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Network SpaceTime AI: Concepts, Methods and Applications

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Abstract: SpacetimeAI and GeoAI are currently hot topics, applying the latest algorithms in computer science, such as deep learning, to spatiotemporal data. Although deep learning algorithms have been successfully applied to raster data due to their natural applicability to image processing, their applications in other spatial and space-time data types are still immature. This paper sets up the proposition of using a network (&graph)-based framework as a generic spatial structure to present space-time processes that are usually represented by the points, polylines, and polygons. We illustrate network and graph-based SpaceTimeAI, from graph-based deep learning for prediction, to space-time clustering and optimisation. These applications demonstrate the advantages of network (graph)-based SpacetimeAI in the fields of transport&mobility, crime&policing, and public health.

Key words: spatiotemporal intelligence; network; graph; deep learning; spatiotemporal prediction; spatiotemporal clustering; spatiotemporal optimization

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1 Introduction

Geographic Information Science (GIS) has a long history, starting with Dr. John Snow using the manual map to reveal the association of Cholera cases with the water pumps near Broad Street in central London. Since then, the field has gone through rapid technological advances, in particular the advent of computer-aided desktop mapping (such as using ArcInfo) in the 1970s and subsequently web-based spatial analysis (e.g., ArcGIS) in the 2010s. With the development of mobile technologies, IoT, Big Data, and AI, GIS is moving quickly from GeoComputation towards GeoAI, a topic that has risen to prominence as a field of study that applies the latest methods from computer science, such as deep learning, to geospatial problems. While GeoAI methods have had great success in image processing tasks due to their natural applicability to raster data, their application to other spatial and spatiotemporal data types remains underexplored.

Due to the uniform nature of rasters, there have been vast recent advances in the application of machine learning to image understanding (using Convolutional Neural Networks (CNNs) as a representative) in GIS such as urban object detection[1] and street view analysis[2]. To make use of CNNs, some traffic forecasting work involving traffic, telecommunication and other networks is performed by converting spatial data structures (such as networks and points) into grids[3]. There are three potential issues of this grid-based ap-

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proach: ① Gridding leads to the loss of point accuracy of the original vector data, which in turn leads to inaccurate subsequent analysis results. The grid size usually used for spatiotemporal analysis and prediction is large, ranging from several hundred meters to several kilometres[4-5]. Such grids may contain multiple features of different types of geographic objects (such as lakes, roads, and railway stations); ② Grids of different sizes may lead to different analysis results, and there will be a Modifiable Area Unit Problem (MAUP)[5]; ③ The grid structure is not suitable for urban applications and management, such as urban traffic, because the traffic flow must follow the street network, not moving in an artificially divided grid[7]. Grid-based methods push traffic into spaces where there is no traffic at all (outside of roads), which will further lead to unsuitable analysis results for practical use.

On the contrary, the network-based spatial representation will have the following advantages compared with the grid-based approach: ① Network-based ST modelling can provide fine-grained analysis in high accuracy compared with the region- or grid-based forecasting. The network-based quadrat method derives a more accurate estimate of the local spatial similarity. For instance, regarding the predictive crime mapping, Rosser et al.[6] have demonstrated that the network-based model substantially outperformed a grid-based alternative in crime prediction accuracy, and hence should be used for operational policing. This might be because a network, as a naturally underlying structure, can capture the spatial correlation better than a gridded structure; ② Network-based spatial structure avoids converting the original observations in urban studies into grids in different sizes which leads to MAUP; ③ Network-based ST analysis is practical and usable. The intrinsic structure of many spatiotemporal data in urban studies is network-based since the road network is a crucial determinant of urban systems, such as traffic, crime, telecom, energy, and sensor networks. It is natural to expect that the network topology will affect the spatiotemporal correlation[8-9] and the distribution of such ST phenomena is constrained by the layout of the networks[9]. Using Euclidean planes (e.g., grids or regions) in this case may distort the representation of spatial distribution patterns on the network and the computation of spatial distances. Considering its practicality, network-based analysis and prediction can be more convenient to use in practice. For example, crime hotspot prediction based on the street network can guide police patrolling the city more intuitively than grid-based prediction[10]. There are therefore many potential advantages to using the network as the spatial basis for spatiotemporal analysis.

