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A Survey on Spatio-Temporal Prediction Methods

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***Abstract*—The domain of deep-learning has shown immense advancement in recent years, along with the rapid increase in the computational power of our systems. The current trend of representing the collected data in the form of graphical structures has not gone unnoticed, with the wide-scale use of these graphs within models to encode spatial and temporal dependencies for better performance. Usage of spatio-temporal graphs has proven to be critical for various domains such as public safety, medical statistics and transportation. This study provides a structured review on methods and principles employed in order to predict data and events using spatio-temporal modelling. We provide the taxonomy of models and the key challenges that they address and the methodology they follow. For each methodology, we introduce its theoretical basis and discuss its advantages and disadvantages.**

Index Terms*—Graph Neural Networks, SpatialTemporal Model, Deep Learning, Covid-19, Conflict Prediction, Trajectory and Motion Prediction, Traffic Prediction

I. INTRODUCTION

Non-linear patterns in large datasets can be converted into their compressed counterparts using neural network architectures. Historically, these algorithms were applied on grid-like samples, such as a vectorized table or an image. However, in recent research, these techniques have been applied to graphs. Graphs do not follow a rigid structure since nodes can be connected to a variable number of edges. This has led to the proliferation of geometric deep learning techniques over graphs and manifolds to handle the variable structure of data, such as spatio-temporal graph networks. There are multiple directions of research and applications that can employ spatio-temporal graphs along with neural networks. Given spatial data samples with defining features and a target variable at different locations and times, the spatiotemporal prediction model learns from the provided historical data and aims to predict the target variable based on its defining features. These prediction models have proven to be very popular in recent years with the immense progress made with the development of spatial data mining. This field is used to find the non-trivial, previously unknown, but valuable patterns from large datasets[18]. Yet methods developed by different research communities tend to use different terminologies and solve problems from various perspectives. A structured review that compares these methodologies is missing. Taking this into consideration, this paper provides a systematic overview of different spatio-temporal prediction methodologies that are at par with the current proposed models. We categorise the methodologies followed based on the different challenges they address and list out their pros and cons. The final goal is to provide concise details about each of the models to enable researchers to choose an appropriate technique to solve the intended problems in their application domain easily and understand the basic ideation as well as identify open research opportunities in spatio-temporal graph prediction.

II. DEFINITION

Spatio-temporal is a term that combines two words, where spatio represents space and temporal stands for time. It can be defined as a system that describes the structural relationship, providing the information of space and time. When these components together are represented in the form of a graph, the whole system can be called ”Spatio Temporal Graphs”. The modelling of these graphs play an important role in analysing the spatial relation and temporal trends of a system. These graphs can make a neural network to study static structures and time-varying data.

III. PREDICTION METHODS

A. Traffic speed prediction methods

1) **“Spatio-temporal Dynamic Forecasting and Analysis of Regional Traffic Flow in Urban Road Networks Using Deep Learning Convolutional Neural Net- work.”**

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The STGCN-BiLSTM(Spatio-temporal Graph Convolution Network Bi-Directional Long Short-Term Memory)[1] model is used to dynamically predict traffic flow in road networks given the complexity and highly non-linear nature of traffic data (weather conditions, factors such as holidays and travel opportunities). STGCN is utilized for extracting spatial features of urban road networks and BiLSTM is employed to optimise the STGCN. Moreover, in combination with clocked linear units, STGCN can extract short-term temporal dependencies in the time dimension. The two alternately combine the features to form a spatio-temporal convolution block. The model's structure consists of a stack of space-time convolution blocks. BiLSTM uses both forward and backward dependencies to ensure that valuable information is not filtered or passed through the LSTM's chain-gate structure. As we will see in the next section, the proposed algorithm yields higher accuracy and robustness. However, the model does not take into consideration static factors such as road structure, number of lanes, and weather characteristics. Furthermore, it does not include optimal route planning, only traffic information for all possible lanes within the scope of the project.

2) **"Hybrid Spatio-temporal graph Convolution Network:Improving traffic prediction with Navagation data."**
The H-STGCN[2] model is a technique for estimating the expected amount of traffic from an online browser engine.The spatial dependency is captured by graph convolution. A composite neighborhood matrix reflecting the proximity of own traffic is also constructed.Experiments on real-world datasets show that H-STGCN outperforms the benchmark techniques, notably for predicting non-recurring congestion.
This paper's design showcases a revolutionary formalism for embedding physics knowledge in a data-driven model that may be easily applied to general spatio-temporal forecasting applications. Non-recurring congestion, on the other hand, is particularly difficult to predict due to a lack of contextual information. Forecasting's spatial resolution is insufficient for key real-world applications.

