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A MULTI STREAM FUTURE FUSION APPROACH FOR TRAFFIC PREDICTION

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ABSTRACT

Accurate and timely traffic flow prediction is crucial for intelligent transportation systems (ITS). Recent advances in graph-based neural networks have achieved promising prediction results. However, some challenges remain, especially regarding graph construction and the time complexity of models. In this paper, we propose a multi-stream feature fusion approach to extract and integrate rich features from traffic data and leverage a data-driven adjacent matrix instead of the distance-basedmatrix to construct graphs. We calculate the Spearman rank correlation coefficient between monitor stations to obtain the initial adjacent matrix and fine-tune it while training. As to the model, we construct a multi-stream feature fusion block (MFFB) module, which includes a three-channel network and the soft attention mechanism. The three-channel networks are graph convolutional neural network (GCN), gated recurrent unit (GRU) and fully connected neural network (FNN), which are used toextract spatial, temporal and other features, respectively. The soft-attention mechanism is utilized to integrate the obtained features. The MFFB modules are stacked, and a fully connected layer and a convolutional layer are used to make predictions.We conduct experiments on two real-world traffic prediction tasks and verify that our proposed approach outperforms the state-of-the-art methods within an acceptable time complexity.

1.INTRODUCTION

Short term traffic prediction is an important component of intelligent transportation systems (ITS). The time complexity, quality and reliability of prediction affect the response speed and performance of ITS directly. Real-time and accurate traffic flow prediction models are of great significance for decision making of both travelers and managers . Due to the influence of weather, events, holidays and other factors, traffic conditions are nonlinear and time-varying, which introduces significant challenges in traffic prediction.

Traffic flow has various features in spatial and temporal dimensions. Therefore, whether the features can be captured effectively determines the quality of prediction results. With the acquisition of traffic big data and the development of artificial intelligence, machine learning methods have been applied for traffic prediction and they have obvious superiority over traditional methods .

In recent years, the rise and development of graph-based neural networks introduce new opportunities and challenges for accurate traffic prediction. The road sensor network has a typical non-Euclidean structure. In a traffic detection system, the number and locations of monitor stations are known, and the upstream and downstream stations for each monitor station are fixed. Thus, the road sensor network can be simplified as a typically directed graph . Graph convolutional neural network (GCN) has natural advantages in processing this structure, but its prediction performance is strongly related to the property of graph construction.

This paper addresses the following two challenges for traffic prediction in a directed road sensor network. The first challenge is to construct a road sensor graph. Two nodes are likely to have a stronger connection if they have similar flow distribution . But this assumption may vary in the road sensor network. For example, if the flow distribution of monitor stations is similar while their locations are far away, their connection cannot be considered strong. Recent research proposes a variety of heuristic methods to construct a graph. The distance-based methods are popular, which calculate kernel-based Euclidean distance between monitor stations as the adjacent matrix. However, it may not reflect the real spatial similarity. In Fig. 1, stations 401808 and 401809 are close in geographic location but without connection because they are located on the opposite side of the road. Adjacent matrices can also be constructed based on similarity or distance , but this increases the computational complexity and also requires additional prior information. Based on a data-driven approach , the adjacent matrix is trained as parameters in the network, which requires less prior information, but it may affect the model convergence. Therefore, how to construct an effective adjacent matrix and present the road sensor network structure needs further research.

Secondly, we aim to balance the time complexity and model performance. It is becoming increasingly difficult to store and deploy deep neural network-related models in resource-limited devices. The large storage and computing overhead limit the application of the predictive model in low-power fields . Finding an easy-to-deploy deep learning model needs to be carefully considered . In this paper, we focus on improving the predicting performance within acceptable time complexity.

To address both the above-mentioned challenges, we propose a traffic prediction model using the multi-stream feature fusion method. A multi-stream feature fusion block (MFFB) is constructed, which includes graph convolutional neural network (GCN), gated recurrent unit (GRU) and fully connected neural network (FNN). They focus more about extracting spatial, temporal and other physical features, respectively. In the GCN network, the data-driven adjacent matrix is composed to present the road sensor network. Then, the soft-attention mechanism is utilized to integrate the various extracted features. We highlight how the proposed model tackles the challenges:

• We harness the power of GCN, GRU and FNN in a joint model that captures the complex nonlinear relations of the traffic dynamics observed from the road sensor network, which improves the model's ability to express traffic features.

• The architecture for feature extraction is parallelized instead of in cascade, which is helpful for accelerating the training and inferring process of the model.