On another note, graph-based deep learning has been gaining popularity as the latest approach to deal with irregular data in non-Euclidean space, which has been advanced in biology, chemistry, and social network analysis. Given their flexibility, any spatial data could be represented as graphs, to take full advantage of graph-based deep learning for spatial and spatiotemporal modelling. Therefore, this paper proposes to use networks (graphs) as the analytical framework to advance SpacetimeAI. Networks (graphs) are proposed as the spatial structure to represent space-time processes that are conventionally represented as spatial units: points, lines/networks, or polygon/areas.

This paper aims to provide a systematic theoretical research framework, and thus does not review all relevant application literature, but the examples cited in the paper are the precedents of network-based spatiotemporal intelligence methods-prediction, clustering, and optimisation. For the subsequent application and improvement of related methods, reference may be made to other related documents.

This paper is organised as follows. After the Introduction, Section 2 illustrates how to represent space-time data and processes as graphs. It describes how a network (graph) can be used as a general spatial structure to represent spatiotemporal processes usually expressed as points, lines/networks or polygons/areas/grids. We categorise the broad SpacetimeAI methods according to the categories of space-time analytics presented in Literature [11], including spatiotemporal modelling and prediction, spatiotemporal clustering, and optimisation. Section 3 reviews the use of graph structures for spatiotemporal prediction and practical applications in the fields of transportation, crime, and public health. Section 4 introduces network-based spatiotemporal clustering and optimisation, and their applications in understanding travel behaviour and guiding police patrolling. Finally, Section 5 outlines directions for future research.

2 Graph-based Representation of Space-Time Data and Processes

The terms "network" and "graph" are synonymous to a large extent[12]. However, network terminology is generally used in the analysis of real network structures, either physical objects (e.g., road networks) or virtual systems (e.g., Internet networks and social networks). Network science primarily aims to address issues such as, detecting community, quantifying connectivity or determining the relevance of specific entities[13]. A graph is an abstract mathematical concept that does not exist in the real world[14]. It is a general data representation method that can conveniently describe the geometric structure of complex networks. Therefore, most network issues are also reduced to graph-based problems.

Graph theory offers a way of tackling abstract concepts like relationships and interactions where the edges in a graph represent types of relationships between the vertices. Typically, vertices of a graph are associated with discrete entities (e.g., road intersections) and the edges refer to the relationships between the entities. The weight associated with each edge in the graph represents the similarity or distance between the two connected vertices. The connectivity and the edge weight are either derived from the physics of real scientific questions or inferred from the data. For example, we can convert a road network to a graph showing its connectivity with an adjacency matrix, or we can convert it to a spatial weight matrix containing distances (or inverse distances). The spatial weight matrix can be of first or higher order to represent spatial associations of different spatial entities. Furthermore, networks (or graphs) can be both undirected and directed[7]. Fig.1 shows how the spatial units are transformed into a network graph.

This graph-based representation of the network brings mathematical convenience to model spatio-temporal network processes. There are two ways to convert a network into a graph. The first one is to represent the network node as the graph vertex, and the network link into the graph link. The other way is to turn the network link into the graph vertex, and the network adjacency as the graph link. The data defined on the graph is a set of values residing on a set of vertices of the graph, which is referred to as a graph signal[13] as shown below in Fig.2.

