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Optimization of Relevant Functions of Urban Computing in the Direction of Traffic Flow Prediction

Ruihui Zhang[1,a,*]

[1]*School of Traffic & Transportation Engineering, Central South University, Changsha, Hunan, China*
a. 8212220126@csu.edu.cn
**corresponding author*

Abstract: As an important application direction of urban computing, traffic flow prediction plays an important role in modern traffic management, urban planning and sustainable development. In recent years, many cutting-edge studies in the field of traffic flow prediction have had a significant impact and promoted the development of practical applications in this field. This paper mainly focuses on the research results of various traffic prediction directions. According to the actual environment and the functional characteristics of the research results, the research is classified into three aspects: data acquisition, feature engineering, and prediction model optimization. It also summarizes the optimization effects of research on traffic flow prediction in sensor data acquisition, data outlier processing, neural network prediction technology, etc. This paper first proposes three important aspects that affect traffic flow prediction and classifies recent research results. Then, the functions and impacts are analyzed from various aspects, and the advantages and progress of the research results are analyzed by comparing most mainstream methods. Then, the problems and limitations of the research are analyzed and discussed in combination with the actual road environment. Finally, the future research direction and development trend of this field are prospected, and the full text is summarized.

Keywords: urban computing, traffic flow forecasting, predictive models, feature engineering, Data acquisition.

1. Introduction

The concept of urban computing was first proposed by Urban computing is an interdisciplinary subject and an emerging field in computer science that takes cities as the background and integrates urban planning, transportation, energy, environment, sociology, and economics [1]. The application of urban computing in the field of traffic flow prediction is a relatively mature and widespread direction at present. By optimizing the traffic flow prediction process, it helps to improve traffic management and urban planning development. This paper mainly focuses on the detailed classification, overview, and analysis of the research results of emerging technologies in the field of traffic flow prediction in recent years, reflecting the technological advancement and cutting-edge nature of its research. Finally, combined with practical factors, the shortcomings and possible solutions of traffic flow prediction are discussed.

The current traffic flow prediction process can be divided into the following key steps. The first is data collection. At present, data related to traffic flow can be collected through sensors, cameras, GPS devices, etc. The second is feature engineering, which includes data preprocessing, temporal feature extraction, spatial feature extraction, historical traffic feature selection, feature construction, and multi-source data fusion. Then the prediction model is selected and trained. After the prediction is completed, the model is evaluated based on the results. Finally, the prediction results are continuously monitored and fed back. This paper reviews three important aspects that affect traffic flow prediction, namely data collection, feature engineering, and prediction models, based on the main clustering direction of prediction errors and technical optimization directions in actual road environments. This paper classifies various research results in recent years and summarizes and analyzes their specific functions and impacts. In terms of data collection, a variety of optimization methods have been proposed to address the problems of incomplete data and incomplete data collection in data sources such as sensors, cameras, and GPS, such as dynamic sparse training DynST [2]. In terms of feature engineering, recent research has achieved significant optimization effects on major issues such as data outlier processing, data missing value processing, and feature extraction. For example, the prediction-based anomaly detection framework GST-Pro [3]. In terms of prediction models, new methods such as deep learning based on neural networks have achieved optimization of prediction models by combining self-supervision mechanisms, attention mechanisms, and the complexity of the spatiotemporal distribution of data. For example, a deep learning model based on spatiotemporal learning with multi-scale feature enhancement [4]. Compared with traditional mainstream prediction models, the new models have significantly improved in terms of prediction accuracy and model generalization ability.

Sections 2, 3, and 4 of this paper will analyze and introduce the latest research results and research status in detail from the above three main aspects. Section 5 analyzes some of the problems that still exist in the field of traffic flow prediction in combination with realistic factors, points out the problems that may be faced, proposes possible solutions, and looks forward to the future development prospects of this field. Section 6 summarizes the article.

2. Technical optimization of data collection direction

The main data sources in traffic flow prediction at present are sensor data, GPS data, traffic management systems, etc. With the popularization of monitoring equipment and the advancement of technology, the data sources of road information have become more extensive and the data integrity has also been improved. However, the quality of data obtained at this stage often cannot meet the high-precision and real-time traffic flow prediction effect. It faces problems such as inaccurate collected data due to failures or false alarms of sensors and monitoring equipment; incomplete data due to lack of sufficient monitoring equipment in some areas; poor real-time prediction and difficulty in integrating different types of data.

