A Research on Traffic Forecasting using Machine Learning and Deep Learning Techniques

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Abstract

Accurate and timely traffic flow information is currently strongly needed for individual travelers, business sectors, and government agencies. It has the potential to help road users make better travel decisions, alleviate traffic congestion, reduce carbon emissions, and improve traffic operation efficiency. The objective of traffic flow prediction is to provide such traffic flow information. Here presented a study on forecasting traffic flow using different machine learning and deep learning methods some of them includes Spatial Temporal Convolutional Neural Networks, Temporal Graph Convolutional Network, Graph Multi Attention Network, Adaptive Graph Convolutional Recurrent and many more.

Keywords: - Deep learning, Neural Network (NN), Traffic flow forecasting, Spatial Temporal Convolutional Neural Networks (STCNN), Temporal Graph Convolutional Network (T-GCN), Graph Multi Attention Network (GMAN), Adaptive Graph Convolutional Recurrent Network (AGCRN).

Introduction

With the progress of urbanization and the popularity of automobiles, transportation problems are becoming more and more challenging. Traffic flow is congested, accidents are frequent, and the traffic environment is deteriorating. In 2021, NYC drivers lost an average of 102 hours in congestion – and before the pandemic that score was even worse. How often do you yourself get stuck in the jam wishing you'd known about it in advance and took a different route? And how often do you have to apologize to your customers for your drivers being late because of traffic? Traffic prediction means forecasting the volume and density of traffic flow, usually for the purpose of managing vehicle movement, reducing congestion, and generating the optimal (least-time or energy-consuming) route. Traffic prediction is majorly important for two groups of organizations. National/local authorities: In the last ten to twenty years, many cities adopted intelligent transport systems that support urban transportation network planning and traffic management. These systems use current traffic information as well as generated predictions to improve transport efficiency and safely by informing users of current road conditions and adjusting road infrastructure. Logistic companies: Another area of implementation is the logistic industry. Transportation, delivery, field service, and other business must accurately schedule their operations and create the most efficient routes. Often, it's not only related to current trips, but also to activities in the future. Precise forecast of road and traffic conditions to avoid congestion are crucial for such companies planning and performance. In order to predict traffic volume, data needs to be collected, processed, cleaned and then feed to a machine learning algorithm that analyze and find patterns in data and then uses those patterns to predict new incoming data. Traffic flow prediction heavily depends on historical and real-time traffic data collected from various sensor sources, including inductive loops, radars, cameras, mobile Global Positioning System, crowdsourcing, social media, and so forth. Weather data (historical, current, and forecasted) is also necessary as meteorological conditions impact the road situation and driving speed

Literature Review

Yaguang Li, Rose Yu, Cyrus Shahabi, Yan Liu [1] used Spatiotemporal forecasting and diffusion convolutional recurrent neural network for traffic forecasting and observed 12-15% improvement over state-of-the-art baselines. They use bidirectional graph random walk to model spatial dependency and recurrent neural network to capture the temporal dynamics. They integrated the encoder-decoder architecture and the scheduled sampling technique to improve the performance for long-term forecasting

To capture the spatial and temporal dependence simultaneously, Ling Zhao, Yujiao Song, Chao Zhang, Yu Liu, Pu Wang, Tao Lin, Min Deng, Haifeng Li [2] proposed neural network-based traffic forecasting method, the temporal graph convolutional network (T-GCN) model, which was in combination with the graph convolutional network (GCN) and gated recurrent unit (GRU). Specifically, the GCN was used to learn complex topological structures to capture spatial dependence and the gated recurrent unit is used to learn dynamic changes of traffic data to capture temporal dependence. Then, the T-GCN model was employed to traffic forecasting based on the urban road network.

Zonghan Wu, Shirui Pan, Guodong Long, Jing Jiang, Chengqi Zhang [3] proposed that existing methods are ineffective to capture the temporal trends as the RNNs or CNNs employed in these methods cannot capture long-range temporal sequences. So, they developed Graph WaveNet, for spatial-temporal graph modeling. By developing a novel adaptive dependency matrix and learn it through node embedding, their model can precisely capture the hidden spatial dependency in the data. With a stacked dilated 1D convolution component whose receptive field grows exponentially as the number of layers increases, Graph WaveNet was able to handle very long sequences. These two components were integrated seamlessly in a unified framework and the whole framework was learned in an end-to-end manner.

Chuanpan Zheng, Xiaoliang Fan, Cheng Wang, Jianzhong Qi [4] focused on spatio-temporal factors, and proposed a graph multi-attention network (GMAN) to predict traffic conditions for time steps ahead at different locations on a road network graph. GMAN adapts an encoder-decoder architecture, where both the encoder and the decoder consist of multiple spatio-temporal attention blocks to model the impact of the spatio-temporal factors on traffic conditions. The encoder encodes the input traffic features and the decoder predicts the output sequence. Between the encoder and the decoder, a transform attention layer is applied to convert the encoded traffic features to generate the sequence representations of future time steps as the input of the decoder. The transform attention mechanism models the direct relationships between historical and future time steps that helps to alleviate the error propagation problem among prediction time steps.