The main contributions of this paper are three-fold:

• We propose a data-driven adjacent matrix instead of a distance-based matrix to map the road sensor network as a graph, which reduces manual design burden andachieves comparable performance than a distance-based approach.

• We construct a multi-stream feature fusion module, in which a three-channel network is used to extract spatial-temporal and other features effectively, and the soft-attention mechanism is applied to integrate them.

• We balance the performance and complexity of the prediction model. Compared to the state-of-the-art methods in two real-world prediction tasks, our model can achieve comparable even better results within acceptable time complexity.

2. EXISTING SYSTEM

Recently, several researchers apply the graph-based deep learning approaches for traffic prediction. Thanks to the powerful expression of graphs for non-Euclidian structures, learning from graphs based on road sensor networks has achieved more accurate results . In this kind of method, the road sensor network is regarded as a graph, where nodes represent monitor stations and contain traffic information, and an adjacent matrix is used to describe the correlation between stations. The construction of an adjacent matrix affects the expressive power of the graph directly.

The graphs can be divided into directed and undirected graphs. The adjacent matrix for undirected graphs is symmetric, such as the connection between social networks and quantum chemistry. It is not the same case in directed graphs, such as paper citation networks and road sensor networks . As to the implementation of GCN, there are two alternative approaches including spectral methods and non-spectral methods. Based on spectral methods, the convolution operation is mapped to the frequency domain, so the convolution in the time domain is replaced by the product operation in the frequency domain. To reduce the computing complexity, localized spectral graph convolution and polynomials approximate expansion are proposed. Yu et al. constructed the ST-block which is composed of graph convolution layers and sequence convolution layers. It can capture spatiotemporal correlation by applying a convolution operation .Based on non-spectral methods, the convolution operation of the adjacent matrix is carried out directly and the pooling operation is replaced by sparsing the adjacent matrix .Later, the graph attention neural network (GAT) is proposed to use the attention mechanism to update the information of nodes .

The graph diffusion neural network implemented by random walk also achieves the same functions . To better extract spatio-temporal information, researchers have integrated temporal models with graph convolution neural networks. Seo et al.

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proposed a temporal sequence model based on convolution spatial information termed GCGRU. The gated product in GRU is changed to a graph convolution operation to extract spatio-temporal features simultaneously . Zhao et al. proposed a T-GCN model, in which GCN and GRU are stacked to extract spatial and temporal features respectively . Graph models combined with other frameworks are also developed. Li et al. proposed a model to capture the spatial dependency using bidirectional random walks on the graph and the temporal dependency using the encoder decoder architecture with scheduled sampling . Liao et al. proposed a hybrid model in which spatial features extracted by GCN and the original features are integrated and fed into the sequence to sequence (seq2seq) structure.

3. PROPOSED SYSTEM

The system highlights how the proposed model tackles the challenges:

• The system harness the power of GCN, GRU and FNN in a joint model that captures the complex nonlinear relations of the traffic dynamics observed from the road sensor network, which improves the model's ability to express traffic features.

• The architecture for feature extraction is parallelized instead of in cascade, which is helpful for accelerating the training and inferring process of the model. The main contributions of this paper are three-fold:

• The system proposes a data-driven adjacent matrix instead of a distance-based matrix to map the road sensor network as a graph, which reduces manual design burden and achieves comparable performance than a distance-based approach.

• The system constructs a multi-stream feature fusion module, in which a three-channel network is used to extract spatial-temporal and other features effectively, and the soft-attention mechanism is applied to integrate them.

• The system balances the performance and complexity of the prediction model. Compared to the state-of-the-art methods in two real-world prediction tasks, our model can achieve comparable even better results within acceptable time complexity.

4. OUTPUTSCREENS

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5. CONCLUSION

This paper proposes a multi-stream feature fusion method, which leverages a data driven approach to construct graphs. We calculate the Spearman rank correlation coefficient between monitor stations to obtain the initial adjacent matrix and fine-tuning it while training the network. We perform experiments on two real-world traffic datasets, demonstrates that our proposed model outperforms the state-of-the-art traffic prediction methods, and achieves comparable performance compared with the distance-based graph constructing approach while relieving the burden of constructing the adjacent matrix.

The limitation of our method is that the fine-tuning operation in the adjacent matrix requires more training parameters. Dealing with the road sensor network which has more monitor stations, the network will become cumbersome and the training efficiency will decrease. Therefore, the method of the fine tuning adjacent matrix with less training parameters will be investigated in our future work. The proposed method can also be used in traditional prediction tasks, such as power demand prediction. Moreover, our work can

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be extended by other structures such as GAN or sequence to sequence.

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