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SURVEY ON SPATIO-TEMPORAL TRANSPORTATION USING DEEP CONVOLUTION NETWORK FOR TRAFFIC FLOW

Tukaram K. Gawali[1], Shailesh S. Deore[2]
[1] Research Scholar, SSVPS's B. S. Deore College of Engineering, Dhule and
Department of Computer Engineering, Govt. College of Engineering, Jalgaon, MH, India
[2] Department of Computer Engineering, SSVPS's B. S. Deore College of Engineering, Dhule, MH, India, [1]t.gawali@gmail.com

Abstract - Spatio-temporal transportations have various issues like traffic congestion, weather and wind direction. The measure problem is to prevent from traffic based accidents. The traffic may be in homogenous and heterogeneous format. In this paper the complete focus is based on heterogeneous traffic flow. In first stage we studied various research and we studied deep convolution network for identifying and measures the traffic accidents and developed a unique spatiotemporal graph-based model for predicting the probability of future traffic accidents. We used hybrid approach to improve the reliability and sustainability of large-scale networks through improving both recurrent and non-recurrent traffic conditions.
Keywords - Fully Connected traffic, K-hop neighbours, Dynamic Spatial Attention, Autonomous Vehicle, Deep Convolution Network

1. Introduction

Despite the fact that spatial-temporal data analysis is still remain in many field of research due to infancy work and that even the most fundamental problems in this subject remain unsolved, Using trajectories, what sorts of patterns may be retrieved and what approaches and algorithms should be used to do so. It's crucial to be aware of them from the beginning of the analysis. It's also crucial to remember that many of these problems have yet to be solved. Interdisciplinary and spatial discretion problems, data features, and minimum research work are some of the general research challenges that must be addressed. With a study on public safety transportation, traffic and monitoring of the way of transportation on earth can analyze based on the social media analysis, pattern mining and outlier identification.

In contrast, time is uni-dimensional and can only travel in one direction — FORWARD. This complicates the interpretation of the results of spatiotemporal studies. Another difficulty is the way the data is characterized, which can have a significant influence on the patterns identified in the data. When it comes to spatio-temporal data, the various problems can't be solve. These problems are around for a long time. Using various spatial/temporal definitions, the same identical investigation might provide totally different conclusions. Researchers may find fascinating but false patterns based on how the data is defined by the investigator. Time, on the other hand, has just one dimension and can only move in one direction.

Patterns can be influenced by how data is defined as well. By comparing space and time, the researchers can get large gap based different results even using dependable data based on Census Tracts to quantify space and time.

2. Literature Survey

Geographic and temporal data analysis techniques are in high demand due to a fast increase of spatial and temporal statistics due to extensive gathering of network and location aware decisions. Most of the time, these massive spatial-temporal data collections conceal potentially fascinating and useful insights. Geotemporal analysis presents numerous obstacles, yet it is a potential application for different fields and research concerns. The complexity and inter-connectivity of transport based networks call are more uncertain on spatiotemporal network based variables such as demand, flow, and speed.

W.Wei et al., in [1], introduced the traffic classification. They classified traffic into homogeneous and heterogeneous traffic with congested and non-congested. They also form clusters to improve the spatiotemporal Morphan scatterplot. For this, they studied case studies of various highways of the Beijing. They were classified urban traffic condition with spatiotemporal scatter plot, and traffic condition. Again, they formed clustering with pre-classification and Spatiotemporal clustering.

L. Wangh et al., in [2], described computation of traffic index for urban traffic network based on floating cars on road available. They worked on a grid model to improve the road network. They visualized traffic flow based on a grid model. Their method distinguished congestion areas with the use of urban networks and was helpful to traffic management. They had planned to use methodology based on data pre-processing, map grid, traffic extraction, and visualize traffic performance index. They got the result for the traffic ratio indicator and traffic index result in the form of a grid model.

Liyan Lui et. al., in [3], combined spatiotemporal aggregation of traffic data to obtain semantic information for traffic flow. Their proposed model equipped with various data from different levels of details and designed to implement visual analytics prototype system for Spatiotemporal graphs. Their designed system was demonstrated and tested based on different case studies with real-world traffic data.

Yoichiro Iwasaki et. al., in [6] proposed an algorithm to vehicle positions and in a result received 96.2% accuracy of detecting a vehicle through pixel values along the time and pattern recognition algorithm. Xu Wang et. al., in [16], identified cellular traffic and based on their experimental demonstration improved traffic flow.

