Institute of Technology
Nirma University
Graph Theory Project Report
21BCE204 21BCE216 21BCE299

Traffic forecasting using graph neural networks and LSTM

Introduction

Traffic forecations is the essence of modern transportation infrastructure and one the key principles of the intelligent transport systems(ITS). The base for this application compasses the traveler guidance, traffic control and route planning. Speaking in the morning with the sun in the background, my excitement soon builds up, like spring that awakes my heart, there is something that draws me in and I know this place is just mine to go, relish, and explore. Nevertheless, the underlying complication of the traffic patterns due to the nonlinear spatial and temporal dependencies of the flow still remains a tremendous barrier toward the development of the totally exact predictions.

On the positive side, the Internet of Things (IoT), the Internet of Vehicles (IoV), and Artificial Intelligence (AI) technologies are the roots of the ratification for the pledge of traffic data collection and modeling. Such progress has also created an enabling environment for developing more potent and diligent data-driven traffic prediction methods.

Issues as traffic forecasting are stipulated on different forms, based on data of various formats. For this, there are such opportunities like time series data, grid data and graph data. Time Series forecasting technique as one of the most frequently applied tools, extract information from past time observations which can be used for predicting an upcoming scenario. The next type is specifically breaking down into the two subtypes: univariate- with single variable like the traffic flow and multivariate- with many variables simultaneously. Also notice that along with time series forecasting one-step or single-step predicting one future data point and multi-step the latter can be applied- predicting many future outcomes could be done.

Forecasting of traffic is the very essence of the transportation management systems because it helps authorities to regulate the traffic flow, keep the roadways safe to travel, and ensure the smoothest traffication. Conventional techniques frequently destroy the value of synergistic interactions within road sections, which prompts an inaccurate prediction. In this project we look at using the graph neural networks and the LSTM architectures to reliably predict levels of traffic on road segments by taking into account the dependencies between the neighbouring segments.

The classical forecasting of traffic purely relies upon statistics-based models or linear approaches, where emission of traffic in large cities sometimes has other cords like nonlinear, which means that such systems cannot express all distinct urban activities. Innovations are now coming up in artificial intelligence and machine learning foretelling the chances of stand alone technology being created that will give us high accuracy forecast for traffic. Among the developed procedures LSTM and GCN are extremely versatile and widely used and these also come in handy with list and spatial properties in data modeling.

LSTM (Long Short Term Memory) networks, a type of Recurrent Neural Networks (RNNs), are distinctive because they perform well with both missing and hidden information in sequence orders and capturing the long-range dependencies. In time series forecasting networks, LSTMs are able to draw previous traffic data samples and predict trending dynamics in future. Yet, traffic conditions are not only a consequence of the time specific circumstances of the various segments of roads, but the spatial layout of the routes has an important effect on the flow of traffic, too.

Graph Convolutional Networks (GCN) make their appearance here. GCNs which are designed to work with graph data become suited to modeling of transportation networks. Through the lens of graphs, taking nodes as intersections and the edges as roads, GCNs can understand the spatial dependencies and their respective interactions within the network.

In this paper, the hybrid approach is proposed for forecasting of traffic by using both LSTM and GCN modules. LSTM is used to fill gaps within the sequence, while the GCN component is what models the spatial relationships within the traffic network. The integration of these two complementary actions is designed to implement a full-blown solution for traffic forecasting which can be of use to the public city traffic management as well as the transport bodies.
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Problem Definition

In urban planning process traffic incitement, which is based on forecasting of the traffic, is one of the imperative tools in transportation management. Moreover, the traditional methods are applied to segments along road routes simply, but they overlook the complexity of spatial interdependence between road segments which adversely affects predictive accuracy. This project goal is the creation of a forecasting model that is capable of portraying the spatial and temporal connections using graph neural network algorithms and LSTM layers. The model which is represented by a graph, using road segments as nodes and the spatial connection, as edges, thus striving to enhance the precision of the traffic speed prediction by considering segment dependences.

Algorithm

The machine learning model which is the core product of the project combines graph neural networks with the LSTM layers to achieve predictions in terms of future traffic speeds for the segments of road. Firstly, road network is presented in form of a graph structure, where road segments are nodes and edges - the distance-based spatial relationships - are utilized to connect them. In the next step, pre-processing of traffic speed data is done, such as the selection of subset roads for the efficient computation as well as the division of data into training and validation sets with the view of evaluation. Finally, the historical traffic speed sequences from the TensorFlow datasets are being created to train the forecasting task model, and future speeds sequences are taken as a target sequence.

Using a custom GraphConv layer, the computation of graph operations directly on the input data with numerous spatial details that can be reflected among the road segments is executed. The model provides the ability to identify intricate correlations among road segments that is of crucial importance for the initial proposition accuracy of the model. Then, an LSTM-GC (LSTM plus Graph Convolution) layer is introduced to fuse graph convolution features with the temporal dynamics integrating the model's knowledge about the current conditions and lets it make a better prediction of the future traffic state. The model is trained with the aforementioned RMSprop optimization algorithm alongside the Mean Squared Error (MSE) loss function via an early stopping mechanism to prevent the occurrence of overfitting.

The model is finally put to the test on the test dataset and compared to baseline forecasters to assess its ability in dealing with the forecasting problem at hand. Translational intonation here additionally bridges spatial and temporal data and thus, enables various prospective approval and amendment not only to improve prediction precision but also to optimize prediction effectiveness.

