Efficient Accident Prediction Using Spatio-Temporal Data

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***Abstract*-Not only to the growing industry of automobiles but also in the public interest, reducing traffic accidents has been a classic problem. Extensive research has been done on it over the past few decades. Using an exclusive dataset which recognizes a variety of attributes such as traffic-events, weather data, points-of-interest and time put together by paper[2][5]. Our aim is to make these predictions in a more efficient manner than the one already in use. Transformer models have been proved to be more efficient to process spatiotemporal time-series data than LSTMs which have been used by the authors of paper[2]. Training a transformer model with the dataset mentioned above should increase the accuracy of the predictions and subsequently the efficiency of the solution.**

Keywords- Accident prediction, Spatio-temporal data, deep learning method, transformer model

I. Introduction

Across the world, almost 1.35 million people lose their lives every year due to road accidents. Road traffic injuries are a major cause of death and disability globally, with a disproportionate number occurring in developing countries. Road traffic injuries are currently ranked ninth globally among the leading causes of disability adjusted life years lost. Moreover, about 90% of the disability adjusted life years lost worldwide due to road traffic injuries occur in developing countries. The problem is increasing at a fast rate in developing countries due to rapid motorisation and other factors[1].

According to numerous studies, environmental factors including the weather, the state of the roads, and the amount of light may have an effect on the likelihood of a traffic collision. Predicting traffic accidents is now more feasible owing to the recent rapid advancement of data collection techniques and the accessibility of large datasets. This is because abundant environmental data, public records transportation, and reports of vehicle crash reports can all be gathered and combined.

However, traffic accident prediction is a very challenging problem. First of all, the causes of traffic accidents are complex. Besides the common factors listed above, random factors such as vehicle mechanical problems and driver carelessness may also cause traffic accidents. Second, traffic accidents are rare events. Precisely predicting individual accidents is challenging due to lack of enough samples. Finally, the factors that may cause traffic accidents vary from place to place. For example, the main factors that lead to traffic accidents in an urban region with busy local roads might be very different from on a rural expressway. Handling the spatial heterogeneity in the data is challenging.

This paper is a survey of 3 papers, each explaining a different approach to accident prediction using deep learning methods on spatio-temporal data as a chief part of the dataset. We have planned to use transformer neural networks on the US-Accidents dataset compiled by authors of paper[2] and CNN as feature extractor, to increase the accuracy.

II. Review of literature

A. Accident Risk Prediction based on Heterogeneous Sparse Data: New Dataset and Insights

The authors of paper [2] have identified the very common and important shortcomings of not having a dataset good enough to train a model with which could be useful to make real-time predictions. These include small-scale datasets with limited coverage, being dependent on extensive sets of data and not being applicable for real-time purposes. To overcome this problem, they have created a large-scale, publicly available database of accident information named US-Accidents. They did so through a comprehensive process of data collection, integration and augmentation.

In the paper, they have employed a special deep neural network model named DAP which utilizes a variety of data attributes such as traffic events, weather data, points-of-interest and time. All these attributes are crucial to perform accident predictions with high accuracy with real time series data.

The DAP model is broken into four components:

1. Recurrent Component: this component uses Recurrent Neural Networks, specifically the LSTM model to process the set of 8 vectors, each of size 24, due to their temporal order. The output of this component is a vector of size 128.

2. Embedding Component: Given the index of a grid-cell, this component provides a distributed representation of that cell which encodes essential information in terms of spatial heterogeneity, traffic characteristics, and impact of other environmental stimuli on accident occurrence. This

representation is then fed to the feed forward layer of size 128 that uses the sigmoid function as their activation function.

3. Description-to-Vector Component: this component utilizes the english description of historical traffic events in a grid-cell. This too is fed into a feed-forward layer of size 128 with sigmoid function as its activation function.

4. Points-of-Interest Component: This component utilizes points-of-interest data (a vector of size 13), which is a representation of spatial characteristics. The POI vector is fed to a feed-forward layer of size 128 which also uses the sigmoid activation function.

The last component Fully-Connected Component utilizes the outputs of all the above four components and makes the prediction.