The statistical features of spatio-temporal networks are also critical inputs for off-line and on-line transportation management for large-scale networks. On the other hand, various data resources, from traditional traffic sensors and emerging sensors are available and have been archived for decades in many mega-cities. With the network models and sensing technologies being developed for decades, there is a lack of study on the understanding of inter-relations of spatio-temporal vehicles/passengers in the network, their causes from demand characteristics, and how big data can help estimate, predict and ultimately intervene any component of network flow aiming for system optimum.

3. Design Methodology

A. The Traffic Dataset And Pre-Processing

In this section, we analyze to make a comprehensive research on the collected heterogeneous spatial-temporal data, later formalizing the dataset according to our need for data handling and model preparation. In this research, we used large-scale heterogeneous data considering accidents, traffic flow, and management collected from the cities of India. Our heterogeneous dataset can be purely categorized into five significant categories as shown below :

Data on traffic Accidents

This dataset basically includes the timestamps and locations of traffic incidents which were gathered on a hourly based from 2014 to 2018. The site of an accident is closely connected to the urban transportation system, implying that current traffic analyses based on neural network that ignore the spatial connections between road segments that are not acceptable.

GPS data from taxis

This dataset basically includes the timestamps and locations of GPS based taxis which were recorded in every five minutes which were based from 2014 to 2018. Additionally, the data contained speed of each vehicle with their GPS activity.

Point of Interest GIS Data

This dataset basically includes the specific physical location which someone may find interesting. This includes 500,000 POI with vehicle name, location and category.

Data from the Meteorological Service

We scour the weather underground for meteorological data. The data was collected hourly between August 1, 2018 and October 31, 2018. This dataset covers meteorological data such as temperature, weather patterns, as well as the link between traffic accident frequency, temperature, and other weather conditions. According to the findings, high temperatures and different weather conditions gives result based on accidents.

Transportation Flow on Highway Network

Data from major different city's road networks is also utilized. The statistics provide essential data on the metropolitan road network.

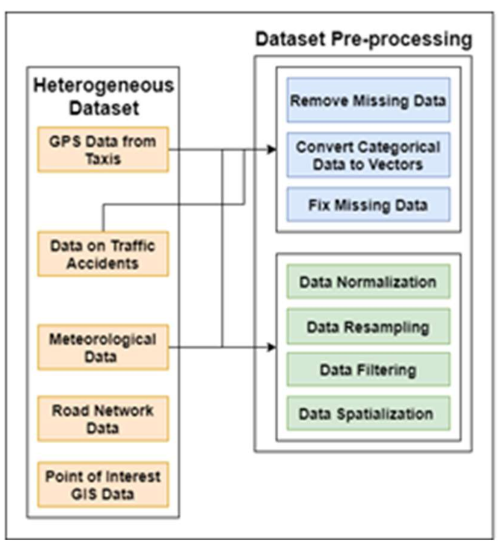

Fig. 1 : Heterogeneous Spatiotemporal Dataset Pre-processing

Several pre-processing techniques have been performed on the heterogeneous dataset for making the dataset compatible for the system working and input. For the GPS data from taxis, data on traffic accidents and meteorological data, we remove missing data columns, convert categorical data to vectors and fix missing data columns. Additionally for meteorological data, we perform data normalization, data resampling, data filtering and data spatialization for handling the data streams and making fusion for a single stream input.

For the point of interest GIS data and data on the road network, undirected graph is defined representing the urban traffic conditions and road segment management represented by the vectors where G represents the undirected graph, V represents the urban road network, represents the connectivity between the point of interest and road segments and the traffic G has Matrix A. If the road segments are connected to each other the adjacency matrix is set to 1 else set to 0.

B. Feature Extraction

An overview to feature extraction is provided in this section, which include generating vectors through road network as well as the extraction of other types of features. Three kinds of impact variables have been identified from the heterogeneous dataset: geographical aspects, temporal features, and external characteristics. Each characteristic feature is described in detail in this section, including how it is generated.

