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Traffic Forecasting with Graph Convolutional Network and Gated Recurrent Unit using Internal and External Factors in Different Domains

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Abstract: ***For intelligent transportation systems (ITS), accurate real-time traffic forecasting is essential, and it also forms the basis of many other smart applications. Deep Learning techniques have shown to be adaptable for modelling complicated issues. Urban traffic planning, traffic management, and traffic control greatly benefit from accurate and real-time traffic forecasts, which is essential to the ITS. In recent years, research on traffic forecasting has focused heavily on spatio-temporal models that integrate dynamic feature modelling neural networks and spatial feature modelling networks. The majority of models in use today are network- or city-specific. As a result, information about various cities may be transferred using traffic forecasting models across several cities.This can increase the forecasting's precision. As a result, a traffic forecasting model using geographical and temporal traffic data from several source domains.***

Keywords: Traffic Forecasting, Graph Convolutional Network, GatedRecurrent Unit, Gradient Reversal Layer.

1. Introduction

The modern city is evolving into a smart city over time. Urban traffic management is under a lot of pressure as a result of the rapid urban population growth and acceleration of urbanisation. A smart city cannot exist without an intelligent transportation system (ITS), and traffic forecasting is a crucial feature of ITS. Analyzing urban road traffic conditions, such as flow, speed, and density, mining travel patterns, and anticipating traffic trends are all part of the process of traffic forecasting. Traffic forecasting can offer security for urban passengers to select appropriate travel routes and increase travel efficiency, in addition to providing a scientific basis for traffic management to feel traffic congestion and limit vehicles in advance. Nevertheless, because of the intricate spatial and temporal dependencies in traffic, forecasting it has never been an easy task. Traffic data contains complex and dynamic spatio-temporal dependencies and is spatio-temporally varying through time and space as a result. The traffic forecasting problem may become insoluble when the spatial characteristics and temporal patterns of traffic states are complicated. Convolutional neural networks (CNNs), graph neural networks (GNNs), and recurrent neural networks (RNNs) are just a few of the deep learning components that are being used in intelligent transportation systems (ITS) to predict the spatial-temporal properties of the traffic data. These spatial-temporal models, which are based on deep learning, excel in forecasting traffic. In order to anticipate traffic across cities, the embedding, which is domain-invariant, is combined with traffic data via a domain classifier.

Contribution

To develop a novel traffic forecasting model using internal and external information captured from different data sources.

2. Literature Survey

Ling Zhao, YujiaoSong [1] present the works use CN for spatial modelling to characterise spatial features. Images, regular grids, and other Euclidean data are widely employed with CNN. Such models will not operate in the context of a complicated topologically structured metropolitan road network. Also, such models didn't consider data from different cities. Thus, it can't perform well with traffic data from other places.

Wenhao Huang and et al [2], Make an attempt to define a deep architecture for traffic flow prediction that learns features with little prior knowledge. According to Hinton et alwork's this is accomplished via training a deep belief network (DBN). The DBN has proven to be quite effective at extracting representative characteristics from data. Without prior information, the DBN can help us learn and identify key elements of a transportation system, such as a typical complex system. It can be enhanced with a regression layer for supervised training. Demonstrate that tasks that are both homogeneous and heterogeneous can boost overall performance. Instead of training all tasks together, an adaptive task grouping strategy is presented to make multitask regression more effective

Wenbin Hu and et al [3], presents a hybrid strategy for accurate real-time flow forecasting that is less complicated to simulate. Unlike ANN, the support vector regression model (SVR) can obtain the global optimal solution and, using a kernel function, may transform a nonlinear regression problem into a linear regression problem. When compared to Genetic Algorithms (GA) and other heuristic algorithms, PSO is simple to implement and requires few adjustments. This research provides a hybrid short-term traffic flow forecasting approach based on PSO and SVR after a thorough examination of SVR and PSO.

Yongxue Tian and et al [4], proposed the Long Short-Term Memory Recurrent Neural Network (LSTM RNN), which can better capture the nonlinearity and randomness of traffic flow while also overcoming the issue of back-propagated error decay through memory blocks, demonstrating superior capability for time series prediction. This method dynamically determines the correct time lags by utilising the three multiplicative units in the memory block.

Michael Defferrard and et al [5], Convolutional neural networks (CNNs) should be able to generalise from low-dimensional regular grids, where image, video, and speech are represented, to high-dimensional irregular domains, such as social networks, brain connectomes, and language embedding, which are represented by graphs. This paper presents a CNN formulation in the context of spectral graph theory, which provides the essential mathematical background as well as effective numerical approaches for designing fast localised convolutional filters on graphs.

