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The Application Prospects of Event Data in Traffic Flow Prediction

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Abstract. Conventional methods of predicting traffic flow can often be based on weekdays, certain holidays, road conditions, or signal light circumstances. Nevertheless, because there isn't always an impact study done for some exceptional occurrences, these forecasting techniques or models might be ineffective. Recent studies have pointed out that social events such as concerts and large-scale events have a huge impact on Traffic flow. Considering these social events, to more accurately predict Traffic flow, this article refers to previous relevant literature, comprehensively describes the significant improvement of event data in traffic flow prediction (TFP) and how to use it, and generally discusses the relevant models that may apply event data to TFP. In detail, the current research results on STG-NCDE and Bi-LSTM models are presented, and the correlation, advantages, and disadvantages of the two are compared. In addition, the problems and challenges faced by the current application of event data in TFP are innovatively analyzed and discussed. Finally, the further achievements and related technology development trends that may be made in TFP based on this research direction in the prospect, and the article is summarized.

1 Introduction

The industry has started to see an increase in the number of software and smart devices that can gather data, thanks to advancements in science, technology, and social development. These devices can collect a large amount of raw data, such as positioning data generated by Global Positioning System (GPS) services, trajectory data generated by taxi-hailing software, and sensor data from road detection points. These raw data can be statistically processed and then converted into orderly traffic data. Traffic flow prediction (TFP) is to establish a reasonable data model after processing the traffic data and using appropriate methods to predict. However, the challenge of traffic flow prediction becomes extremely challenging because of the intricacy, dynamic fluctuation, and nonlinearity of this traffic information.

Utilizing pertinent technology to anticipate TF has been the focus of several studies conducted in the past few years. For example, Graph Wavenet effectively captures the implicit characteristics of spatial relationships by designing an adaptive dependency matrix

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and continuously learning during the training process, greatly deconstructing the spatial dependency of traffic data [1]. The DeepST model proposed by Zhang is a classic traffic prediction model based on raster data. The model converts trajectory data into raster data samples, uses convolutional neural networks to model and capture spatial dependencies, and finally constructs a basic framework for traffic prediction [2]. Zhao proposed the T-GCN model to solve the traffic prediction problem. The gated recurrent unit (GRU) and graph convolutional network (GCN) are combined in this construction. With the majority of global traffic datasets, the T-GCN model outperforms the state-of-the-art in terms of prediction performance and is capable of extracting spatiotemporal associations from the data [3]. Furthermore, Zhang et al. presented a DSTNN model built around an encoder-decoder architecture to predict TF data. Convolution and LSTM serve as the framework's foundation, and the decoder is based on a multilayer perceptron (MLP). Compared with widely used methods, this model can reduce prediction errors by up to 61%, while shortening the measurement interval by up to 600 times [4]. In addition, Zhang et al. integrated GCN into a sequenced framework to achieve multi-step speed prediction, which can ultimately improve multi-level traffic prediction [5]. Furthermore, Liu et al. investigated how events affected TF, created an STCL technique for gathering these characteristics, and employed position encoding to recognize anomalous traffic situations, greatly improving the accuracy of TFP [6]. In addition, the Graph Multi-Attention Network (GMAN) adopts the ST-Attention module based on the encoder-decoder architecture to further deepen the understanding of spatiotemporal correlation [7].

However, existing methods are still unable to accurately predict traffic speed, mainly due to three problems:

The differentiated impact of events is difficult to estimate. It is well known that the impacts of many events in reality are intricate and diverse. Certain events, like seminars and competitions at the school level, for instance, have very limited effect on road conditions and can be largely disregarded; on the other hand, other occurrences, like celebrity meet-and-greets and large-scale events held at the prefecture and city levels and higher, result in the gathering of a large number of participants or spectators, which increases the likelihood of traffic jams and makes it challenging to respond and relieve them promptly.