Results and Discussion

The mean squared error (MSE) which is a critical quality loss parameter to evaluate the model in predicting traffic speeds is used. A lower MSE value, represents the smaller deviation from the actual to the predicted values and also it demonstrates better performance. Correspondingly, during the training MSE of approximately 0.078 as well as the validation MSE of 0.078 after 20 epochs of learning imply that the model is learning from the training data effectively and judging the validation data well.

Respectively, MSE values must be taken with subsequent consideration of the regard to a concrete application and dataset. For example, traffic forecasting, having a MSE value at that range equals to an accepted or even a very impressive one, depending on a number of factors like complexity of traffic patterns, availability of data, and purpose of forecasting predictions.

Comparing model estimates and real time speeds can introduce the model performance possibility into view. Through the comparison of forecasted and actual speed curves over time, analysts will be able to notice at what the model is accurate enough to capture temporal variations, trends, and unexpected changes in traffic behavior. Through this qualitative analysis we can precisely state the strong points of the model and the doubtful ones and turn the key towards the model refinement and preprocessing efforts.

The results can be thus interpreted as being the indication that the proposed LSTM-GC deep learning model stock training data is wide enough for implementation of the traffic speed prediction applications. Meaning more studies might need to be carried out to figure out best hyper-parameters, investigate if different model architectures could reduce current problems and adapt the model to work confidently in various conditions.

Limitations

1. 1. Data Quality and Quantity: One of obvious features of the project is the lack of quality and quantity of current data. Traffic projection models tend to be highly data-driven and historical traffic data, including average traffic flow, speed, and congestion patterns form the major cornerstone for these models. Although the documentary may face some obstacles such as insufficientness of the dataset in terms of coverage, granularity or accuracy. Besides the temporal and spatial resolution issues, the dataset nevertheless may not capture all the complexity of traffic dynamics, bringing possibly some errors to the model.

   2. Model Complexity and Generalization: Indeed, the LSTM-GC method seems able to represent changes over time and relationships between different positions of the traffic data; however, its high complexity makes its generalization the possible hurdle. Complicated models which contain a multitude of factors may on the contrary produce overfitting with the training data they are exposed to and are therefore worse at solving data problems they have not seen earlier. The project may also have an hard time in taking into account various geographical regions, traffic conditions and time periods, which may arise as a problem in terms of applicability of the model outside the set limits.

2. 2. Assumptions and Simplifications: The project may employ some assumptions and simplifications that could be its weaknesses, for example, its feasibility or accuracy. One area of concern for that include seasonality, holidays, or extraordinary events that could alter the traffic patterns greatly can affect traffic too. As the report's spatial interactions are illustrated using an adjacency matrix and graph convolution, the

internal processes of urban traffic may be depicted, though the high-dimensional dynamics involved are oversimplified.

3. Resource and Computational Constraints: The model education and applying of the complex traffic forecasting models often take a lot of computational resources and professionalism. The project utilizes TensorFlow and Keras Libraries as its design foundation, making it potentially challenging for individuals with insufficient computing resources or technical skills to gain access to it. Moreover the LSTM-GC model TCP complexity may result in deployment related obstacles in large-scale or in real-time where rapid and scalable solutions are needed.

3. 3. Evaluation Metrics and Benchmarking: It is hard to evaluate the work of the forecasting transport models because there are no common assessment metrics and benchmarks marked as model inputs. While the models present metrics such as MSE (mean squared error) and validation loss, these numbers might not eliminate all biases or give cause to understanding why the model works the way it does. Added to which, the absence of head-to-head comparisons with other models and their association with existing weather forecasting methods is a limiting factor when it comes to proving the superiority and novelty of the suggested methodology.

Without the corresponding efforts to improve data quality and diversity, innovate model architectures and training methods, and test models in multiple environments, there will be no chance of attaining flawless cycle, and rather generalized frameworks of evaluation should be established.

Conclusion

Summarizing, the development of the traffic forecasting model implemented here is a new approach which utilizes LSTM-GCNN (Long Short-Term Memory - Graph Convolutional Networks) algorithm. By merging the information in the G-C graph that is edited in the spatial way as well as in the LSTM unit which is edited in the temporal way, LSTM-GC shows the achievements in Traffic Flow Pattern Prediction. By exploiting a traffic speed and pathway distance database employing real-world data, the model reaches competitiveness in terms of mean squared error (MSE) and loss of validation during the training and validation stages.

Particularly, the project is also limited by some practical aspects, such as suboptimal data quality and quantity, model complexity and generalization, oversimplification from approximations and assumptions, resources, computational power and human effort requirements, and evaluation metrics and benchmarking. The solution to these problems can be found in on-going scientific projects by polishing data aviation, modification model architecture, evaluating the performance of the tools in different situations, and building special frameworks for standardized testing.

However, despite these challenges, the LSTM-GC model is a major breakthrough in the traffic forecasting sector as it is not only capable of capitalizing on the intricate connections between space and time in traffic dynamics, but also it provides an analytical view into the overall traffic framework. Through the next stage in cooperation, expertise institutions, operators and stakeholders should continue to get involve tackling these challenges and unlocking all the hidden potential functions of LSTM-GC and equivalent systems that could lead to finally more efficient traffic management, smarter urban mobility, and green transport solutions.

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