Xiaofeng Cao and et al [6], create a revolutionary end-to-end model known as the Interactive Temporal Recurrent Convolution Network (ITRCN), which is an image-based technique based on deep learning architectures of Convolution Neural Networks (CNNs) and Gated Recurrent Units (GRUs) Neural Network. The ITRCN model, which employs layers with convolution filters to extract local features using sliding windows and GRUs to record the temporal elements of service traffic sequences, uses CNNs to mine interactive features among all service pairs in the entire network.

Thomas N. Kipf and Max Welling [7] present an approach for semi-supervised learning on graph-structured data that is based on a variant of convolutional neural networks (CNN) which operate directly on graphs. The system learns hidden layer representations while encoding both the node's characteristics and the local graph structure. For neural network models that act directly on graphs, they introduce a layer-wise propagation rule. Then use this model to the quick and scalable semi-supervised categorization of network nodes. Additionally, the suggested GCN model may encode both graph structure and node properties.

Fuxian Li and et. al[8], proposes a traffic forecasting model based on the dynamic characteristics of the network traffic data. The system is built on a GNN and RNN paradigm, and the dynamic adjacency matrix is intended to be produced from an RNN-iterative hyper-network. The efficacy of graph formation is increased by the message transmission of dynamic node features. The performance is then much improved by combining the static and dynamic graphs in the graph convolution module. A universal training approach for RNN-based models increases performance while consuming less time during training.

Ganin, Victor Lempitsky] [9] proposes learning features that combine discriminativeness and domain-invariance. This is accomplished by jointly optimising two discriminative classifiers that operate on features: I the label predictor, which predicts class labels and is used both during training and at testing; and (ii) the domain classifier, which distinguishes between source domains and target domains during training. Utilize optimization strategies next to boost output and cut down on waste. In order to perform better, the model uses a gradient reversal layer (GRL). In order to maximise performance, the GRL is inserted between the domain classifier and the feature extractor.

Rui Fu and Zuo Zhang [10] proposes Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) neural network (NN) methods for short-term traffic flow prediction. The traffic dataset used for the modelling is PeMS dataset. the LSTM and GRU are 2 variants of RNN network. These models can capture the dynamic features in the dataset, which results more prediction accuracy. The authors compare the performance of these networks with ARIMA model. The experimental analysis shows that performance of proposed networks is better than ARIMA model. According to the experimental findings, GRU NNs have a lower MAE by roughly 10% compared to ARIMA models and 5% compared to LSTM NN models.

3. Problem Definition

The administration and design of urban transportation systems may have a scientific foundation thanks to traffic forecasting. Transportation departments can deploy and direct traffic owes in advance based on anticipated traffic states, increasing operational effectiveness. Most of the existing works only considers internal traffic data from single data source. There is a need of accurate traffic forecasting model.

4. Methodology

Traffic forecasting model based on traffic spatio- temporal dependencies among data from different cities. Traditional parametric models feature easy-to-understand algorithms and calculations. Contrarily, these models are predicated on the idea that the system model is static and, as a result, cannot account for the nonlinearities and uncertainties of traffic data as well as the interference of random events like traffic accidents. Nonparametric models effectively address these issues since they just need a little amount of historical data to automatically identify statistical regularity in traffic data.

The suggested system is a model for traffic forecasting that can identify spatiotemporal traffic characteristics from traffic data gathered from various cities. The geographical dependencies are captured using a graph convolution network. A gated recurrent unit captures temporal dependencies. The spatial interdependence and temporal aspects of a traffic network are known as internal features. Traffic dynamic features are collected on each time period. The time information can be considered as the external characteristics of traffic data.

The traffic forecasting work flow diagram is shown in Figure 1. The purpose of traffic forecasting is to make predictions about future traffic conditions based on past conditions and auxiliary data. This article's traffic forecasting task is primarily based on traffic speeds over the previous period of time from several domains.

The static data in the dataset can be expressed as a road network with vertices and edges. Here, the topological structure of the graph data is represented by a road network G = (V, E). E = e_1, e_2,..., e_m, is the collection of edges that indicate the connectivity between two road segments, and m indicates the number of edges. V = v1, v2,...vn represents the collection of road sections, n is the number of road sections, and n represents the number of edges.