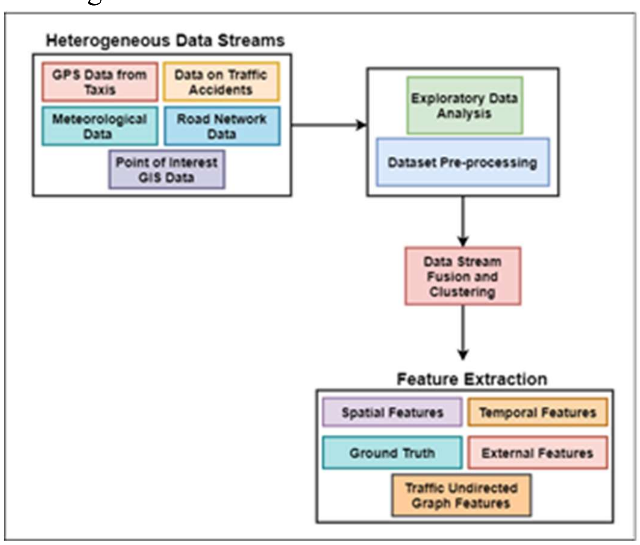

Fig.2: Feature Extraction from Heterogeneous Dataset

Heterogeneous Spatial Traffic Features

In addition to road structural features and POI distribution (X_i^P), the spatial features (X_i^S) includes each road segment that influence on the probability of accidents in traffic. Accidents in traffic are more likely to occur on roads with more difficult circumstances, whereX_i^Sindicates the characteristic of road structure for each road segment V_i. In order to determine the route's geographical location, we average the locations of points on each road section. A number of road-structure-related attributes, such as length and total number of points, may then be retrieved from each road segment.

Traffic accident risk is believed to be indirectly affected by the local surroundings of each road segment, as shown by the POI distribution X_i^p of each road segment V_i. There is an increased chance of traffic accidents on roads with leisure facilities or parking lots nearby, as opposed to routes with calm parks nearby. When predicting traffic accidents, we use POI data and extract POI features since it is a good way to capture the road segment characteristics

$$X_i^{spatial} = X_i^S + X_i^p$$

Road Network Heterogeneous Graph Features

Each crossroad $G' = (\gamma', \varepsilon')$ is represented by a set of nodes (intersection points), while the edges (road segments) connecting them are represented by a set of edges (road segments). So, roads should be considered as nodes in the network if we're trying to anticipate traffic accidents at the road level. As a result, the i[th] node $\gamma i \subseteq \gamma$ corresponds to the i[th] edge $e' \in \varepsilon'$. Then it becomes necessary to form the edge set e', which is created when road segments $\gamma i \subseteq \gamma$ and $\gamma j \subseteq \gamma$ are joined by junction in γ' represented as :

$$\varepsilon = \{(\gamma i, \gamma j) : \gamma i, \gamma j \in \gamma \cap (\exists e' \in \varepsilon' \text{ such that } \gamma i \wedge \gamma j = e')\}$$

Heterogeneous Temporal Traffic Features

Since the traffic flow conditions on road segment can be reflected by this temporal characteristic (Xitemporal =Xiv,t), it can have a temporal influence on the probability of a traffic collision. A traffic accident's likelihood is inversely proportional to the speed of the traffic flow, according to common sense. The average speed flow of road segment in time segment represented by Xiv,t is then calculated. To visit each road section step by step would be costly and impractical since taxi data is so huge. This is accomplished by first dividing each time slot's traffic flow into grids of equal size, and then calculating the average taxi speed in each grid.In the next step, we assign a traffic flow speed characteristic for each route based on its location in a grid. A road segment's traffic speed is governed by its grid location.

Heterogeneous External Traffic Features

Beyond spatial and temporal characteristics, external variables also have a role in determining a traffic collision. We identify different external variables with different characteristics like weather, temperature, dew point and humidity; pressure; wind speed, wind direction, and perceived temperature; With different more than 10 values each for the weather type and wind direction.

Network Architecture

Based on Heterogeneous Spatial-Temporal Traffic, the Deep Convolutional Network of Traffic Flow Accidents is one of the study areas since we can apply on advanced models that influence traffic flow variables on both a spatial and temporal basis to make traffic forecasting more accurate. To simplify the model structure and estimate technique while yet providing high forecasting results, the Graph-based Deep Convolutional Structure was designed. Spatial-temporal traffic flow forecasting models are used in empirical studies, with specific focus dedicated to the methodologies of feature selection and extraction.

The spatio-temporal correlations objects have differnt changes in spatio-temporal and non-spatiotemporal features, as well as the effect of adjacent Spatiotemporal objects that are collocated. Spatial-temporal data is a combination of spatial and temporal representations of data. These qualities comprise non-spatiotemporal, spatial, and temporal properties. They are divided into three categories: Spatial and temporal characteristics are used to describe things that do not have context. Objects have spatial characteristics that determine their positions, extents, and forms. Timestamps and duration of processes denote spatial object (vector) or field as temporal characteristics (raster layers).

