Deep Graph Convolutional Network Approach for Traffic Flow Prediction

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Abstract

Traffic Flow prediction is a challenging task, due to complicated traffic patterns, spatial features, and forecasting weather conditions. To deal with this problem, this paper proposed a deep graph convolution network considering roadways intersection as a graph. There is a preprocessing step that involves feature extraction for data transformation in a network and in a deep component the graph with Long-Short-Term Neural Network predicts the traffic state on a road. The experimental part with a big data set is future work for the given idea.

Keywords—*traffic prediction, graph convolutional network, spatial-features*

Ⅰ. Introduction

Traffic Flow prediction is one of the essential components in the Intelligent Transportation System (ITS) considering the traffic flow on the roadways network due to growth in traffic volume data and forecasting methods. It is important to manage and control traffic with forecasting that includes traffic state on the roads considering different traffic patterns (speed, flow, density, and trends). Traffic predictions improve safety measures in routing and congestion, and also provide security to urban drivers [1]. But some dependencies are challenging for traffic forecasting and management and include temporal and spatial features. The change in the volume of traffic over time reflects the temporal dependence and the change in traffic state due to upstream changes to downstream refers to spatial dependence, both have a high impact on the traffic patterns for forecasting.

There exist many forecasting models that consider temporal dependence, ARIMA (Autoregressive Integrated Moving Average) [2], Support Vector Regression [3], Kalman Filtering [4], Bayesian [5], K-Nearest Neighbor [6], and the partial Neural Network [7] are the models considering the dynamic traffic change by excluding spatial features. Some models use convolutional neural networks [8] to consider spatial features and data representation in the form of grids and images etc. that cannot deal with the complex and topological structure of the roads completely. To deal with this structural problem, graph convolutional networks are one of the good solutions that capture the dynamic changes in the traffic pattern and deal with the spatial features as well.

The graph convolutional network combines with the LSTM neural network to capture the complicated spatial features and dynamic traffic temporal dependences of data. To learn the features there is a preprocessing step that involves scaling and the transformation of categorical data for the graph representation and added to the activation function of the model. The remaining paper consists of literature work, a system model, and an experiment section. In the experiment, there are some results relevant to the traffic prediction by LSTM after performing the feature extraction on the data and it is compared with other ML classifiers.

Ⅱ. Literature Work

The related work discusses the recent researchers' work on the proposed idea.

A. Graph Convolutional Network

In the last few years, graph models have been studied for shortest-path routing [9], dynamic traffic allocation [10], and traffic congestion analysis [11]. Usually, in the graph models the structure is represented with the help of an adjacency matrix for the convolutional neural networks, which gives more flexibility. The spectral graph and diffusion graph are the convolutional neural networks consisting of nodes and edges for representing traffic data and predicting traffic flow in urban areas. Some studies include multi-class graph networks [12] for the traffic learning features in the neighborhoods to extract the spatial features.

B. Traffic Forecasting with Deep Learning

Traffic forecasting superiorly performs well with deep learning as it captures the non-linear spatiotemporal features that affect the traffic pattern [13]. Many neural networks and their combinations estimate the vehicle travel time to forecast the traffic states and these models include generative adversarial networks [14], deep belief networks and auto-encoders [15], fuzzy NN, convolutional NN, and recurrent NN. The variants of recurrent NN, LSTM, and GRU are used to capture the temporal dependencies to forecast the traffic flow, time and speed. For performance improvement, deep learning models are also using some other features incorporated in the prediction that includes, weather data, accident data, and geographical data. The present models work with CNN to deal with the spatial features that require 2D transformation of the data which is hard to depict and data that is converted into images have noise that affects the extraction of more effective features. Moreover, CNN is not enough to capture the road topological structures and traffic attributes for the network. To deal with this problem a graph-based model has been suggested to capture roads as a graph and extract the features and adopt the graph convolutional network for the forecasting.