Limited by the actual environment and hardware technology factors, how to enhance the reliability and data quality of data sources under existing equipment and economic conditions has become a key. At present, most fine-grained flows are based on the observation of coarse-grained flows, but mainstream methods generally believe that some coarse-grained flows are unobservable, resulting in data loss. The UrbanSTA method was proposed based on this problem [5]. It uses spatiotemporal attraction learning to infer fine-grained urban traffic flow so that high-precision prediction can be achieved even when some data is unobservable. UrbanSTA includes two network models: one is the STA module with an asymmetric encoder-decoder architecture, which predicts missing values by extracting spatial and temporal features of urban traffic. The other is a fine-grained decoder with spatial attention, which infers fine-grained features from the predicted coarse-grained features and uses upsampling operations to restore high-resolution feature maps consistent with the original data

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structure. The final function of UrbanSTA is achieved by combining the functions of the two network models. The research team used the Beijing taxi dataset for experimental comparison. UrbanSTA was compared with six baseline methods. The results also proved that UrbanSTA performed best in datasets with different missing degrees. This reflects the advancement of the method.

At the same time, the concept of dynamic sparse training DynST has also been proposed in recent years. Traditional sensor deployment methods often use specific algorithms to design and deploy sensors. For example, random deployment and dynamic deployment [6, 7]. However, the activation strategy is formulated based on historical observations and geographical features, making the method and the resulting model impractical. DynST optimizes resource-constrained spatiotemporal prediction models by adaptively screening sensor deployment, which can both improve the model inference speed and maintain prediction performance. DynST can effectively solve the pruning problem on spatiotemporal data. It uses dynamic training technology to gradually identify and prune sensor areas that contribute the least to future predictions during training so that the model can adapt to changes in time series data; at the same time, through streaming deformation operators, it handles the interference of time dimensions in time series data and effectively converts spatiotemporal data into a format suitable for model processing, thereby reducing conflicts in the pruning process. DynST adopts an iterative pruning strategy and re-evaluates the importance of the remaining areas after each pruning. It ensures that each pruning can maximize the retention of areas that are important to model performance and uses explicit channel stacking to build overlapping saliency maps, which can help evaluate the importance of each sensor in historical data, to perform pruning more accurately.

3. Technical optimization of feature engineering

In traffic flow prediction, feature engineering focuses on data preprocessing, feature extraction, feature construction, and recognition of the collected data. In the past two years, a variety of feature engineering optimization technologies have been proposed in this field, including the framework SAInf that uses surveillance camera data to identify vehicle stop areas [8]; the new prediction-based anomaly detection framework GST-Pro [9]; the new automatic neural network architecture search framework AutoSTG+[10]; and the new trajectory representation learning framework JGRM that combines GPS and route modeling [11].

SAInf consists of two main components: stop event detection and stop area recognition. Traditional stop area detection methods rely on high-frequency GPS data, but due to privacy issues and data acquisition limitations, these data are often difficult to obtain in practical applications. SAInf uses data recorded by surveillance cameras to design a three-stage method to detect stop events and identify stop areas, thereby overcoming the uncertainty caused by sparse trajectories, making trajectory mining more accurate and comprehensive, and improving the reliability and quality of data sources for prediction models. The first stage of the three-stage method is data preparation, which uses GPS trajectory data to construct ground truth by performing trajectory noise filtering and stop area detection algorithms [12]. Then, the SCR pairs are matched with stop events in chronological order; the second stage is stop event detection, which determines whether a stop event occurs by analyzing the driving speed between surveillance camera records and uses data aggregation methods to build a unified detection model to improve the detection effect of stop events; the third stage is stop area identification, which uses the spatial distribution characteristics of vehicles in surveillance records to generate potential stop areas. Then, by establishing a deep learning model, the candidate areas are evaluated, the stop probability of each area is calculated, and the most likely stop area is selected.

GST-Pro is used to detect abnormal events in irregular multivariate time series with missing values. This method combines a graph neural network model based on neural controlled differential equations and a distribution-based anomaly scorer to achieve efficient and accurate real-time anomaly detection

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without the need for current timestamp observations. Its optimization effect in feature engineering is reflected in its ability to efficiently handle missing traffic data caused by sensor failures, network problems, etc., and improve data quality. At the same time, GST-Pro can detect abnormal situations in traffic flow in real-time. The dynamic characteristics of traffic flow over time and space are captured through dynamic graph neural control differential equations.

The AutoSTG+ framework uses spatial graph convolution and temporal convolution operations to capture complex spatiotemporal correlations and uses meta-learning techniques to learn the adjacency matrix of the spatial graph convolution layer and the kernel of the temporal convolution layer from the meta-graph. Through extensive experiments on seven real datasets, AutoSTG+ can automatically find effective neural network architectures and achieve excellent prediction accuracy in traffic, air quality, and water quality prediction tasks. The framework can better capture data features and find suitable neural networks for different prediction types, improving accuracy and efficiency.