3) **"MFDGCN: Multi-Stage Spatio-Temporal Fusion Diffusion Graph Convolutional Network for Traffic Prediction."**
Using the diffuse convolution technique, a deeplearning model called MFDGCN (Multi-stage Spatio-Temporal Fusion Diffusion Graph Convolution Network)[3] was put up to address the problem of the spatio-temporal fusion method's easy ignoring of complex spatio-temporal interdependence in road network traffic forecast. In terms of spatial and temporal dimensions, it employs dynamic and static fusion graph modelling. This can capture both global nodes in the road traffic network in addition to local nodes in the network. In order to identify similar links between non-adjacent nodes, it also creates multi-association graphs. To identify longer-term spatio-temporal dependencies, it employs a multi-stage hybrid spatio-temporal fusion technique. This model proposed has excellent feature learning capabilities, which allows it to anticipate traffic flow well when comparing the long and short term prediction impacts. A significant limitation in this model is that when the forecast duration increases, the long-term prediction performance of each model may degrade.

4) **"GSTNet: Global Spatio-Temporal Network for Traf-fic Flow Prediction."**
To capture and represent the global dynamic spatial-temporal correlations, A Global Spatial-Temporal Network(GSTNet)[4] model was proposed. The architecture of the proposed GSTNet, which is made up of an output layer and several other layers of spatial-temporal blocks. A global correlated spatial module and a multi- resolution temporal module are found sequentially in each spatial-temporal block. The output layer uses a tem- poral domain attention method to automatically choose the relevant historical traffic data. Many existing meth- ods only take localised spatial correlations into account. The spatial correlations over various traffic network nodes, however, are both local and non-local. The same is the model's main focus. In terms of temporal di- mension, GSTNet is likewise excellent. Only allows for short-term forecasting. The framework can therefore be expanded in order to address multi-step and long-term prediction in future studies.

5) **"Traffic Flow Prediction via Spatial Temporal GraphNeural Network"**
The proposed model is a "spatial temporal graph neural network"(STGNN) framework[5]. Such Graph neural networks which have a position-wise attention mechanism are used to study the spatial and temporal relation- ships in the urban road network. The framework consists of 3 components, namely spatial graph neural network layers, GRU layer and the transformer layer. The spatial relations between roads are captured by the GRU layer, the temporal relations are sequentially captured by the GRU layer and the long-range temporal dependance is directly captured by the transformer layer. The proposed model is then compared with some baseline models to demonstrate the efficiency. Traditional GNNs and RNNs are taken as the baseline models. The STGNN model can handle complex traffic situations and shows a good performance in long-term prediction. We discuss the detailed efficiency of the proposed model in comparison to the baselines in the next section. Future work could include a further analysis of the

characteristics and the dynamic features of other networks and use the advantages of the proposed model for social network analysis and other prediction problems.

B. Trajectory and Motion Prediction Methods

6) **"Social STGCNN: A Social Spatio-Temporal Graph Convolutional Neural Network for Human Trajectory Prediction."**
A deeper understanding of pedestrian behaviour will al- low a greater progress in modeling interactions between vehicles and humans. Human trajectories are determined not only by the movement of a pedestrian on the side- walk but also by their surroundings. This study proposes a Social Spatial-Temporal Graph Convolution Neural Network (Social-STGCNN)[6]. The model is made up of two major parts: the Time-Extrapolator Convolution Neural Network (TXP-CNN) and the Spatio-Temporal Graph Convolution Neural Network (ST-GCNN). To extract features, the ST-GCNN performs spatiotempo- ral convolution operations on the graphical illustrations of pedestrian pathways. These extracted features are closely-packed versions observed history of the pedes- trian's trajectories. These features are then input into the TXP-CNN, which predicts the trajectories of all pedestrians in the near future. The main differences between Social-STGCNN and ST-GCNN are: First, the Social STGCNN constructs the graph with a novel kernel function, as opposed to ST-GCNN. Next, beyond the spatiotemporal graph convolution layers, the pro- posed model has additional flexibility in manipulating the time dimension using the TXP-CNN. The given model takes into account different social behaviours of pedestrians, such as avoiding collision with surrounding objects, coming together from trajectories of different directions and walking in parallel within a given group in predicting the possible movements and trajectories. However, it did not include multimodal settings and other moving objects that a pedestrian might encounter, such as bicycles and other obstacles.