3 Graph-based Deep Learning for Space-Time Modelling

Deep Learning (DL) refers to the advanced developments of traditional machine learning methods. It has made breakthroughs in video processing, language translation, games, etc.[2,15-16]. In addition, deep learning has also been successfully applied to solve many urban problems. Compared with traditional machine learning methods, DL models have three advantages. First, DL models achieve "end-to-end" learning. It accepts input data in raw format and automatically extracts latent features to model underlying, complex, and nonlinear relationships in the data to generate the desired output. This feature greatly simplifies the workload of feature extraction. Second, the deep structure with thousands of trainable variables enables modelling of the complicated unknown relationship between the input and the output for predictive learning. Third, DL models have a powerful capability of handling nonlinearity leveraging nonlinear activation functions.

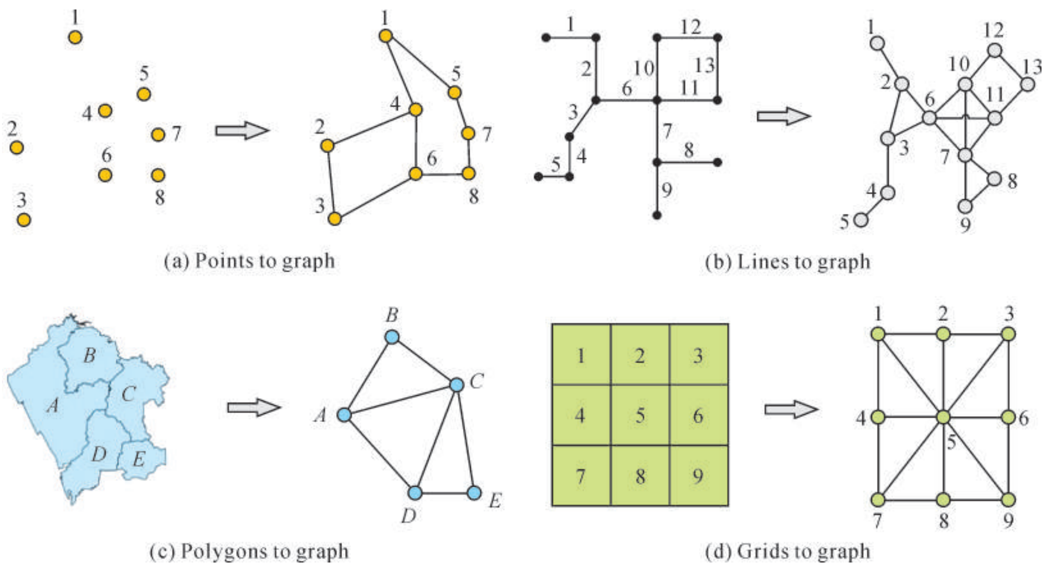


Fig.1 Converting spatial representations such as points, lines, polygons and grids into graph structural representations

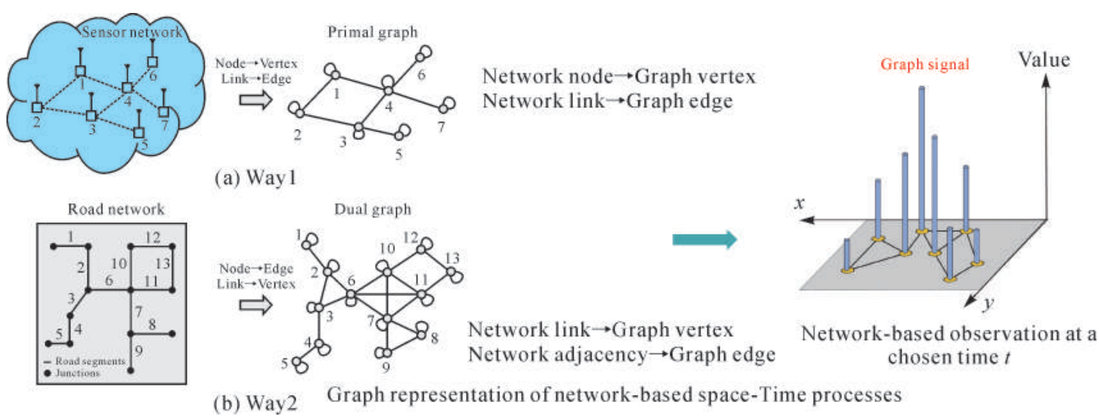


Fig.2 Graph representation of network-based Space-Time processes

There is a wide range of DL structures being used for either spatial or temporal data modelling, as briefly explained in the following two sub-sections. The three most popular DL architectures for modelling time series data include RNNs, LSTMs, and GRUs:

- Recurrent Neural Networks (RNNs): RNNs are a class of neural networks in which connections between nodes form a directed graph along a time series[17] to exhibit temporal dynamic behaviour. Unlike classical ANNs, RNNs can use their internal state (memory) to process input sequences. It is suitable for them to process the tasks such as speech recognition and language translation. However, RNNs suffer from short-term memory. When sequences are long enough, it is difficult for them to transfer information from earlier time steps to later time steps. RNNs also suffer from gradient vanishing, which means that gradients shrink back-propagated over time.

- Long Short-Term Memory (LSTM): LSTM[18] is a variant of RNN. LSTMs have a similar control flow to RNNs but are created as a short-term memory solution. A typical LSTM[19] has an input, a forget, and an output gate, which respectively determines whether to pass the new input, block the current state, and let the current state affect the output at each time step. It also has a cellular state that, in theory, could carry information from earlier time steps, reducing the impact of short-term memory.

- Gated Recurrent Unit (GRU): As a new generation of RNN, GRU is very similar to LSTM, but simpler[20]. GRU uses a hidden state to transmit early information without a cell state. It only has two gates, a reset gate and an update gate. The reset gate is another gate used to decide how much past information is forgotten. The update gate determines which information is passed and which new information is added, similar to the forget and input gates of LSTMs.

Two typical DL architectures include CNNs for regular spaces and GCNs for irregular spaces:

- Convolutional Neural Network (CNN): CNN was first proposed by LeCun and Bengio[21]. It is mainly used for image processing. CNNs typically have a series of convolutional layers that treat the image as a 2D plane. In a convolutional layer, each grid (pixel) of an image is only connected to its neighbour grid (e.g., local awareness), not all cells. It uses weight vectors to extract features (called feature maps). Grids located at different locations on the image have the same weight vector (weight sharing) and stacking multiple convolutional layers can capture long-range spatial dependencies from regular Euclidean space.

- Graph Convolutional Networks (GCNs): Classical CNNs operate on regular grid topologies and lack the ability to handle network/graph structured data. DL for graphs, especially GCNs, has attracted a lot of attention in recent years. In general, there are two classes of GCNs: spatial methods and spectral methods. In spatial methods, convolution operators aggregate the features of adjacent nodes for spatial information extraction[22]. Spatial methods can work on directed or undirected graphs, but it is not easy to share weights between different locations of the graph[23]. In spectral methods, graph convolution is defined in the spectral domain by a graph Fourier transform on the graph Laplacian[24]. So far, most methods have been limited to undirected graphs, because convolution requires a symmetric Laplacian matrix to obtain an orthogonal eigendecomposition.

Early developed DL models are often used to predict spatiotemporal data with a grid-based representation, because these models employ CNNs to capture spatial dependencies. However, spatiotemporal data naturally exists in network-space in applications such as transportation, sensors, energy, and social networking. The network-based representation can express spatiotemporal data accurately and practically, so that graph-based deep learning can be used for modelling spatiotemporal data, either dense or sparse.

To model the dependencies of spatiotemporal data, a straightforward and effective approach is to integrate spatial and temporal modelling components into DL models, which can be grouped into four main types (Fig.3)[25]: (a) Integrate spatial operators into temporal modelling structures. A typical example is ConvLSTM[26], which is essentially a recurrent layer (e.g., LSTM), but the internal matrix multiplication is replaced by a convolution operation. It can learn complex spatiotemporal patterns in datasets through nonlinear and convolutional structures. (b) Integrate temporal operators into spatial modelling structures. This type of hybrid deep learning approach integrates recurrent mechanisms into spatially modelled deep learning structures, such as recurrent CNN (RCNN) that incorporates recurrent connections into each convolutional layer[27]. (c) Time modelling first, then spatial modelling. For example, the LSTM-CNN architecture is very suitable for face anti-spoofing by utilizing LSTM to find long relations from its input sequence and extract local and dense features through convolution operations[28]. (d) Modelling in space first and then in time. This approach learns spatiotemporal information by sequentially connecting spatial and temporal deep learning structures. For example, a combination of CNN-LSTM structures has been used for PM 2.5 prediction[29] and traffic prediction[30] in smart cities.