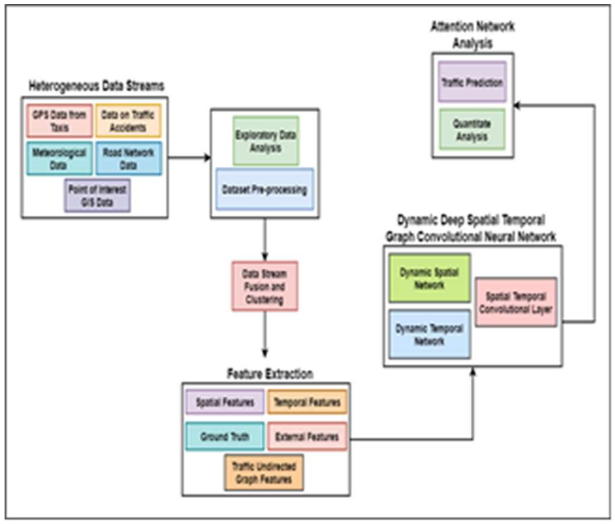

Fig. 3 : Architecture for Heterogeneous Spatial-Temporal traffic based Deep Convolutional Network

To begin, DSTGCN examines several sorts of features for each training sample based on the Spatial Convolution Layer, the Spatio-temporal Convolution Layer, and the Embedding Layer, in order. This compact representation is input into a Fully Connected network to identify relationships between multiple characteristics and forecast the probability of future traffic accidents using the processed hidden features. Last but not least, real-world datasets are used to test the suggested model. Comparisons are made with both classical and current baselines, as well as the impact of different model characteristics and structures.

In order to build our model, we use three sorts of modules. When we represent spatio-temporal links between road segments with road network architecture, we use graph convolutions to capture spatio-temporal correlations, as opposed to the Fully Connected layer, which is followed by an activation function. As a means of spreading spatial data, a graph convolution layer is used. Spatial Convolutional Layer can be described as follows :

$$\boldsymbol{h}_{it}^{(l+1)} = \boldsymbol{\sigma}\left(\boldsymbol{b}^{l} + \sum_{j \epsilon N(i)} \frac{1}{Cij} \boldsymbol{h}_{j}^{(l)} \boldsymbol{W}^{l}\right)$$

where, $\boldsymbol{h}_{i}^{(l+1)}$ is graph signal equivalent to $\mathbf{R}^{\mathbf{F}}$.

This layer combines spatial information from road segments and their surroundings. As part of our model's initialization and training, we employ a batch normalization to enhance the model's resilience, as well as a Multi - layer perceptron to enhance its training speed.

While our model is initially set up using batch normalization to enhance robustness and speed up training, we also utilize the ReLU activation function to capture non-linearity correlation. To update the signal at each node, a conventional convolution layer in time is used to merge the nearby data in successive time slots, while the graph convolution operations collect neighboring data in spatial dimension.Temporal Convolutional Layer can be described as follows :

$$H_{ik}^{(l+1)} = \sigma\left(b_f^{(l)} + \sum_{k=0} \frac{1}{Cik} H_{ik}^{(l)} * W^l\right)$$

=

the cross-correlation operator * is valid in this case, k, which is the k^{th} channel of the input signal $H_{ik}^{(l+1)}$ at the layer level l. With a stride of l and zero padding of l, the convolution kernel size is 3x1. The ReLU activation function to capture non-linearity correlation can be denoted by :

$$H^{external} = ReLU(BN(H_{ik}^{(l)} * W^{\alpha}))$$

We fuse the spatial, temporal and external features and fuse them with a multi-view perspective in mind, as well as to predict future mishaps.

$$H_{it}^{spatial} + H_{ik}^{temporal} + H^{external} = h_{it}^{(l+1)} = \sigma\left(b^l + \sum_{j \in N(i)} \frac{1}{Cij} h_j^{(l)} W^l\right) + H_{ik}^{(l+1)} = \sigma\left(b_f^{(l)} + \sum_{k=0} \frac{1}{Cik} H_{ik}^{(l)} * W^l\right) + ReLU(BN(H_{ik}^{(l)} * W^{\alpha}))$$

Improving the mobility, safety and reliability of the transportation systems after implementation, we will get to know how properly we can manage the uncontrolled traffic flow, prevent accidents flow, abnormal activities on road and traffic.