7) **"STGCN: For Modeling Vehicle Trajectory in High- way Scenario."**
The suggested approach for forecasting vehicle trajecto- ries on roads is based on STGCN[7]. This technique considers vehicle contact and lane information. TCN (Temporal Convolutional Network) is utilised in this study to extract spatial characteristics, and it outperforms RNN in long term predicting. According to the results of the trial, the ST-GCN performs well in forecasting vehicle trajectory in the highway pilot. Although its overall performance isn't the best, it simply calls for a small-scaled community and less enter parameters from the belief module. This is due to the fact the prediction version takes interplay and scene statistics into account, which permits it to perform successfully on NGSIM data. This model lowers the quantity of data from the perception module; it just requires lane information and the real-time coordinates of cars, implying a minimal degree of computational resource consumption. STGCN, on the other hand, is not as good at short sequence pre- diction as it is at long sequence prediction. (The model's adaptive ability is insufficient) In future research, this model will need to be expanded to include many more scenarios such as crossings, ramps, and crossroads.

C. COVID-19 and Disease Forecasting Methods:

8) **"Combining Graph Neural Networks and Spatio-Temporal Disease Models to predict COVID-19 casesin Germany."**[8]
A multimodal learning approach that combines the bene- fits of statistical regression and machine learning models was proposed for forecasting local COVID19 incidents in Germany. This innovative methodology enables the use of a wider range of data kinds, such as mobility fluxes and co-location likelihood. To simultaneously account for network-valued data and tabular data, the prediction can be made by merging epidemiological models with graph neural networks. The overall ap- proach integrates interpretability of distributional regres- sion with a GNN architecture to flexibly learn each district's latent representation from the network data. However, the analysis cannot be relied upon as the only basis for future decision-making because it only covers a small portion of the mechanisms involved in the transmission of COVID-19. Additionally, it disregards the necessity of a solid data foundation and the biases in reporting and observation that are typically inherentin such data.

9) **"A Spatio-temporal Graph Based Hybrid Infectious Disease Model With Application To Covid-19"** IeRNN[9] A hybrid spatio-temporal model[9] that com- bines SEIR (susceptible-exposed-infectious-recovered) and RNN (Recurrent Neural Networks) is proposed to achieve efficiency and accuracy in predictions. The graph structure has two features: edge feature node feature. I-equation is derived from SEIR for the node feature and for the edge feature, an RNN model is designed. The hybrid model (IeRNN) is then used to predict new COVID-19 state-level cases from the US. IeRNN is achieved by combining LSTM and I-equation. Forecasting is done in terms of one day ahead and seven day ahead forecasts. Using RNN as external input to the I-equation greatly improves the robustness to parameter initialization. In future work, the traffic

data can expand the inflow effect beyond geographically close neighbours and the strength of I-equation can also be increased by social control mechanisms. The standard models RNN, SEIR and ARIMA are outperformed by the proposed model. The next section of this paper gives a detailed overview of how the proposed IeRNN outperforms its baseline models in terms of accuracy and efficiency.

10) **"Examining COVID-19 Forecasting using Spatio-Temporal Graph Neural Networks."**[10]

The version given on this studies learns from a unmarried large-scale spatio-temporal graph, wherein nodes replicate vicinity-degree human mobility, spatial edges suggest inter-vicinity connection primarily based totally on human mobility, and temporal edges constitute node attributes throughout time. When paired with graph-primarily based totally deep gaining knowledge of algorithms, this sparkling supply of information may be a extensive device for information the dissemination and evolution of COVID-19. When as compared to the pinnacle appearing baseline models, this novel technique to mobility led in a 6This modelling technique is easily adaptable to regression problems involving huge amounts of spatiotemporal data, such as illness status reports and people mobility patterns with many temporal and geographical dimensions. However, there was no specific modelling paradigm for infectious illness based on GNNs and high resolution mobility data at the time the model was introduced.

11) **"COVID-19 Dynamic Monitoring and Real-Time Spatio-Temporal Forecasting"**[11]

This study presents a strategy for predicting the spatio-temporal spread of Covid-19 in Brazil, specifically in the state of Pernambuco (a Brazilian state). The COVID- SGIS program then collects data on Covid-19 cases on a daily basis. Base for the throat area. The cumulative number of cases of illness is then determined for each municipality in the state of Pernambuco and for the entire country. Instances and coordinates of the munici- pality.

The preceding step's databases are then delivered to an interpolation module and blended into training data sets. The instance count in a particular module is spread over an inhomogeneous grid based on the latitude and longitude of the corresponding community centroid. The interpolation algorithm then generates a regular grid. The IDW (Inverse Distance Weighting) interpolation technique is used to find each point on this regular grid. This method is used to estimate the distribution of cases of infection and death. Spatial distribution maps are then created for each reporting day. Therefore, the distribution maps are constructed to show maps from three consecutive days.The technique based on spa- tiotemporal analysis allowed for a more comprehensive examination of those in areas with a high concentration of confirmed Covid-19 cases. However in this work, they did not incorporate meteorological variables or sociodemographic aspects that may influence disease dynamics while developing models.