To tackle the time series prediction problem in traffic domain. Instead of applying regular convolutional and recurrent units, Bing Yu, Haoteng Yin, Zhanxing Zhu [5] formulated the problem on graphs and build the model with complete convolutional structures, which enable much faster training speed with fewer parameters. Experiments showed that their model, STGCN effectively captures comprehensive spatio-temporal correlations through modeling multi-scale traffic networks and consistently outperforms state-of-the-art baselines on various real-world traffic datasets.

Lei Bai, Lina Yao, Can Li, Xianzhi Wang, Can Wang [6] argued that learning node-specific patterns is essential for traffic forecasting while the pre-defined graph is avoidable. They proposed two adaptive modules for enhancing Graph Convolutional Network (GCN) with new capabilities. A Node Adaptive Parameter Learning (NAPL) module to capture node-specific patterns and A Data Adaptive Graph Generation (DAGG) module to infer the inter-dependencies among different traffic series automatically. They further propose an Adaptive Graph Convolutional Recurrent Network (AGCRN) to capture fine-grained spatial and temporal correlations in traffic series automatically based on the two modules and recurrent networks. Experiments shows that AGCRN outperforms state-of-the-art models on two real-world traffic datasets by a significant margin.

Due to the time-varying traffic patterns and the complicated spatial dependencies on road networks, Traffic forecasting is a particularly challenging application of spatio-temporal forecasting. They learnt the traffic network as a graph and proposed a deep learning framework, Traffic Graph Convolutional Long Short-Term Memory

Neural Network (TGC-LSTM), to learn the interactions between roadways in the traffic network and forecast the network-wide traffic state. An L1-norm on graph convolution weights and an L2-norm on graph convolution features were added to the model's loss function to enhance the interpretability of the proposed model. Experimental results showed that their proposed model outperforms baseline methods on two real-world traffic state datasets.

Lingbo Liu, Jiajie Zhen, Guanbin Li, Geng Zhan, Zhaocheng He, Bowen Du, Liang Lin [8] said that the key challenge in Traffic Flow prediction lies in how to integrate diverse factors (such as temporal rules and spatial dependencies) to infer the evolution trend of traffic flow. To address that problem, they proposed a unified neural network called Attentive Traffic Flow Machine (ATFM), which was able to effectively learn the spatial-temporal feature representations of traffic flow with an attention mechanism. ATFM was composed of two progressive Convolutional Long Short-Term Memory units connected with a convolutional layer. First ConvLSTM unit takes normal traffic flow features as input and generates a hidden state at each time-step, which was further fed into the connected convolutional layer for spatial attention map inference. Second ConvLSTM unit learns the dynamic spatial-temporal representations from the attentionally weighted traffic flow features. They developed two deep learning frameworks based on ATFM to predict citywide short-term/long-term traffic flow by adaptively incorporating the sequential and periodic data as well as other external influences.

Most existing methods usually use separate components to capture spatial and temporal correlations and ignore the heterogeneities in spatial-temporal data. Considering this fact, Chao Song, Youfang Lin, Shengnan Guo, Huaiyu Wan [9] proposed Spatial-Temporal Synchronous Graph Convolutional Networks (STSGCN), for spatial-temporal network data forecasting. The model was able to effectively capture the complex localized spatial-temporal correlations through an elaborately designed spatial-temporal synchronous modeling mechanism. Multiple modules for different time periods are designed in the model to effectively capture the heterogeneities in localized spatio-temporal graphs. In this multiple modules for different time periods are designed in the model to effectively capture the heterogeneities in localized spatialtemporal graphs.

Shengnan Guo, 2 Youfang Lin, 3 Ning Feng, 3 Chao Song, 1, 2 Huaiyu Wan 1, 2, 3 [10] argued that most existing traffic flow prediction methods, lacks the abilities of modeling the dynamic spatial-temporal correlations of traffic data, thus cannot yield satisfactory prediction results. They proposed a attention based spatial-temporal graph convolutional network (ASTGCN) model to solve traffic flow forecasting problem. ASTGCN mainly consists of three independent components to respectively model three temporal properties of traffic flows, which are recent, daily-periodic and weekly-periodic dependencies. Each component contains two major parts, the spatial-temporal attention mechanism to effectively capture the dynamic spatial-temporal correlations in traffic data and the spatial-temporal convolution which simultaneously employs graph convolutions to capture the spatial patterns and common standard convolutions to describe the temporal features. The output of the three components were weighted fused to generate the final prediction results.