B. Attention based Stack ResNet for Citywide Traffic Accident Prediction

The aim of this research paper [3], was to tackle the challenge of aggregating the various types of cross-domain data, which contain spatial and temporal dependencies, to predict accidents using deep learning models. Existing traffic accident predictions models (as of 2019) have used classic machine learning approaches, using historic accident records, that fail to capture the periodical patterns and trends due to the inter-correlation between temporal dimensions. In order to overcome these limitations, the author has proposed an Attentive based Stack ResNet model. The dataset used is traffic-related, cross-domain data in New York City (except Staten Island) from 2017. The dataset, which includes diverse attributes for Road Network Structure, Meteorological Data, Social Data, Human Mobility Data and Calendar Data, has been categorized into three types:

Type I : Variables spatially varied but temporally static

Type II : Variables both spatially and temporally varied

Type III : Variables only temporally varied but spatially static

The model comprises of three components, (i) CNN feature extractor: the 2017 NYC datasets are split into one-hour interval subsets with each feature assigned to its corresponding region and then encoded into vectors, (ii) Citywide Speed Inference Model: the author makes the assumption that, road average speed depend on the following region wise casualties: (1) geographically adjacent road segments tend to share similar traffic speed patterns and (2) those road segments which are geographically distant but have the same road type and functionality share similar average speed, to fill the missing speed values. Thus, the inference model can be formulated as a weighted-regression problem, (iii) ASRAP: the proposed model consists of three ResNet and three stacked CNNs structures to model the properties of Type I data in the form of multi-channel frame and Type II data in the form of feature maps. Type III data is encoded by two fully-connected layers. This attention mechanism reweights the different temporal dependencies autonomously.

The study conclusively showed that, ResNet and attention mechanisms used for accident prediction tasks, outperforms other deep learning methods in terms of MSE and accuracy rate, and reach 0.16 and 88.89% respectively. In conclusion, this paper gave us an impeccable insight into the approach that can be employed to find a solution to our problem statement, as the type of data used here and our problem statement seem to intersect.

C. Spatio-Temporal Transformer for Accident Prediction

Paper [4] seeks to forecast traffic accidents with increased accuracy based on a spatio-temporal Transformer. Compared with traditional data mining techniques, deep learning possesses the ability of using distributed and hierarchical feature representation to model complex linear phenomenon. Transformer, a deep learning method, takes a sequence as the input, scans through each element in the sequence and learns their dependencies. This feature makes the transformer intrinsically good at capturing global information in sequential data. Based on this, the enhanced spatio-temporal Transformer is able to depict both the time and spatial dependence of the traffic flow sequence.

The paper uses two sets of real large-scale high-speed traffic flow data sets, and data fusion with the real high-speed traffic accident data sets, to obtain a traffic data set with accident labels.

The proposed framework for accident prediction, ST-TAP is shown to predict accidents accurately and give corresponding risk warnings. The model is composed of four main parts, which are the input layer, the spatial pre-order codec Transformer, the temporal Transformer and the prediction layer. The input layer consists of parallel convolution neural networks for feature extraction of the time-sorted traffic speed matrix and traffic flow matrix. In the spatial-temporal Transformer module, the model captures the temporal and spatial features of the data.

It is found that the spatial features of traffic flow can be divided into static spatial-temporal dependence and dynamic spatial-temporal dependence.In order to capture the static and dynamic spatial dependence of traffic flow, the spatial Transformer is used in the spatial-temporal Transformer block first.Compared to the temporal Transformer, spatial Transformer uses static image convolution and dynamic image convolution to capture spatial dependance. So as to detect the spatial dependence, It is essential to ensure the simultaneous capture of the temporal and spatial aspects of the traffic flow at various periods since the input of this paper is a time-labeled road upstream and downstream traffic speed matrix and traffic flow matrix with distinct temporal and spatial steps. To solve this problem, the paper implements spatiotemporal position embedding in the spatiotemporal Transformer results.

The paper defines road topology as a graph constructed on the basis of physical connectivity and distance between the sensors. The static spatial dependance determined by road topology is captured using a static graph convolution network.The dynamic graph convolution captures implicit spatial dependencies that change over time like the hot spot location of traffic flow, by training and modeling high-dimensional latent spaces.To capture long-distance time dependence,the paper uses self-attention mechanism combined with the sliding window.

Since the spatial dependence of static graph convolution and dynamic graph convolution learning cannot be directly fused, it is necessary to use a gating mechanism for feature fusion.After spatial-temporal Transformers extract the spatial-temporal features of the traffic flow, the output traffic flow sequence is used as the mapping between the input training of the convolutional neural network and the accident.The traffic mapping probability and the velocity mapping probability obtained are passed through the fully connected layer to obtain the final output, indicating whether there is an accident.