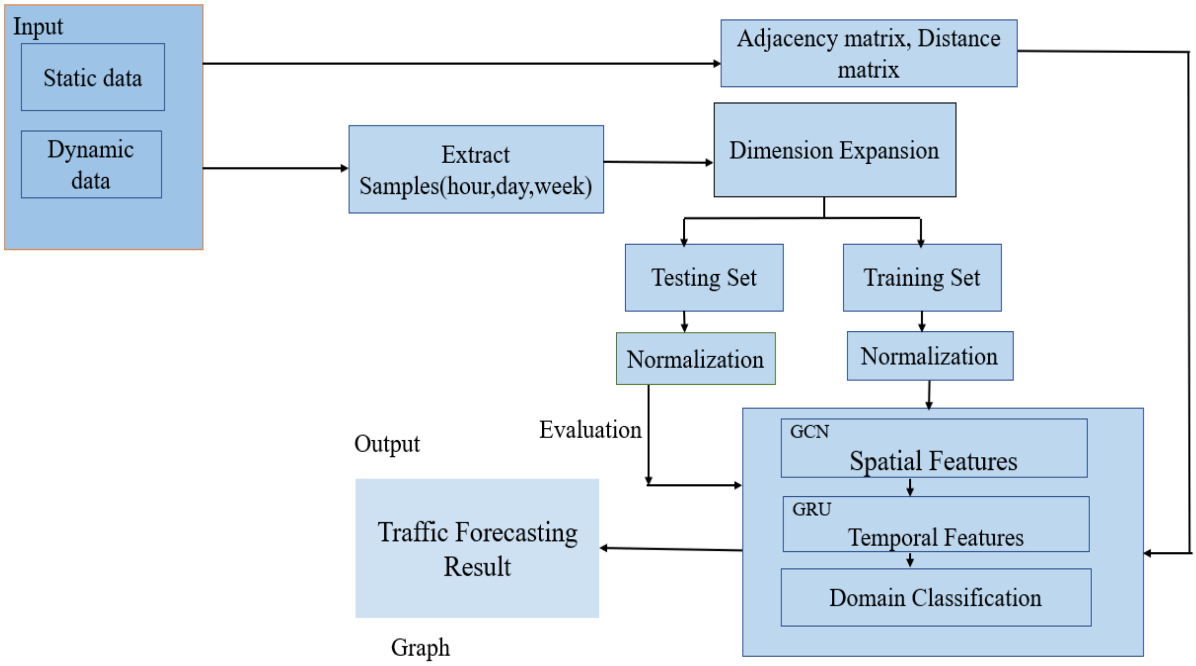

Figure 1: Work Flow Diagram

The adjacency matrix A is used to depict the connection of the road network without losing its generality. When G is an unweighted network, A is a matrix made up of 0 and 1, where 1 indicates that comparable road segments are connected and 0 otherwise.

The three elements of the traffic forecasting model are the domain classifier, the gated recurrent unit, and the graph convolutional network. The graph convolution network captures spatial features within the traffic data. For dynamic feature modelling gated recurrent unit is used. To model domain invariant forecasting system, domain classifier is used. These characteristics produce a deep, adaptable paradigm for traffic forecasting across cities that is network-wide.

Graph Convolutional Network

As a generalisation of the CNN, the graph convolutional network (GCN), which can handle any graph-structured input, has recently garnered a lot of attention. The GCN model has been shown to be effective in a number of applications, including document classification, unsupervised learning, and image classification. Utilize a graph convolution neural network to extract static characteristics from a dataset. The major goal of adopting GCN is to portray each road section while taking adjacent road sections' influence into account. The adjacency matrix is typically used by graph convolutional networks to represent the topology of a graph. At various time steps, GCN produces representations of road segments that capture the spatial interdependence on the road network.

Gated Recurrent Unit:

For processing sequence data, the recurrent neural network is now the most often used neural network model (RNN). On the other hand, due to flaws such gradient disappearance and gradient explosion, the standard recurrent neural network has limitations for long-term prediction. In order to model the temporal dependencies and obtain hidden traffic states, the time-varying representations are fed into GRUs. Reset gates and update gates can be thought of as constituent parts of the GRU model. Take gates at t into consideration. Rt is the reset gate that is utilised to combine the previous traffic state, ht1, with the representation of the road section at time t in order to obtain the candidate concealed state, ct. In order to calculate the final concealed traffic state ht, the update gate, also known as ut, can be utilised to decide how much of the prior traffic state ht1 should be discarded and how much new information from ct should be incorporated.

Domain Classification:

To differentiate the original domain of node embedding, gradient reversal layer (GRL) and a domain classifier were used. As an identity transform during forward propagation, the GRL has no parameters. GRL uses the gradient of the next level as input and sends the preceding layer its negative value during backpropagation.