(2) Dependencies between space and time, or the spatiotemporal properties of traffic data. Every event is assigned a Global Positioning System (GPS) coordinate and a start time. Consequently, part of modeling the link between traffic speed and event effect includes understanding and assessing the spatiotemporal aspects of occurrences.

(3) The connections between the well-connected road segments, both apparent and tacit. Assume that the traffic speeds of the surrounding road segments have an explicit direct relationship with the traffic speeds of the adjacent road sections and, at the same time, an imperceptible implicit relationship with other roads when events like large-scale concerts or variety show recordings take place in certain specific locations. The continual changes in traffic circumstances make it challenging to replicate and assess these linkages [8].

Traditional TFP methods ignore the fact that events, such as celebrity meet-and-greets, sports events, concerts, or large gatherings,have a substantial effect on the TF of adjacent roadways. However, by integrating the spatiotemporal information of these events, the prediction model can more accurately predict changes in traffic conditions. Traditional TFP models are usually based on historical data and ignore the impact of events that may occur in the future. In addition, the introduction of event data can make the prediction model more responsive to future emergencies.

In this regard, some relevant studies have noticed that some related models can effectively collect event data and apply them to TFP. This paper conducts relevant research on the integration of the STG-NCDE model and the Bi-LSTM model with TF technology.

2 Analysis of the current research status

2.1 Traffic prediction technology

Researchers have been using Graph Convolutional Networks (GCNs) and Recurrent Neural Networks to learn spatial and temporal correlations in traffic data, with STGCN developing a temporal gated convolutional layer for capturing road network changes.Models such as DCRNN and DST-ICRL combine encoder-decoder architectures with efficient neural networks like LSTM to extract spatiotemporal dependencies of traffic speed and passenger flow. Methods like MVGNCN, as well as STG-NCDE and GSNet, enhance prediction accuracy by introducing multi-view fusion and graph neural network techniques. At the same time, models such as AutoSTG and Att-MED enhance the model's ability to capture important features in traffic sequences through convolutional operations and attention mechanisms. To further improve their accuracy, many researchers have integrated various data sources (such as GPS trajectories, social media data, etc.) with features (such as time, space, weather, etc.), effectively enhancing the learning effects of multiple models through information from different sources.

2.2 Application of graph attention networks in traffic prediction

Due to the Graph Attention Network's remarkable performance in capturing spatiotemporal dependencies in road networks, it has been widely applied to solve traffic problems. For instance, the GMAN model introduces multiple ST-attention blocks and a transformation attention mechanism to accurately predict traffic speeds. The GAIN architecture integrates neighborhood information from different subspaces by employing various types of aggregators and aggregator-level attention mechanisms. Moreover, the Adaptive Structural Fingerprinting (ADSF) model and the User Heterogeneous Information Embedding (UHIE) method improve the capture of structural details between nodes through attention mechanisms and adaptive techniques, thereby enhancing model performance and avoiding the over-smoothing issue.

However, considering that traffic networks are dynamically changing, some research has begun to combine attention mechanisms with the concept of dynamic graphs for real-time updates and capturing.

2.3 Dynamic learning TFP STG-NCDE model framework

The STG-NCDE model framework utilizes neural-controlled differential equations to dynamically learn the temporal and spatial dependencies of traffic conditions and combines them into one framework [9. 10].

The specific logic is as follows: Considering a time series graph by the applicable theory$\{G_{ti} = (V, E, F_i, t_i)\}$,Where V is a group of nodes that is fixed, E is a predetermined set of edges, F_i is an occasion in time when it gets noticed, and t_i comprises the D-dimensional input characteristics of the nodes in a temporal characteristic matrix.

The model's observations indicate that while node input properties do vary over time, V and E do not—that is, the graph topology is constant.

For this task, the researchers designed a method based on neural controlled differential equations (NCDEs). NCDEs are considered continuous analogs of RNNs.

The STG-NCDE model framework has powerful spatiotemporal modeling capabilities, but its performance is still affected by parameter settings and optimizations as well as the burden of large-scale computation. The researchers experimentally verified multiple factors that affect model performance and used parallel computing methods to provide a suitable setting scheme.