III. Method

In this part, the description of the DGCN (Deep Graph Convolutional Network) is given, as how this model predicts the traffic flow in the urban areas. In Figure 1, the first step is the preprocessing component that is responsible to remove the anomalies data and by using the kernel trick the categorical data is set for a graph network that is used to depict the topological structure of roads containing spatial features. In the second component, deep, the graph neural network is combined with the LSTM for final prediction after the activation function and fully connected layered network.

The graph structure consists of edges and nodes that represent the traffic information including lanes, intersections, speed, number of roads, etc. Sensors are used to collect traffic state information based on location and road segment measurement. For consistency, the nodes are used to represent road segments representing the sensing location of the traffic and the edges are used to denote the intersection between sensing location roads. Moreover, some roads are directed but can be considered bi-directional for propagation from upstream to

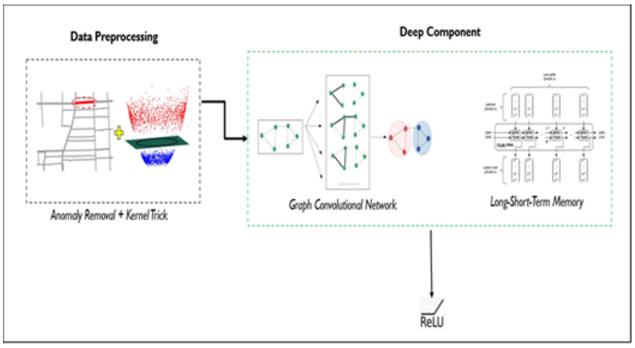

Fig 1. Overview of the system, data preprocessing, and deep component with the activation function.

downstream. The graph network setup can be represented as;

$$\text{Undirected Graph } G = (V, E)$$

$$\text{N Nodes } v_i \in V$$

$$\text{Edges } (V_i, V_j) \in E$$

The DGCN workflow is described in Figure 2, the historical data can be input into the system and GCN is used for the spatial features and LSTM catches the temporal dependencies and gets the final prediction for a traffic flow. The limitation in the CNN to capture the complex topological structure of roads that cause inaccuracy in spatial features representation can be dealt with in this graph network. The GCN in traffic forecasting captures the spatial features with node structure as shown in Figure 3. The central node is connected to the neighborhood nodes in a topological manner of the road and these networ attributes capture the spatial features.

Temporal dependence capturing is also an important factor in the network, previously RNN is used to capture the temporal feature but due to its gradient vanishing problem, the variants of RNN are introduced LSTM and GRU were used instead of RNN. The basic working of both variants is the same, using a gated structure to memorize the long information. The LSTM model is used to capture the temporal dependence in this system because it has the capability for learning more parameters, however, some hidden layer time is required in the computation process.

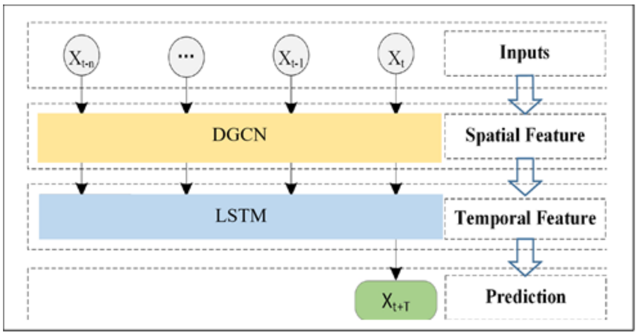

Fig 2. Prediction of traffic flow upon the input and features of the model.

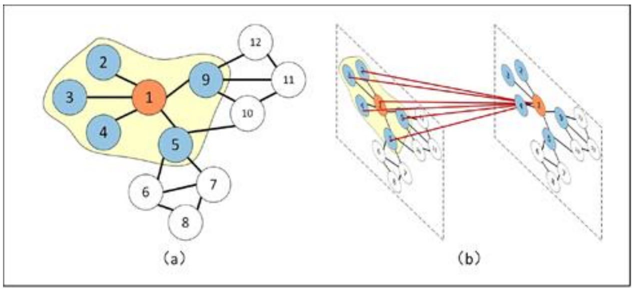

Fig 3. Node 1 depicts the central node and (a) the neighborhood nodes and (b) captures the spatial features of the network.