D. *Conflict forecasting*

12) **"Conflict Forecasting with Event Data and Spatio- Temporal Graph Convolution Networks "**

Three model components are explored to improve the performance and efficiency prediction over the ViEWS baseline. Neural networks which achieve spatial tem- poral dependency, CAMEO coded data which is event based and CRPS (continuous rank probability score) are used. The three main components of the model are: input data, learning algorithm and the evaluation metrics of the prediction. The proposed STGCN models are STGCN- LSTM [12] STGCN-TCN[12]. In the STGCN-LSTM model, there are 2 layers of the GCN modules and each layer aggregates content and information of 1-hop. Next, the embedding which is generated by the first layer is fed to the next GCN layer. Finally, the embedding generated passes through LSTM to follow a sequential modelling process. Each module in the STGCN-TCN model com- prises of TCN and GCN structures. Both TCN GCN are concatenated to extract information and to form the hybrid STGCN-TCN model. The results as shown in the next section indicate that the "spatiotemporal graph convolutional neural network" (STGCN) models improve prediction performance of prediction over the benchmark.

13) **"Spatio-Temporal Extreme Event Modeling for Ter- ror Insurgencies.."**[13]

A self-exciting marked spatio-temporal model is pro- posed to model terror attacks in which the heterogeneous baseline intensity is described as a function of covariates is introduced in this study. Its trigger strength is modeled using a post-distribution Gaussian process to capture the complex spatio-temporal dependencies between random attacks and historical terrorist attacks. On extrapolating the parameters, we can emphasize certain spatiotemporal regions where seizures are likely to occur. A new mixed distribution of fatalities is introduced by taking into account the consequences of attacks in terms of deaths from attacks. This distribution caters to both small and large numbers of victims. It also takes into account the discrete nature of the data via the popular ZipfF distribution. To estimate the

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parameters, the model uses a fitted Markov chain Monte Carlo (MCMC) method. The database used is the Global Terrorism Database corresponding to terrorist activity from 2013 to 2018in Afghanistan.

E. Framework for time-evolving social networks.

14) **"STGSN: A Spatio-Temporal Graph Neural Network framework for Time-Evolving Social Networks."** The STGSN(Spatial-Temporal Graph SocialNetwork)[14] is a novel spatial-temporal graph neural network framework designed primarily for social network modeling. It models the spatial and temporal characteristics of social networks that change over time, which is particularly helpful for criminal network analysis. This approach is the first attempt to use graph-embedding attention mechanisms to enable the framework to model a social network's temporal properties. The suggested method's robust, expressive capability is thoroughly examined by establishing five categories for temporal attention allocation and discussing how they influence the downstream predictions. However, creating a better graph representation technique that takes into consideration the node ID, node attributes, and edge attributes of the neighbourhood and developing an improved time-slicing technique for improved temporal segmentation can be considered. demonstrating its ability to efficiently group points and describe long term relationships while conserving spatial structure. The challenge faced was for long term prediction: all the models that have been displayed in this paper show a progressive loss of shape.

F. Point-Cloud prediction

15) **"Spatio-Temporal Graph-RNN for Point Cloud Pre- diction."**
In this paper, a learning network was suggested to decipher dynamic PCs (Point Clouds)[15] and create the right predictions of the future outcomes. They made a Graph-RNN cell that can use learned characteris- tics that describe the nearby geography to produce "spatio-temporal graphs" from which temporal corre- lations might be determined. The network's ability to represent short and long term movements while keeping spatial association was demonstrated by experimental data. The methodology they made can deliver precise PC predictions.

IV. Key applications

The characteristics and features of spatio-temporal graphs can be applied on various public issues which include (1) traffic, (2) covid-19, (3) trajectory, (4) conflicts. Current applications on these issues involve the use of traditional machine learning and deep learning methods. However, these applications can be enhanced with the use of the new- generation graph methods containing spatio-temporal contexts. This provides the ability to include a more enhanced andexpanded set of functionalities.