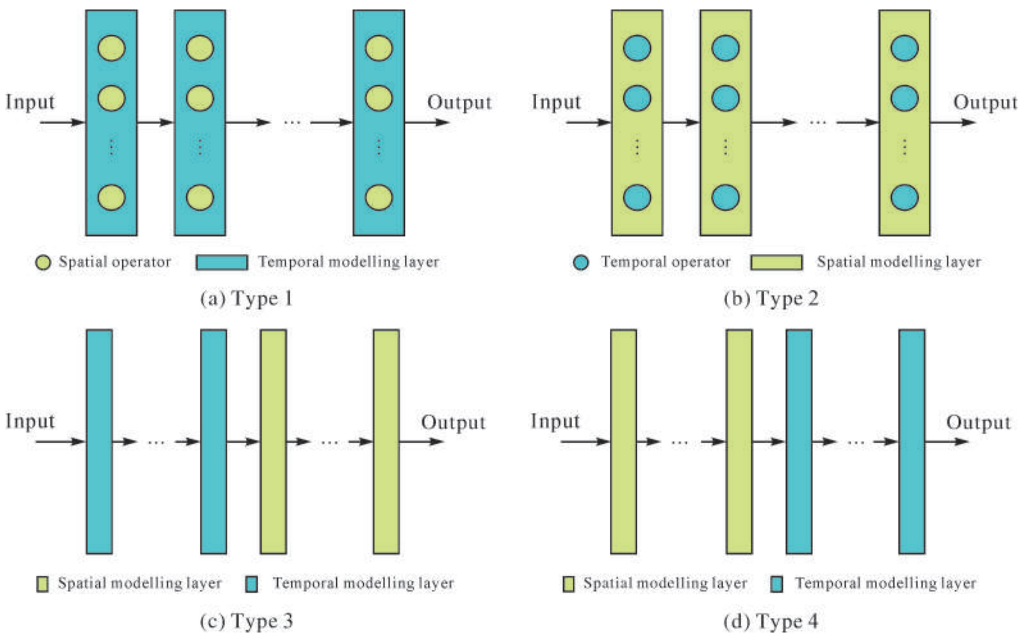


Fig.3 Four typical deep learning configurations for spatio-temporal data modelling[25]

3.2 Show cases of network-based SpaceTime forecasting

A spatiotemporal process can be spatially dense (everywhere) or sparse (just somewhere). For spatially dense processes, we usually use SpatioTemporal Sequences (STS) to represent them; for sparse processes, they are often referred to as SpatioTemporal Point Processes (STPP)[31]. The applications of graph-based spatiotemporal prediction methods in traffic, crime, and health areas are used to further explain the DL architecture in Fig. 3, and the advantages of graph-based spatiotemporal intelligence.

3.2.1 Traffic flow prediction—intensive spatiotemporal sequence process

In transport studies, traffic prediction has been a hot topic, and various approaches have been developed, from time series and STARIMA (or its various forms), to grid-based LSTM modelling. Early DL work partitioned the space into grids and then used CNNs to model daily and hourly patterns of the week for prediction. Ren et al.[32] developed the first network-based deep spatiotemporal residual neural network. It is the first time to directly use the network links (road segments) to be the modelling node of the neural network. In Ren's work, spatial adjacency matrices are used to model spatial associations, e.g., different layers use different spatial adjacency orders. This turns a fully connected deep learning neural network into a localised deep learning network. In a follow-up study, Ren et al. developed a deep learning structure combining CNN and LSTM to predict traffic flow[33]. Yang et al.[16] developed the first graph-based spatiotemporal sequence prediction-the RGC-LSTM network. Due to the strong temporal dependence of traffic flow, both Ren and Zhang's work integrated spatial convolution operators into temporal deep learning models.