Work Flow

Traffic forecasting modelling starts with the dataset. Here, 4 datasets for the study- PEMS03, PEMS04, PEMS07, and PEMS08. It consists of static traffic network data as well as the dynamic traffic features like speed, flow and occupancy of different cities. The static information is stored in.csv files. Additionally, dynamic data are stored in.npz files. Pre-processing of dynamic data is the first task to perform.

Dimension expansion, normalization are the pre-processing tasks on dataset and splits the dataset into training set and testing set. Also, generate adjacency metrics and distance metrics from the static data for further processing. Design the neural network with the capability of spatial modelling and dynamic modelling with domain invariant feature. Thus, design the GCN, GRU and domain classifier. To capture domain invariant feature, add domain label to each dataset. Domain classifier computes the possibility node vector belonging to each domain. After training, testing set is applied to test the model. It demonstrates that using traffic input data, a trained forecasting model can predict the state of traffic for a subsequent time period.

The geographical dependencies are captured using a graph convolution network. A gated recurrent unit captures temporal dependencies. Graph convolution networks and gated recurrent units are used to simulate traffic forecasting utilising the generated matrix for each timestamp. The proposed work is a traffic forecasting in domain- invariant manner. Thus, a domain a classifier is incorporated along with spatio-temporal models to capture domain-invariant information. This leads to more accurate forecasting system. A domain label is included with data in each domain. This domain label along with data in each domain is given to the domain classification block. Thus, by incorporating this feature, this system can make forecasting in a target domain, other than input domain.

Data Sets:

The traffic time series datasets PEMS03, PEMS04, PEMS07, and PEMS08 have a priori graph structure. The Caltrans Performance Measurement System (PeMS) collects the data in real time every 30 seconds. From the raw data, the traffic statistics are compiled every five minutes. The system includes more than 39,000 detectors installed on the highway in California's biggest cities. The databases contain geographic data about the sensor stations. Three different traffic measurements—total flow, average speed, and average occupancy—are taken into account in studies. Data about road traffic is both static and dynamic.

PeMS03: The North Central Area's 358 sensors are used in this subset. This dataset's most popular time frame in 2018 is from September 1 to November 30.

PeMS04: There are 3848 detectors on 29 roadways in the San Francisco Bay Area, which is where the traffic data is located. From January through February of 2018, this dataset's time frame. Assign the remaining data to serve as the test set, and the first 50 days of data as the training set.

PeM07: This subgroup makes use of 883 Los Angeles-area sensors. This dataset's most frequently utilised time frame in 2012 is from May to June.

PeMS08: It is the traffic statistics from July to August of 2016 in San Bernardino, which includes 1979 detectors on 8 roadways. The training set consists of the first 50 days' worth of data, and the test set consists of the latest 12 days' worth of data.

Data Preprocessing

The goal of pre-processing is to improve the data so that it may be processed further. It entails data cleansing, transformation, reduction, and handling of missing values, among other things. The data preprocessing approach utilised in this research is data normalisation. A key element of data mining is data normalisation. It entails data transformation, or putting the raw data into a format that makes it possible for quick data processing. Data normalization's main objective is to decrease or get rid of duplicated data. This is a crucial issue since it is getting more and harder to manage data in relational databases, which hold similar data across numerous places.

Modelling

A model is developed to represent the spatiotemporal dependencies in real-world traffic data using Graph Convolutional Networks (GCNs) and Gated Recurrent Units (GRUs). GCN's main objective is to depict each road section while accounting for the influence of connected road sections. Using enhanced matrices of several time steps and the adjacency matrix of the road network as inputs, GCN creates representations of road sections that capture the spatial dependencies on the road network at various time steps. These time-varying representations are then employed with GRUs to build hidden traffic states and simulate temporal dependencies. Reset and update gates can be compared to the GRU model. In order to collect domain information, a domain categorization module was also built after GRU. To accomplish so, each domain's dataset has a domain label attached to it. A model that can predict traffic flow over a specific time period is subsequently developed.

5. Result and Discussion

Here, experiment is conducted on PEMS dataset. 4 datasets – PEMS03, PEMS04, PEMS07and PEMS08 are chosen for the study from different cities. Each dataset includes a .csv file and .npz file. CSV file contains the road network topology data and NPZ file contains the dynamic traffic data. Train these datasets on the network model for 80 epochs. After training completes the model performs forecasting for next time period. The figure 2 shows the graphical representation of traffic flow in the test output. The figure 3 represents the forecasting traffic flow output for the test input. Figure 4 represents the combined graph that denotes target and prediction output in hours and minutes.

