicles and introduced evolving artificial intelligence computing architectures requiring real-time traffic prediction for autonomous systems. We propose the use of novel AI methodologies, including deep learning, machine learning, and other computational intelligence algorithms that exploit models of drivers, vehicles, transportation networks, or system dynamics to advance towards real-time capabilities. Different contexts of transportation, smart cities, and potential applications of the concept of artificially intelligent traffic prediction are also discussed. The paper outlines the potential research challenges that could hinder the development and adoption of real-time traffic prediction in the future.

Hitherto, traffic prediction has been researched mostly in the context of passenger and freight, rather than automotive systems intelligence. Consequently, very little work is reported in the automotive systems domain in this area. An evolved approach to traffic prediction would empower it as a powerful tool in AI market systems. AI and ML technologies offer potential solutions to the complex traffic system in urban areas if such technologies could be assimilated by stakeholders for better human life with data. Traffic flow prediction still has many serious challenges and limitations. Conclusively, six broad research themes are highlighted as critical for further exploration and research in future intelligent traffic prediction and traffic flow management systems. It is hoped that the state of the art presented here would inspire further work and collaboration along these lines that are critical for future intelligent transportation and mobility systems.

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