IV. Experiment

In this section some experiments are performed to check the performance of a proposed idea, as we can see in Figure 4, the slowness percent of the model, and Figure 5, describing the different traffic slowness parameters in combination to reflect the traffic flow at specific occurrences of the feature. Also, performed some comparisons of the proposed model with the other ML classifier shown in Figure 6 based on MAE.

```
Slowness_in_traffic_percent =

  2.9028 * Hour=8:00,13:30,12:00,12:30,8:30,10:30,10:00,11:00,14:00,9:00,1
  1.1523 * Hour=9:00,11:30,13:00,15:30,9:30,15:00,14:30,16:00,16:30,17:00,
  1.1749 * Hour=16:00,16:30,17:00,17:30,20:00,18:00,18:30,19:30,19:00 +
  0.985  * Hour=16:30,17:00,17:30,20:00,18:00,18:30,19:30,19:00 +
  1.4808 * Hour=17:00,17:30,20:00,18:00,18:30,19:30,19:00 +
  0.9792 * Hour=17:30,20:00,18:00,18:30,19:30,19:00 +
 -0.9446 * Hour=20:00,18:00,18:30,19:30,19:00 +
  2.0186 * Hour=18:00,18:30,19:30,19:00 +
  1.5188 * Hour=18:30,19:30,19:00 +
  3.8472 * Occurrence_involving_freight +
  6.2849 * Lack_of_electricity +
  8.4266 * Point_of_flooding +
      4.65
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Fig 4. Traffic Slowness Percent by DGCN+ LSTM.

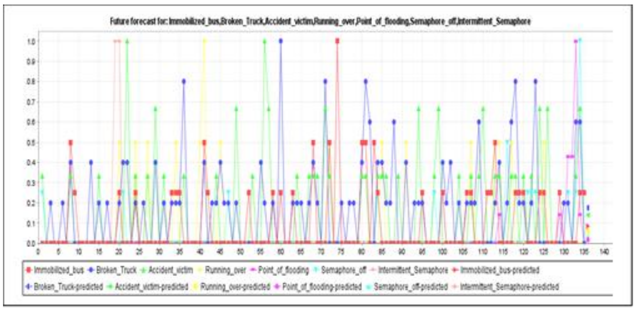

Fig 5. Traffic forecasting with respect to different combination of parameters to reflect the effect on the speed of traffic

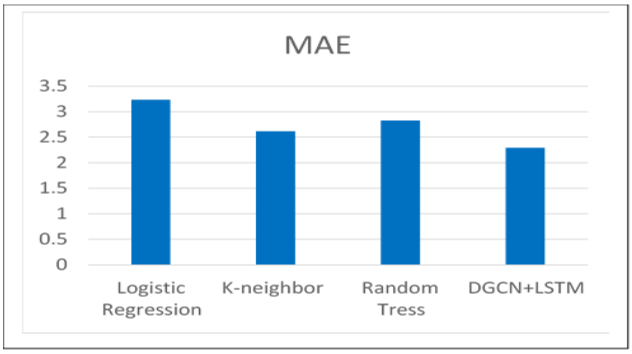

Fig 6. Comparisons of ML Classifiers w.r.t MAE

V. Conclusion

To overcome the challenge of predicting traffic flow, we suggest a deep graph neural network framework in this research. To capture the spatial dependencies of traffic nodes in the urban road network, we employ graph neural networks, and to capture information about traffic flow sequences in the temporal dimension, a long-short term memory is employed. The suggested framework's superiority and efficacy in solving traffic prediction problems are shown by experimental findings. We intend to keep the benefits of this deep model to big road network research and prediction tasks in the future with further examination of big data.

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