Finally, to verify the advance of the proposed framework, the research paper compares it with a variety of existing methods.It concludes that the presented model has a shorter training time and the model optimization is realized faster. The model also obtains a higher accuracy rate because the use of dynamic graph convolution to capture the hidden space dependence of road changes over time.However, it is found that the recall rate of the model is less effective than ST-GCN i.e Spatial-Temporal Graph Convolutional Networks.

III. Dataset

We intend to use the US-Accidents dataset for the course of the work[2][5]. The dataset contains more than 2.8 million cases of traffic accidents which covers 49 States of the USA from February 2016 to Dec 2021. The data attributes are mainly belong to the following categories:

- Traffic: consists of traffic events(i.e., accident, broken-vehicle, congestion, construction, event, lane-blocked, and flow-incident).
- Time: includes weekday, hour-of-day and daylight.
- Weather: comprises 10 weather attributes including temperature, pressure, humidity, visibility, wind-speed, precipitation amount and special events like rain, fog, and hail.
- POI: encompasses amenity, speed bump, crossing, give-way sign, junction, no exit sign, railway, roundabout, station, stop sign, traffic calming, traffic signal, and turning loop.
- Location: Latitude and Longitude in GPS coordinates of start and end points.
- Description: natural language description of the accident.
- Severity: Shows the severity of the accident, a number between 1 and 4, where 1 indicates the least impact on traffic.

IV. Initial Insights

Data cleaning, EDA and Visualization

- We performed data analysis and visualization on the US-Accidents dataset put together by the authors of paper[2][5].
- We considered accident durations that are over one day and over the 3rd quartile and found that the average accident duration is about 2 hours and 45 minutes and about 1 hour and 30 minutes respectively.
- After considering duration of fewer than 24 hours, it was observed that accidents with a severity of 1 (minimum severity) have the minimum duration, but accidents with the severity of 2 are the ones that have the maximum rather than a severity of 4 (maximum severity). aren't even close to the maximum duration.
- We can say that there is a relationship between a decrease in duration and a decrease in severity.

This conclusion is due to unfair accident frequency, hence a different method was deemed appropriate, i.e, taking the mean of duration and severity fields.

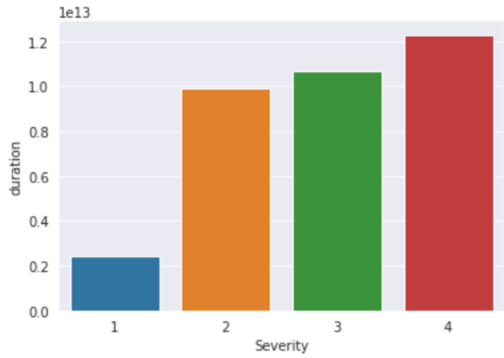


Fig.1 Graph showing positive relationship between duration and severity of accidents.

- 7 am - 9am and 12am - 8pm are the two major periods that accidents occur in.
- The three major days of the week that have the most accident occurrences are Friday, Thursday and Wednesday, on the contrary, the least two days of the week are Sunday and Saturday, Fig 2. Accidents seem to occur more in the months of October, November and December, Fig 3.