To handle directed traffic flow, Zhang et al.[34] further developed a directed graph deep learning model. It represents network-based spatiotemporal data as a series of signal "well-behaved" graphs with directions, whose vertices are network links, and whose edges represent adjacency relationships. This well-behaved graph enables the topology of directed networks to be incorporated into spatiotemporal predictions. The dynamics of the network flow are then modelled as Markov chains on the graph with edge weights determined by the Markov TPM. In addition, they designed a novel spatiotemporal graph convolution-STGC operator which capture various spatio-temporal dependencies from different spatial scales, tackling the spatio-temporal heterogeneity to a large degree. Additionally, this is the first time the inception residual learning technique has been used for network-structured STS prediction. The approach was evaluated on a large traffic network consisting of 4089 segments in Chengdu, China, for 10-min, 30-min, and 60-min ridesharing flow prediction (Fig.4).

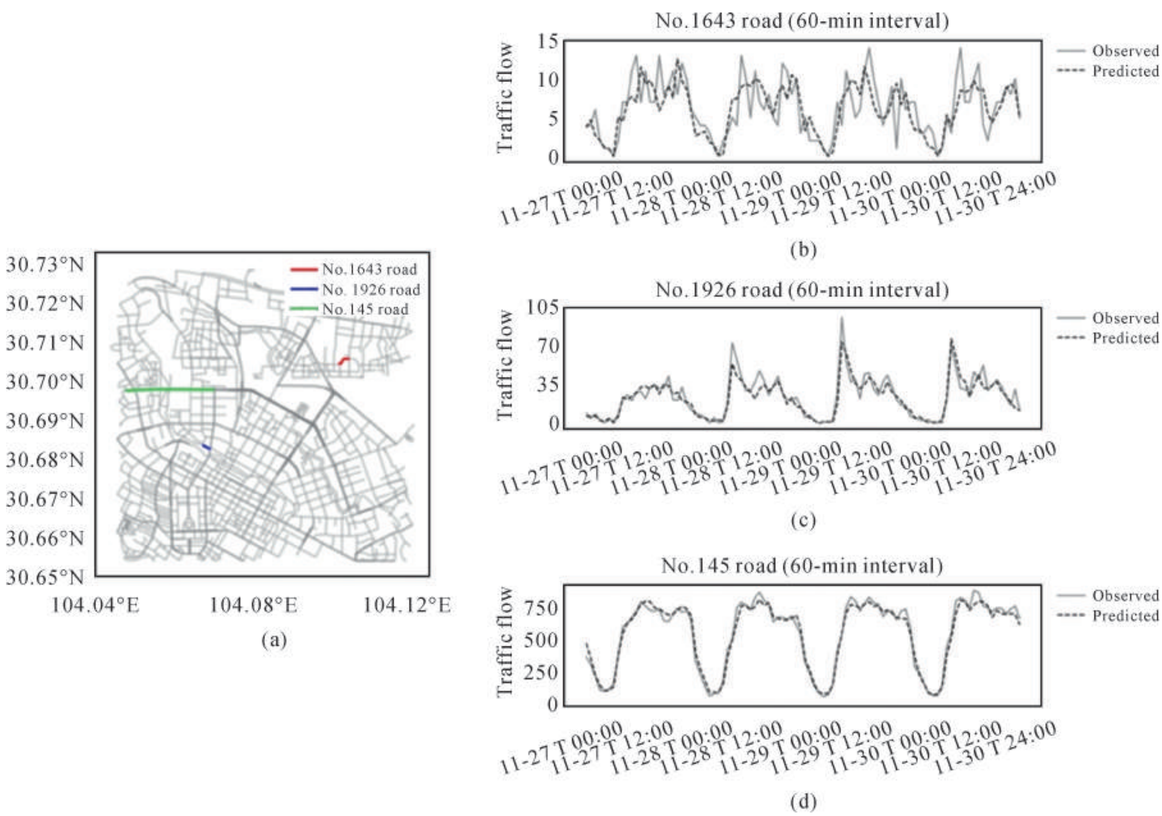


Fig.4 short-term traffic forecasting in Chengdu[34]