A. Traffic

Traffic forecasting plays a major role in ITS (Intelligent transportation systems). In recent years, many countries have been committed to finding new methods to develop and improve traffic forecasting accuracy. Forecasting traffic has been a serious issue for over a decade. It plays an important role especially on highways where the speed of vehicles and the traffic congestion is directly proportional which adversely affects the traffic capacity. Advance prediction will allow the traffic management authorities to provide traffic control and intelligent route guidance which will help in solving the congestion issues in the system[20]. Prediction and forecasting has always been considered challenging as the traffic flows are never linear, they usually show complex and non-linear patterns. The key issue of such prediction problems is the lack of ability to model the spatial-temporal correlations of the data. Hence, considering the structure of the traffic network and the dynamic spatio-temporal patterns of traffic data, the use of spatial-temporal graphs is an emerging and trending concept for efficient and accurate forecasting and prediction

B. Covid-19

Covid-19 has been a huge public health issue all throughout the world. The COVID-19 epidemic has claimed many lives throughout the world and poses an unprecedented threat to public health, food systems, and the workplace. There have been 590,659,276 confirmed cases of COVID-19 to date. 6,440,163 fatalities were recorded. We have all observed Covid's influence on our personal lives.

Spatiotemporal analysis assists in a variety of pandemic situations and aids in the fight against COVID-19 by slowing the virus's spread.This strategy can also be used to combat other pandemicsExamining the spatiotemporal clustering of confirmed Covid-19 infections using a spatiotemporal scan and analysis has benefited in the reduction of viral spread on a broad scale. In other words, it is realistic to predict that future cases in a location will be impacted by its own historical data as well as that of other regions, persons travelling to/from that region, places with comparable epidemic trends, and so on.This is where this strategy might help influence multilevel plans for coronavirus management, as well as appropriate allocations of public health and healthcare resources.

C. Conflict prediction

Conflicts include any form of violent outbreaks or terrorist activities. Conflict prediction is complex as it consists of a wide scope of belief systems, reasons, objectives, and par- takers. It proves dangerous not only to legislatures and orga- nizations, but to humankind as a whole. Therefore, focusing on people and areas that are at high risk of being attacked can give insight into the precautions and measures necessary to be taken to prevent such an act. Utilizing historical data, spatio-temporal graphs and deep learning can be implemented to make predictions to learn future terrorist targets or conflict hotspots. Associations and patterns among spatially and tem- porally close attacks and outbursts can be especially useful for this. Researchers have asked for the formation of a specialized field dedicated to the examination of contentions, nationwide conflicts, and terrorist attacks. Although the attacks occur at random, the people are carefully chosen for their shock values. It ought to be noticed likewise, that once an attack has taken place in a certain area in a specific time frame, the probability that a similar attack will occur in the same area within a considerable time frame is very high. This is what is usedto make predictions using spatio-temporal models.

D. Trajectory Prediction

As a result of enhanced computer comprehension of pedes- trian behaviour, the modelling of interactions between agents, such as autonomous vehicles and humans, utilising spatio- temporal models, can evolve more quickly. In addition to the pedestrians' own movements, interactions with adjacent objects also have an impact on the pedestrians' paths. More and more self-driving technologies are being implemented as automatic driving technologies advance, even in the area of vehicle trajectory. More than simply observation, planning, and controlling need to be taken into account if autonomous vehicles are to be safe. Therefore, for effective decision-making control and to guarantee the security of automatic driving, fast and accurate trajectory prediction is crucial.

V. METHOD COMPARISONS

The results mentioned in the above methodologies show that the spatio-temporal prediction techniques outperformed baseline prediction methods in all applications. The methods we have reviewed implemented different models to encode both spatial information and represent this spatial information over time. The models along with their error values are summarised as follows:

Table I. Average performance comparison of different ap- proaches

MODEL	RMSE	MAE	MAPE
STGCN-BiLSTM	4.60%	5.46%	7.73%
H-STGCN	0.04911 ± 0.00041	0.03496± 0.00031	7.1691 ± 0.1130
MFDGCN	2.75%	1.30%	2.75%
GSTNet	–	24.30 ± 1.12	21.02 ± 0.78
STGNN	4.99%	2.62%	6.55%
Social-STGCNN	1.44%	3.01%	3.04%
STGCN	2.96%	1.36%	2.90%
STGSN	–	2.068 ± 0.021	6.265 ± 0.228

VI. CONCLUSION

Spatio-temporal prediction methods have gained traction in recent years and are proving to outperform baseline pre- diction models with respect to their performances[19]. In this survey, we give a comprehensive overview of the latest spatio-temporal prediction methodologies which we divide into categories based on their applications: healthcare, conflict prediction, human and vehicle trajectory and geographical prediction. We then summarize and compare the methods in each group. The methodologies, as well as metrics and datasets of these models are also introduced here. Although this is a budding domain, it is not devoid of numerous obstacles and unresolved issues. We hope that our survey assists further research and development in utilizing spatio-temporal modelsfor prediction applications.

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