The most popular datasets on this subject, six benchmark datasets gathered by the California Traffic Performance (PeMS), were employed in the studies, and they were contrasted with twenty baseline approaches. In order to create a framework, two NCDEs were created to learn the geographical and temporal interdependence of traffic situations. In addition, NCDE is built to withstand erratic time series. Because of this characteristic, the experimental approach is also resistant to time series irregularities, which might result in the loss of certain findings.

Finally, after several rounds of iterations, the STG-NCDE model successfully achieved dynamic learning of temporal and spatial dependencies.

2.4 TFP based on Bi-LSTM

The Bidirectional Long Short-Term Memory network (Bi-LSTM) is composed of two stacked LSTM layers, which retains the ability of LSTM to preserve long-term dependencies and is also conducive to handling events with long time intervals. The structure of combining forward and backward LSTM sequences takes into account the influence of changes in both preceding and following data [3].

In a single LSTM unit, the flow of data is controlled by the forget gate, update gate, and output gate, which protect and control the information. The internal structure is shown in Fig. 1. The forget gate decides what information to discard from the cell state, the update gate determines what information the cell needs to update, and the output gate determines what cell state needs to be output. Here, c, a, x, and y represent the long-term memory, activation value, input value, and output value, respectively.

Before application, the preprocessing of raw data is a crucial step. Researchers perform cleaning, normalization, and other processes to extract features that significantly affect the prediction results. To further improve the accuracy of predictions, they can be integrated with other models, that is, by combining the forecast results of multiple models. Of course, the complex and variable traffic system can also be captured by a Bi-LSTM hybrid model integrated with CNN, attention, and other network structures.

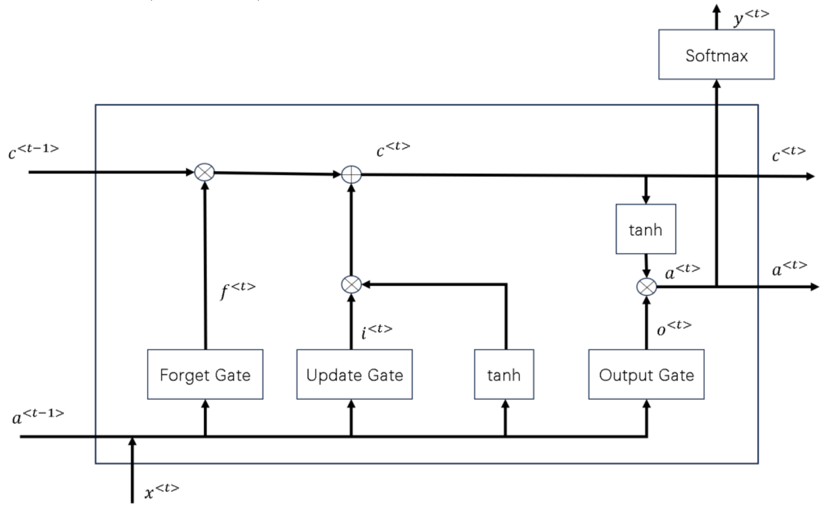

Fig.1. Visualization of Hidden Layer Units [9]

Fig. 2 shows the Bi-LSTM model, with horizontal and vertical directions representing forward and backward LSTM sequences. The horizontal direction adjusts the influence of previous and subsequent states on the current cell unit state, reflecting the bidirectional flow of the time series, and the vertical direction shows unidirectional flow from the input layer to the output layer.