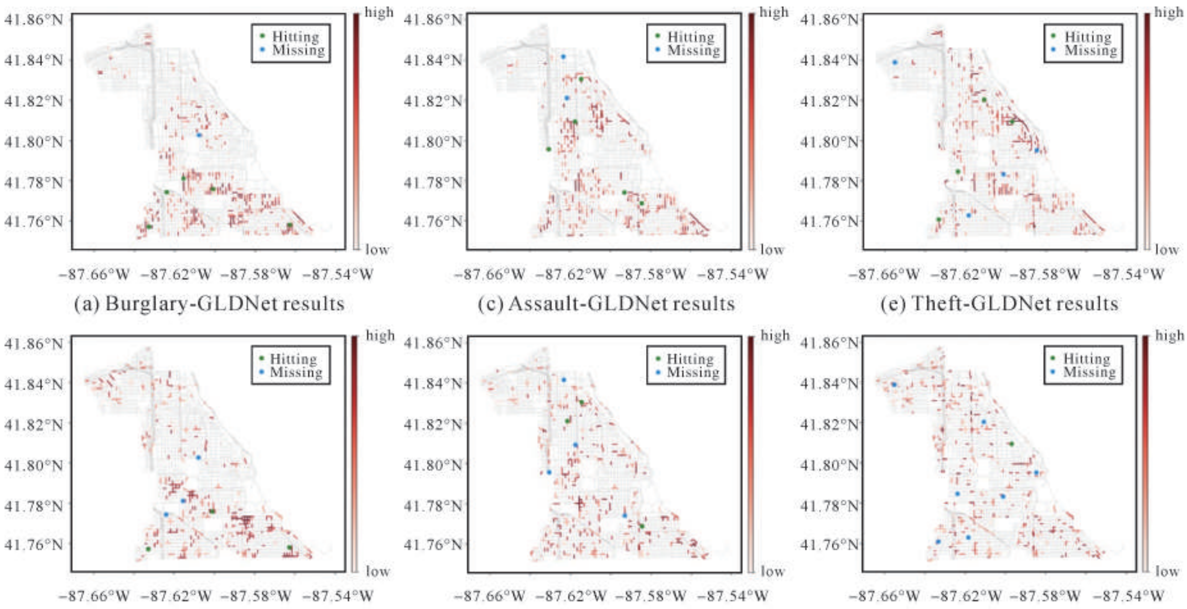
Compared with other traffic prediction methods including ARIMA, SVR, LSTM, CNN, STGCN, and RGC-LSTM, the directed graph deep learning model significantly improves the prediction accuracy and efficiency, especially performing well during peak hours (e.g., Fig.4(d)). In addition, no additional processing is required for traffic accidents and congestion, and the entire prediction process is fully automated. This algorithm does not need to artificially divide the road segment into 10-meter small road segments, as used by Google, to create additional network nodes. Therefore, it has higher learning and computational efficiency, and thus has good application prospects, especially for real-time traffic prediction in large cities.

3.2.2 Crime hotspot prediction-an example for sparse point processes

Hotspot mapping could highlight areas/locations with higher incidents and sparsely distributed in space and time, which are characterised by Spatio-Temporal Point Process (STPP). Early efforts on hotspot mapping are primarily retrospective, aiming to measure and detect space-time clusters of historical sparse ST data, including public safety, earthquake, crimes, and some issues in epidemiology and environmental science. Recently, there has been an increasing interest in using historical data to produce hotspot maps for predictive purposes owing to its prospective benefits. For instance, accurate crime forecasting can help police enforcements to prevent criminal behaviours, and traffic accident prediction is useful for road safety interventions and traffic reengineering.