4. Results and Discussion

The As a first step, we offer a strategy for dealing with sparse data called under-sampling. Finally, the model configurations are tested. Last but not least, we describe the assessment measures and baselines that will be used to compare the proposed model. Only a tiny percentage of roads suffer traffic accidents at any one moment. As a result of a lack of positive samples, the model would likely provide all-zero outcomes, resulting in an unacceptable performance. An under-sampling approach is used to tackle the problem of sparse samples. Every accident report begins with a road location and is followed by a road network based on the location and the road's k-hop neighbors. Then, we extract spatial, temporal, and external characteristics of the route and its k-hop neighbors.

It is possible to generate a graph of the road's K-hop neighbors, including their characteristics, by following the procedures outlined above. In the end, we gather positive samples after considering all traffic accidents. We next randomly choose a route where no traffic accidents occurred during the specified time period and extract the information as described above to create a negative sample of the road in question. A last step in the under-sampling process would be to stop when the positive samples outnumber the negative samples by an equal amount. Our model predicts if there will be a traffic collision in the target road segment based on the extracted spatial, temporal, and external characteristics of the target road segment and its k-hop neighbors. If accidents have occurred there, we record the ground truth with 1, otherwise 0.

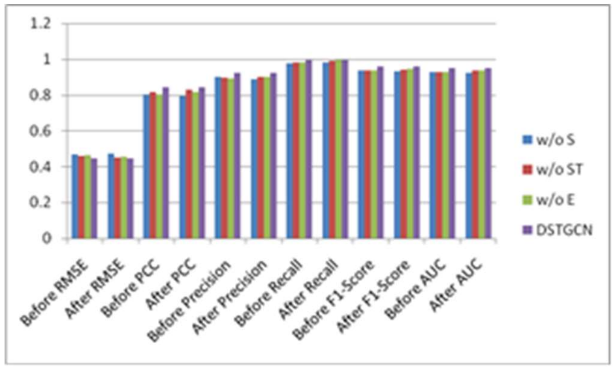

Fig. 4 :Future Scope to get effects of different features on before and after prediction performance.

In order to forecast the road's k-hop neighbours, a produced training sample comprising the road's spatial, temporal, and external characteristics must be used. Instead of feeding graph-structure data containing topological information into baselines, we process the graph topology structure as follows. As an example, for spatial and temporal aspects, we averaged the related information from both the projected route and its k-hop neighbours, allowing us to get two vectors of spatial and temporal data correspondingly. If you want your k-hop neighbours to be predicted, you'll need a training sample that includes the road's spatial and temporal features, as well as its exterior attributes. This is an alternative of feeding graph-structure data including topological information into baselines. Our geographical and temporal dimensions, for example, were averaged using information from both the predicted path and its K-hop neighbours.

We run each model ten times in a row to eliminate the possibility of unexpected outcomes. After 150 epochs of training, the models with the greatest performance on validation sets are selected for testing and further refinement. Our measurements are summarized using the mean and standard deviation. There is a very tiny variation in the standard deviation of LR, LASSO or SVM, which is why we indicate them as 0. Summary of the results may be made. Primarily because it uses a kernel technique to identify the optimum line separator gap, SVM outperforms LR and LASSO in terms of learning complicated nonlinear functions. DT outperforms other conventional machine learning models in the majority of measures because it is better at identifying more essential characteristics relevant to traffic accidents and less susceptible to noise in the inputs than other models. The deep learning models outperform the traditional machine learning models, demonstrating the capacity of deep architectures to represent complicated connections. And the standard deviations of deep learning models are within a narrow range, demonstrating their stability.

5. Conclusion

The Here, we looked at the topic of traffic accidents and developed a unique spatiotemporal graph-based model for predicting the probability of future traffic accidents. As a result of this aim, a large amount of data was collected and important characteristics were retrieved. It has three main parts: the Spatial-temporal layer was used to capture both spatiotemporal connections and temporal dependencies in temporal characteristics. To learn meaningful and dense representations of external characteristics, the embedding layer was used. A comparison of the proposed model to current techniques was carried out using real-world datasets. The suggested approach may be used to alert individuals of possible risks in advance and help them pick safer travel routes.

We are improving the results of this research by analyzing latest models, increasing model accuracy and performing a comparative analysis of algorithms for boosting performance. We implement this research on dataset based on foreign dataset. After implementation, we will get to know uncontrolled traffic flow, prevent accidents, predict traffic jams, proper and correct navigation factors, abnormal activities on road and traffic. We use the new methodology based on a hybrid approach to improve the reliability and sustainability of large-scale networks through improving both recurrent and non-recurrent traffic conditions. We detect abnormal events on road traffic to prevent accidental cases, road traffic management, structural management, prediction of traffic flow.

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