The JGRM framework uses the complementary advantages of GPS trajectories and route trajectories to jointly learn the representation of road sections and trajectories, which can better capture the interactive information between mobile objects and geographic space, and train the model through self-supervised learning. Better accurate trajectory data mining. JGRM can significantly enhance the trajectory representation capability in traffic flow prediction. It generates a richer and more accurate trajectory representation by jointly modeling GPS trajectories and route trajectories. This representation not only captures the details of vehicle movement but also combines the structural characteristics of the road, improving the understanding of traffic flow dynamics; at the same time, it has the effectiveness of self-supervised learning and can be trained on a large amount of unlabeled data, thereby reducing the dependence on labeled data. It enables it to maintain good prediction performance in different traffic scenarios. Multimodal information fusion is also one of the characteristics of JGRM. By fusing different types of trajectory information and comprehensively considering multiple influencing factors (such as traffic signals, road conditions, weather, etc.), the feature accuracy of the data is enhanced.

4. Optimization of prediction model direction

The prediction model is the core part of traffic flow prediction. For traffic flow prediction, its data has the characteristics of uneven temporal and spatial distribution, strong timeliness, complex data types, and high correlation. Using a single neural network often cannot obtain good and efficient prediction results. In response to this existing problem, multiple optimization models have been proposed in recent years. Including deep learning models based on spatiotemporal learning with multi-scale feature enhancement [4], MMSTNet model [13], dual-track spatiotemporal learning framework [14], and NuwaDynamics framework [15].

A deep learning model based on spatiotemporal learning with multi-scale feature enhancement is used for traffic flow prediction. The model consists of three core modules: spatiotemporal dependency feature enhancement module, traffic network topology feature enhancement module, and spatiotemporal attention learning module. The spatiotemporal dependency feature enhancement module selectively retains important historical spatiotemporal dependency features through a memory enhancement mechanism to provide contextual information for future predictions. The traffic network topology feature enhancement module introduces a learnable matrix to capture the complex spatial dependencies between nodes. The spatiotemporal attention learning module effectively integrates spatiotemporal information and realizes effective modeling of complex traffic flow data.

The complex spatial correlations handled by most advanced traffic prediction methods can be regarded as micro-correlations. However, there are also macro-correlations between regions, each of which is composed of multiple road segments or artificially partitioned areas. Macro-correlations

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represent another type of interaction within a road segment and should be carefully considered when predicting traffic. A macro-micro spatiotemporal neural network model MMSTNet was developed for this purpose. MMSTNet creates an input layer for receiving traffic data, which includes time series and spatial information. Then, graph convolutional networks and spatial attention networks are used to capture micro and macro spatial correlations respectively; temporal convolutional networks and temporal attention networks are used to learn temporal patterns; finally, hierarchical learning representations are integrated based on the designed attention mechanism to achieve good prediction results.

The dual-track spatiotemporal learning framework focuses on time series data and spatial distribution data. Through dual-track learning, the model can more comprehensively understand the changing laws of urban traffic. The implementation of this framework uses the time track to process time series data using recurrent neural networks (RNN) or long short-term memory networks (LSTM) to capture temporal dependencies. At the same time, the spatial track is used: convolutional neural networks (CNN) are used to process spatial distribution data to capture spatial correlations. Finally, the information on the time and space tracks is combined through a fusion mechanism to generate the final prediction results. Adaptive normalization is performed.

The proposal of the NuwaDynamics framework solves the problems of data sparsity and lack of interpretability faced by spatiotemporal prediction models. The framework implements causal reasoning and data amplification through two-step processing. The first is the discovery phase, in which the model uses self-supervised learning methods to identify causally important regions in the data. This is achieved by analyzing the characteristics and patterns of the data, helping the model understand which regions have a greater impact on the prediction results. At the same time, through the analysis of important patches, it acquires broader knowledge and conducts targeted interventions on unimportant patches to infer the potential test distribution; the second is the update phase, in which the model applies the knowledge gained through the discovery phase to specific spatiotemporal prediction tasks to improve its causal perception ability. Subsequently, through the understanding of causal relationships, the model can make predictions more effectively, thereby performing better in various spatiotemporal tasks.

5. Current limitations and prospects

5.1. Existing limitations

For most traditional traffic flow prediction methods, when faced with problems such as low data quality and availability, complex and dynamic traffic patterns, and large differences in traffic flow characteristics across regions and periods, there are large errors and accurate predictions are often not possible.

In recent years, research in this field has optimized the important steps that affect traffic flow by introducing currently popular theories and learning mechanisms and improving the prediction level. However, there are still certain limitations in the complex conditions of real roads.