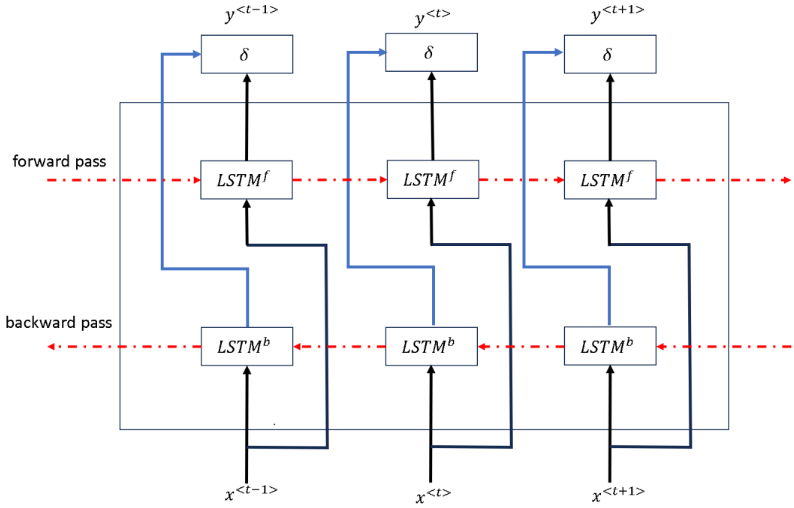

Fig.2. Bi-LSTM Model Unfolded Diagram [9]

3 Empirical research

3.1 Event-driven graph attention fusion network EGAF-NET

3.1.1 Results and advantages

Qiu et al. conducted extensive experiments on three real-world data. Their model effectively constructed a road network map, and the actual result is that it quickly responded to the events that would be affected by time and space, and could spontaneously construct a dynamic time map. It is found that compared with the past robust approach Q-Traffic, EGAF-Net achieves better performance in the forecast [8].

In order to achieve more accurate traffic flow prediction, it combines the temporal and spatial correlation of road network efficiently.

3.1.2 Problems and challenges

Because this model is not a well-known model, innovative development in the future is still to be studied, and there may be performance bottlenecks in high-load environments. In addition, the model relies on a time-space database, and the vulnerability and error of these dependencies will affect the stability of EGAF-Net. Very straightforward dynamic graphs can also have their drawbacks, if there are algorithmic vulnerabilities, dynamic graphs will be unknowingly misleading.

Therefore, the level of algorithm maintenance and update still needs to be studied.

3.2 Spatio-temporal graph neural controlled differential equation STG-NCDE

3.2.1 Results and advantages

In Choi's experiment, six real-world traffic data sets were used and several models were compared with STG-NCDE. Its complex factors and process can be called a large-scale data experiment rarely seen in the field of transportation prediction, and multiple data set training tests were conducted [9].

The model has two NCdes for time processing and space processing. In particular, the graph convolutional network based on NCDE can explain the NCDE of spatial processing.

The proposed method STG-NCDE embodies the optimal average accuracy, and even all the compared methods show relatively large errors in the index. Unlike other model designs, which consider irregular time series, STG-NCDE can do this without changing the model. [9]

3.2.2 Problems and challenges

In addition, some input observations may be missing when the model performs variable-filled TFPs, which is a very real problem setting that is still being considered missing from existing methods. Future research direction can consider the space-time processing method combined with NCDE and GCN [9].

3.3 Bidirectional-long short-term memory network based on multiple factors Bi-LSTM

3.3.1 Results and advantages

In Zhang's experiment, the expressway toll data of Shaanxi Province were screened. Combined with the actual experimental data, it is determined that the weather factors will not affect the effective information of this experiment, and the deletion can reduce the data load and will not affect the integrity of the overall experimental data information.

(1) To show the prediction effect more clearly, the error generated and compared between the prediction results of LSTM, GRU, and Bi-LSTM models and the real value is compared. It is found that the predicted value of Bi-LSTM is more consistent with the real value. It shows that the prediction model based on multiple factors is better than other models in short-term prediction. Therefore, the model can make more accurate predictions of current TF based on historical data and other weather factors [10].

3.3.2 Problems and challenges

Due to the variety of factors affecting the TF, the paper only considers the weather, holidays, tolls, and other aspects of the impact. However, traffic accidents and traffic control also have a significant impact on short-term TF. So in future research, these aspects of research are promising.