Comparing Results from different methods mentioned above

Reference Paper	Dataset	Model	Evaluation Metric	Evaluated Value
[1]	METR-LA	DCRNN	RMSE(1 hr)	7.60
	METR-LA	GCRNN	RMSE (1 hr)	8.16
[2]	SZ-taxi	T-GCN	RMSE(1 hr)	4.0141
	Los-Loop	T-GCN	RMSE(1 hr)	7.2677
[3]	METR-LA	Graph Wavenet (forward backward adaptive)	Mean RMSE	6.09
	PEMS-BAY	Graph Wavenet (forward backward adaptive)	Mean RMSE	3.52
[4]	Xiamen	GMAN	RMSE(1 hr)	24.15
	PeMS	GMAN	RMSE (1hr)	4.32
[5]	PeMSD(M)	STGCN(Chebyshev Polynomial Approximation)	RMSE(45 min)	6.77
	PeMSD(L)	STGCN(Chebyshev Polynomial Approximation)	RMSE(45 min)	7.45
[6]	PeMSD4	AGCRN	RMSE	32.26
	PeMSD8	AGCRN	RMSE	25.22
[7]	LOOPf Data	TGC-LSTM	RMSE	4.63
	INRIX Data	TGC-LSTM	RMSE	2.18
[8]	TaxiBJ	SPN	RMSE	15.31
	BikeNYC	SPN	RMSE	5.59
[9]	PEMS03	STSGCN	RMSE	29.21
	PEMS04	STSGCN	RMSE	33.65
	PEMS07	STSGCN	RMSE	39.03
	PEMS08	STSGCN	RMSE	26.80
[10]	PeMSD4	ASTGCN	RMSE	32.82
	PeMSD8	ASTGCN	RMSE	25.27

Conclusions from above

By analyzing the above table and going through the Literature review, it can be seen that most of the scholars/researchers focused on the Recurrent Neural networks and their different types like, Spatial Temporal Convolutional Neural Networks (STCNN), Temporal Graph Convolutional Network (T-GCN), Graph Multi Attention Network (GMAN), Adaptive Graph Convolutional Recurrent Network (AGCRN). Results also shows that these types of RNN performs much better then the traditional Recurrent Neural Networks.

Recurrent Neural Networks (RNN)

A recurrent neural network (RNN) is a special type of an artificial neural network adapted to work for time series data or data that involves sequences. Ordinary feed forward neural networks are only meant for data points, which are independent of each other. However, if we have data in a sequence such that one data point depends upon the previous data point, we need to modify the neural network to incorporate the dependencies between these data points. RNNs have the concept of 'memory' that helps them store the states or information of previous inputs to generate the next output of the sequence.

References

[1]. Diffusion Convolutional Recurrent Neural Network: Data Driven Traffic Forecasting ICLR 2018 by Yaguang Li, Rose Yu, Cyrus Shahabi, Yan Liu.

[2]. T-GCN: A Temporal Graph Convolutional Network for Traffic Prediction 12 Nov 2018 by Ling Zhao, Yujiao Song, Chao Zhang, Yu Liu, Pu Wang, Tao Lin, Min Deng, Haifeng Li.
[3].

Graph WaveNet for Deep Spatial-Temporal Graph Modeling 31 May 2019 by Zonghan Wu, Shirui Pan, Guodong Long, Jing Jiang, Chengqi Zhang.

[4]. GMAN: A Graph Multi-Attention Network for Traffic Prediction 11 Nov 2019 by Chuanpan Zheng, Xiaoliang Fan, Cheng Wang, Jianzhong Qi.

[5]. Spatio-Temporal Graph Convolutional Networks: A Deep Learning Framework for Traffic Forecasting 14 Sep 2017 by Bing Yu, Haoteng Yin, Zhanxing Zhu.

[6]. Adaptive Graph Convolutional Recurrent Network for Traffic Forecasting NeurIPS 2020 by Lei Bai, Lina Yao, Can Li, Xianzhi Wang, Can Wang.

[7]. Traffic Graph Convolutional Recurrent Neural Network: A Deep Learning Framework for Network-Scale Traffic Learning and Forecasting 20 Feb 2018 by Zhiyong Cui, Kristian Henrickson, Ruimin Ke, Ziyuan Pu, Yinhai Wang.

[8]. Dynamic Spatial-Temporal Representation Learning for Traffic Flow Prediction 2 Sep 2019 by Lingbo Liu, Jiajie Zhen, Guanbin Li, Geng Zhan, Zhaocheng He, Bowen Du, Liang Lin.

[9]. Spatial-Temporal Synchronous Graph Convolutional Networks: A New Framework for Spatial-Temporal Network Data Forecasting 3 Apr 2020 by Chao Song, Youfang Lin, Shengnan Guo, Huaiyu Wan.

[10]. Attention Based Spatial-Temporal Graph Convolutional Networks for Traffic Flow Forecasting IJCAI-19 2019 by Shengnan Guo, 2 Youfang Lin, 3 Ning Feng, 3 Chao Song, 1, 2 Huaiyu Wan 1, 2, 3∗.