In terms of data collection, the number of sensors and cameras deployed and the detection accuracy of the equipment itself largely determine the reliability of the data source. Although the UrbanSTA method can infer fine-grained flow data based on coarse-grained flow data, its prediction ability is still greatly affected by data missingness. The team only showed a maximum of 60% missing cases, did not continue to explore the inference effect of more missing cases, and failed to take into account the lack of sensors and GPS signals in remote areas. At the same time, the team did not propose countermeasures for abnormal trajectory data caused by sudden traffic conditions. A large number of sudden abnormal values will cause errors in the attraction of points of interest. To make the model more stable, different data sets with larger missing ranges and outliers near the points of interest can

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be used for experimental training, and the problems in the experiment can be re-analyzed and studied. For DynST, its function can determine the importance of the data in the deployment area, delete the data in unnecessary areas, and thus improve the overall efficiency allocation. However, for the problem of poor overall data set quality and sensor malfunction in some important areas, it cannot optimize the data as a whole and can only achieve the optimal level under the existing conditions.

In terms of feature engineering. SAInf relies too much on the accuracy and comprehensiveness of the point of interest data in the identification of the stay area. If the point of interest data is incomplete, it may affect the final recognition result. At the same time, the acquisition of camera data often involves some privacy issues. In reality, this limitation will lead to the loss of data at key locations and a decrease in accuracy. During the traffic construction stage, the road conditions change frequently, and the model may need to be updated regularly to adapt to the new data mode. The same problem exists with JGRM. Although JGRM performs well in transfer learning between different cities, differences in traffic patterns and driving habits in different cities or regions may affect the applicability of the model. To optimize this problem, a personalized module can be added to conduct associated learning of different traffic feature sections and driver habits, considering the impact of these factors on trajectory data mining; at the same time, the training and optimization of the model are mainly based on historical data, which may not be able to quickly adapt to real-time changing traffic conditions. The calculation speed of the model needs to be improved to enhance the real-time performance of its trajectory representation.

In terms of prediction models, the deep learning model based on spatiotemporal learning with multi-scale feature enhancement uses multi-scale convolution and combines LSTM and GCN for spatiotemporal modeling, which increases the computational complexity of the model. The enhancement of multiple features may cause certain delays in the prediction process. Ensuring the prediction effect, simplifying the calculation steps, and improving the overall model's operational efficiency are some improvement directions of this method. Both MMSTNet and the dual-track spatiotemporal learning framework include data fusion processes. Multiple data sources may contain duplicate information or contradictory data. Further efficient processing of these redundancies and conflicts can help optimize model functions.

There are some common problems in research in various aspects. For example, the model is too complex, resulting in long calculation time and the real-time performance cannot be guaranteed. The learning and feature extraction process needs to be simplified. The basic data acquisition facilities (sensors, cameras, GPS signals) are deployed unevenly or at low density, which interferes with the stability of data collection optimization. The evaluation indicators of the optimization model verification experiment (MSE, MAE, MAPE) have certain shortcomings and cannot evaluate the model performance more comprehensively. Better evaluation criteria need to be proposed. Most deep learning models lack interpretability, which may cause trust issues.

5.2. Future Outlook

The future development direction of traffic flow prediction can focus on advanced data analysis technology. With the development of big data and machine learning technology, traffic flow prediction will be more accurate. Combining prediction models with different training methods and theories can better handle complex traffic data. At the same time, the direction of real-time data integration is also worthy of attention. In the future, through the Internet of Things (IoT) technology, real-time information from traffic sensors, cameras, and GPS data will be obtained in real-time, and the timeliness and accuracy of the prediction data source will be improved at a higher level. Finally, multi-source data fusion will also be one of the development directions in this field. A more accurate combination of data from different sources (such as social media, weather data, historical traffic data, etc.) will enhance the ability of prediction models and provide more comprehensive traffic flow analysis.

6. Conclusion

By providing real-time and future traffic flow data, traffic flow prediction technology not only helps daily traffic management and decision-making, but also has a profound impact on improving traffic safety, reducing environmental pollution, and supporting intelligent transportation systems. It is an indispensable part to realize the intelligent development of cities in the future. The latest research results in this field have greatly optimized the traffic flow prediction effect from three aspects: data collection, feature engineering, and prediction models. This article provides an overview and analysis of various technical studies that have significant improvement effects and demonstrates the cutting-edge technology level and progress in this field through comparative analysis of experimental data sets. At the same time, it demonstrates the huge development potential in this field. The latter part of the article discusses the functional limitations of each latest research result by combining the current technical level and external conditions and analyzes and points out potential problems in this field. It provides valuable ideas and directions for subsequent research.

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