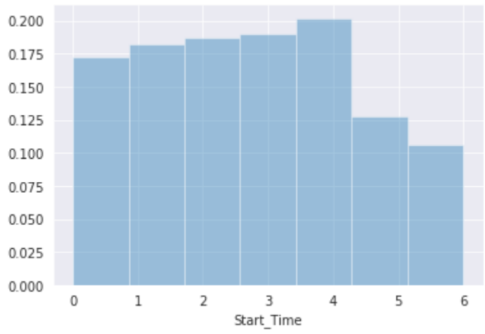


Fig.2 Graph showing accident frequency and days

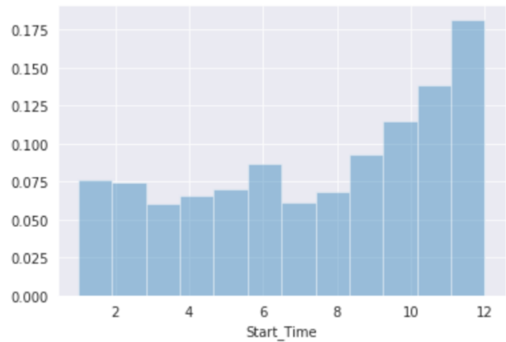
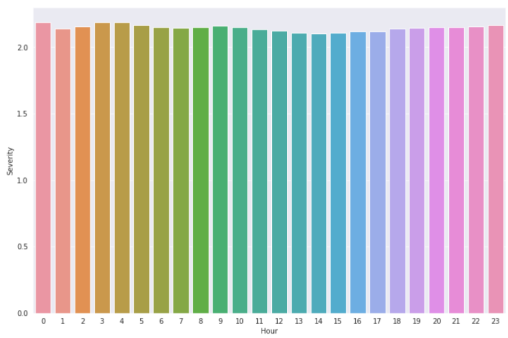
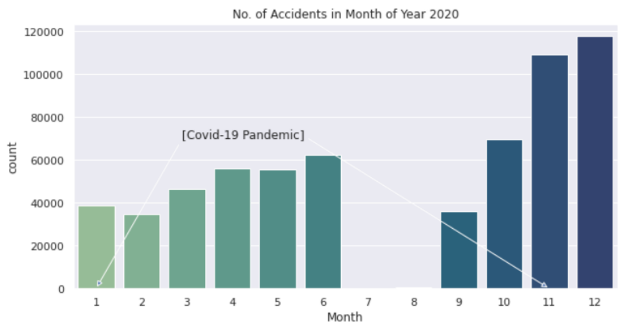


Fig.23 Graph showing accident frequency and months

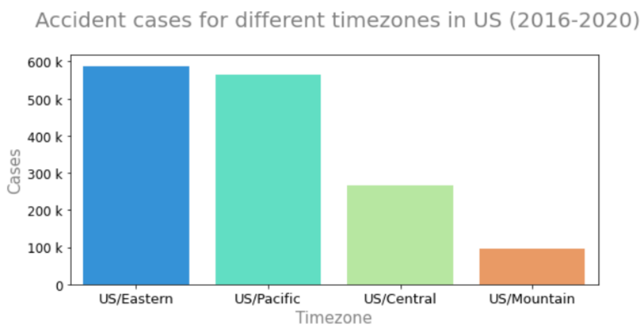
- The severity of accidents differ according to the hours, but not significantly.



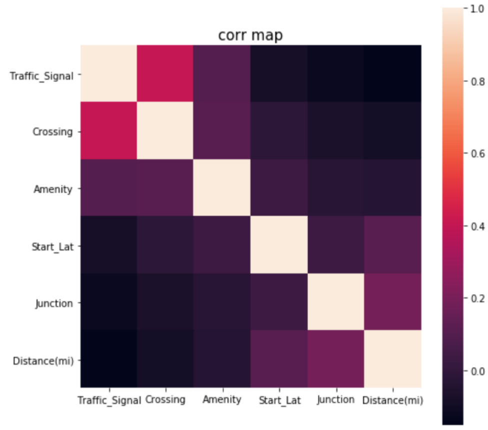
- There is no significance dependence observed between the severity of accidents and days/months.
- It was observed that the quarantine in 2020 affected the frequency of the accidents.



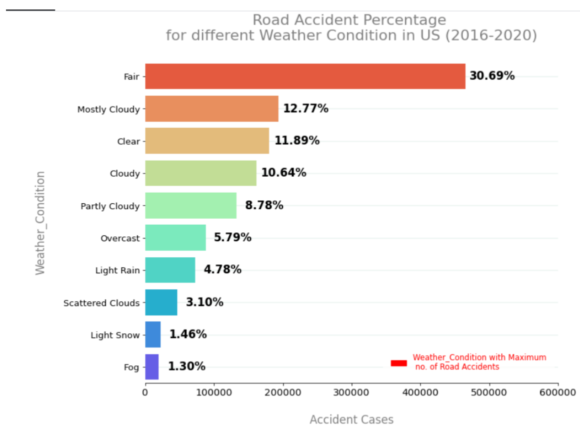
- The US/Eastern time zone region accounts for about 38.84% of the accident cases.
- Eastern and Pacific time zone regions account for about 76% of the accident cases. Interestingly, these two regions also accounts for about 72% of the population (excluding those 14 split time zone states)
- Us/Mountain region reported the lowest number of accident cases. It agrees with the fact that Mountain timezone region has the least population, thus lowest no of accidents are reported there.