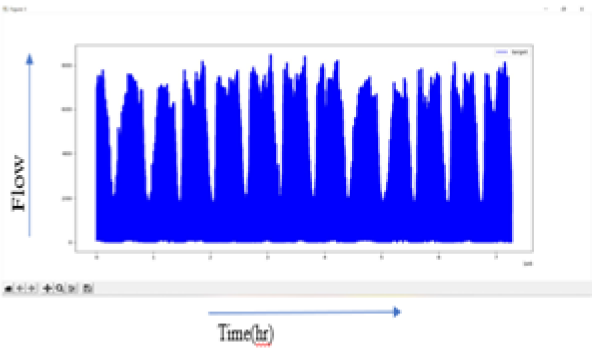

Figure 2: Test Output

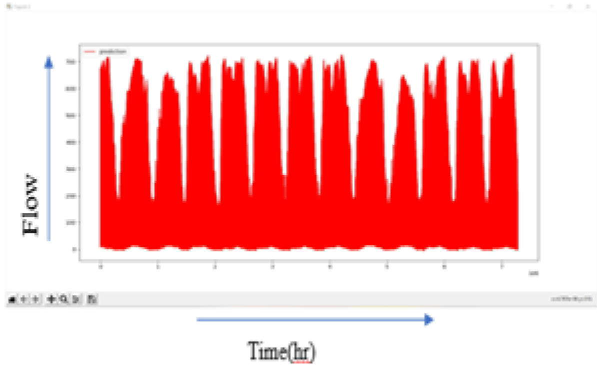

Figure 3: Traffic Forecasting output

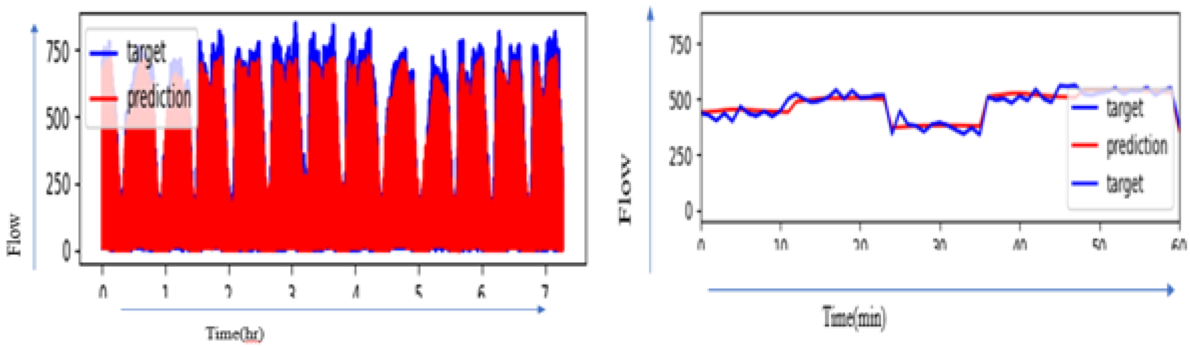

Figure 4: Combined Graph of Traffic Forecasting

Calculate the Mean Absolute Error (MAE), the Root Mean Squared Error (RMSE), and the Mean Absolute Percentage Error to assess the efficacy of the forecasting model (MAPE).

Table 1: Performance Comparison

Performance Measures	TGCN	Proposed System
MAE	20.65	12.05
RMSE	28.77	20.76
MAPE	15.06	0.11

Table1 shows the performance comparison of the proposed system with T-GCN. The values of evaluation metrices shows that proposed model outperforms the T-GCN(Temporal Graph Convolutional Network).

6. Conclusion

The GCN and the GRU are combined to create a unique neural network-based method for traffic forecasting in this study. A graph network is used to model the urban road network, with the nodes on the graph serving as the roads, the edges serving as the cost of connecting the roads, and the nodes' attributes being the traffic data on the roadways. To acquire the spatial dependency, the spatial topological structure of the graph is captured using GCN. To capture the dynamic change of node property and determine the temporal dependence, the GRU model is introduced. In addition, domain data is employed with the suggested GRL. The ultimate result of this work is a domain-classifying traffic forecasting model built on spatiotemporal traffic data.

7. Future Scope

Traffic forecasting not only depend on internal traffic data, but also, external traffic data like weather conditions, point of interest etc. In the future work, it is possible to work with traffic forecasting with external traffic data along with spatio-temporal internal data from different cities. And then, evaluate the performance of new system and can study how external factors affect the traffic forecasting system.

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