This model still needs innovation at the level of high-precision and high-intensity long-term prediction, and can be combined with the latest research models to achieve a comprehensive interlace prediction model.

3.4 Technical summary and comparison

In these three groups of studies, extensive training has been conducted to highlight the advantages of the model. The part that needs to be paid attention to is that there are loopholes left in the process of pursuing efficiency and precision.

(1) Lack of factors STG-NCDE and Bi-LSTM lack the consideration of variables, and their research methods are insufficient, and they have not found a method that can take into account all factors.

(2) Over-dependence problem Both EGAF-Net and STG-NCDE will have vulnerabilities due to highly dependent data, so it is necessary to expand and improve the source of required data.

4 Problems and challenges

The key to traffic forecasting is to use the historical traffic information obtained in a specific period to predict future traffic conditions. This is a universal concept, including traffic speed forecasting, TF forecasting, and traffic demand forecasting.

However, due to the uncertainty of the event, that is, the event may cancel or change the time for some special reasons, the realization of the forecast based on the previous data often leads to the inaccuracy of the results, which requires the prediction model to be flexible to deal with the dynamically changing data.

At the same time, the quality and integrity of the data may be affected due to the immaturity of the technology. The reliability and integrity of event data are essential for effective TF forecasting. The data collection process may encounter missing or incorrect data, which will directly affect the accuracy of the forecast. In addition, data from different sources may be heterogeneous, requiring complex data integration efforts.

In addition, the complexity of multimodal traffic systems will also affect the prediction of TF with event data. Transportation systems in modern cities include multiple modes of transportation (such as cars, subways, bicycles, etc.). Understanding the interactions between different models and incorporating them into predictive models increases the complexity of designing models.

In addition, data events are also affected by other types of data, such as temperature, precipitation, etc., which requires us to combine data events with other data for analysis. This presents a greater challenge in model design and data processing.

5 Future research direction

Firstly, to address the uncertainty of events, the credibility of traffic data needs to be further enhanced, and machine learning models are used for the predictive completion of traffic data that may be missing or contain errors. Meanwhile, standardizing the traffic data and integrating different data sources (such as weather, social media, GPS, etc.) can address the heterogeneity of the data.

To enable models to process dynamically changing data quickly and efficiently, stream processing technologies (such as Kafka) can be used to analyze data in real-time to cope with emergencies on the road. Additionally, predictive models should be further upgraded to dynamically adjust data parameters and their weights.

Furthermore, to address the complexity of multimodal transportation systems, advanced models such as Graph Neural Networks can be introduced to model different traffic objects (private cars, buses, bicycles, etc.) and conduct simulation training, reflecting the interactions between various traffic objects, thereby further improving the accuracy of predictive models.

Lastly, reinforcement learning can be used to optimize the model's predictive capabilities. At the same time, traditional statistics can be combined with machine learning to construct more comprehensive predictive models.

6 Conclusion

All along, the traditional TFP model has ignored the impact of event data on TF, which leads to the non-negligible variable of TF.

Through the integrated study of event information, this paper finds that the techniques and models proposed by many researchers enable not only to predict the TF change at a specific time and place more accurately but also to help the prediction model capture the spatiotemporal dependence in the traffic network. In addition, the introduction of event data is so pivotal that the TFP model can dynamically adjust its prediction strategy and react quickly.

Secondly, the introduction of event data could not only improve the prediction performance but also boost the system's capability to adapt to and respond to urban dynamics, which is an indispensable direction for the development of intelligent transportation systems.

The results show that the complementarity of event data and deep learning model is obvious.

However, the scope and depth of application of future event data in TFP are still waiting for further mining and analysis.

Looking at the development in recent years, future research also needs to be further innovated and improved in many aspects, such as solving uncertainties, solving problems more efficiently, solving model complexity, and enhancing model learning ability. And keep up with the pace of the Times, to promote the application of event data in TFP once again breakthrough.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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