- The effect of road conditions based on different attributes were as follows: Almost in every case (99.98%) Bumper was absent from the accident spot. In 5.7% cases, road accidents happened near the crossing. In 98.83% cases, there were no stops near the accident area. 13.49% road accident cases recorded near the junctions. There are no accident cases recorded near the Turning Loop. 11.21% road accident cases recorded near the traffic signal.



- 45% of the road accidents occurred in the temperature range of 61(F) - 91(F), maximum cases (15.74%) of road accident occured in the humidity range of 81% - 91%, 67.32% of road accident cases with the air pressure range between 20(in) - 30(in), the wind chill range is between 51(F) - 71(F) for (26.37%) of the cases, for around 35% of cases, the wind speed range is between 5(mph) - 10(mph), 77.71% cases occurred in the Visibility range of 9(mi) - 10(mi) and in most of the cases (30.69%), the weather was Fair and approximately in 13% cases it was mostly cloudy.



V. Problem Statement and Approach

In real-world circumstances, traffic accidents frequently result in serious human casualties and significant economic losses. A timely, accurate traffic accident forecast has a significant deal of potential to safeguard public safety and minimize financial damages. Due to the complicated causality of traffic accidents, which involves numerous aspects such as spatial correlations, temporal dynamic interactions, and external impacts in traffic-relevant heterogeneous data, it is difficult to anticipate traffic accidents.

Classical methods of accident prediction aim at fitting regression models or other models to predict the number of traffic accidents on specific roads or certain regions. Some other work at identifying correlation between attributes(e.g., weather, road topology etc.) and the accident risk. The major drawback of these data mining techniques is that they

apply to small scale traffic accident data with limited features. They also have low accuracy since they don't address unique data properties like spatial and temporal characteristics.
Recent research tries to tackle the traffic accident prediction problem using deep learning models.A major criticism that has been raised about these models is that although conventional neural network models can fit the training data with high precision, when it comes to prediction, they may produce predicted values with unacceptable variances. The main reason for this is overfitting and neural network models that suffer from the over-fitting problem generally have poor generalization ability, which limits their applicability for accident predictions.
To address some of these problems, we propose a spatio-temporal Transformer model to predict accidents accurately. The model will be built using the data from US-Accidents. We also plan to experiment with various models in order to select the most optimal one.

Acknowledgment

We wish to extend our special thanks to Prof.Anand M S and the team of Data Analytics Course, for providing us guidance, suggestions and resources over the course of our project. We would also like to acknowledge the Department of Computer Science and Engineering at PES University, for encouraging us to gain more practical knowledge and for providing us the exposure and opportunities in the industrial and research fields.

References

[1] Nantulya VM, Reich MR. "The neglected epidemic: road traffic injuries in developing countries." BMJ. 2002 May 11;324(7346):1139-41. doi: 10.1136/bmj.324.7346.1139. PMID: 12003888; PMCID: PMC1123095.

[2] Sobhan Moosavi, Mohammad Hossein Samavatian, Srinivasan Parthasarathy, Radu Teodorescu, Rajiv Ramnath,"Accident Risk Prediction based on Heterogeneous Sparse Data: New Dataset and Insights". In: *Proceedings of the 27th ACM SIGSPATIAL, International Conference on Advances in Geographic Information Systems (2019),*
URL: https://doi.org/10.48550/arXiv.1909.09638

[3] Z. Zhou, "Attention Based Stack ResNet for Citywide Traffic Accident Prediction," *2019 20th IEEE International Conference on Mobile Data Management (MDM)*, 2019, pp. 369-370, doi: 10.1109/MDM.2019.00-27

[4] W. Liu et al., "ST-TAP: A Traffic Accident Prediction Framework Based on Spatio-Temporal Transformer," *2021 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Comput -ing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/ -CBDCom/CyberSciTech)*, 2021, pp. 360-365, doi:10.1109/DASC-PICom-CBDCom-CyberSciTech52372. 2021.00068.

[5] Moosavi, Sobhan, Mohammad Hossein Samavatian, Srinivasan Parthasarathy, and Rajiv Ramnath. "A Countrywide Traffic Accident Dataset.", arXiv preprint arXiv:1906.05409 (2019).