Although a network-based structure can better capture the micro-level variation of ST events, existing deep learning methods for sparse events forecasting are either based on area or grid units. The key challenge of DL for predictive hotspots mapping of network based STPP lies in how to model the complex spatio-temporal dependencies of sparse events along the network. The sparsity means that counting the events over space and time results in many zero counts of some segments/links of the network. The difficulties are in three aspects: (1) The sequence of event counts in the time domain is not a continuous function that can be approximated in traditional deep learning models[35]. (2) Graph-based DL models commonly used in the spatial domain use a weight sharing strategy to learn spatial dependencies[4]. Since many linked observations are zero, if this method is directly applied, the weights will be all zero, and the prediction map cannot be generated. (3) If the prediction map directly uses the standard regression loss function for parameter learning, the DL model will be prone to overfitting, combined or all-zero predictions, which leads to the creation of imbalanced regression learning scenarios[36].

Yang & Cheng[16] developed a novel and effective graph-based DL framework, named Gated Localised Diffusion Network (GLDNet), to generate predictive hotspot mapping of STPP in network space. This model uses the configuration of Fig.3(d) to combine space and time-where the street network is represented as a weighted and undirected graph, and event counts are defined as the values on the vertex set of the graph. In GLDNet, the temporal propagation of historical events is modelled by a gated network, and the associated spatial propagation is captured via a localised diffusion network using network distance and topology, which overcomes the spatial heterogeneity. In the process of model training, a weighted regression loss function is employed to solve the issue of many zero observations. The proposed model is evaluated using crime data from the City of Chicago, Illinois, USA to prove its feasibility and effectiveness (Fig.5). To our best knowledge, it is the first attempt to develop graph-based DL approaches for predictive hotspot mapping of sparse ST data on networks.



(a) Burglary-GLDNet results (c) Assault-GLDNet results (e) Theft-GLDNet results

(b) Burglary-NTKDE results (d) Assault-NTKDE results (f) Theft-NTKDE results

Fig.5 Network-based predictive hotspot mapping of crimes in Chicago[16]

3.2.3 Health-prediction of the COVID-19 cases globally

In the early stage of the COVID-19 pandemic, modelling the spread of coronavirus globally and learning trends at global and country levels were crucial for tackling the pandemic. Although there were a number of statistical and epidemiological models to analyse the COVID-19 outbreak, these models had many assumptions in assessing the impact of intervention plans, which resulted in low accuracy and inaccuracy deterministic predictions[37]. Therefore, it is vital to develop new methods for predicting and responding to the virus spread[38]. Among others, Ibrahim et al.[39] introduced a novel Variational Autoencoder- LSTM model to predict the spread of the COVID-19 virus across the globe. This spatio-temporal model does not only rely on the time-series data of the virus spread, but also incorporates the urban analytics data represented in locational and demographic indicators (such as population density, urban population, and fertility rate), and an index that represents the governmental measures and response amid toward mitigating the outbreak (includes 13 measures).

The proposed model uses a graph structure to represent 139 countries as nodes of the graph. Then it uses Long Short-Term Memory (LSTM) to learn not only from the previously defined timestamps for each country, but also from other countries at each timestamp. To learn the relations between its inputs and outputs at local and global levels, a self-attention mechanism has been introduced to the LSTM units. The graph was first initialised based on the spatial weight among all infected countries using their global distances. However, the spatial weight may change between days due to different policies and measures that are taken by countries. Instead of feeding the model with a static graph, a variational autoencoder graph is used to learn and output a variation that could meet the changes from day to day, country to country, or even the overall measures of the entire globe. Therefore, this model uses the framework of Fig. 3(a). As shown in Fig.6, the model is more accurate in predicting the number of infections by country than other existing models.

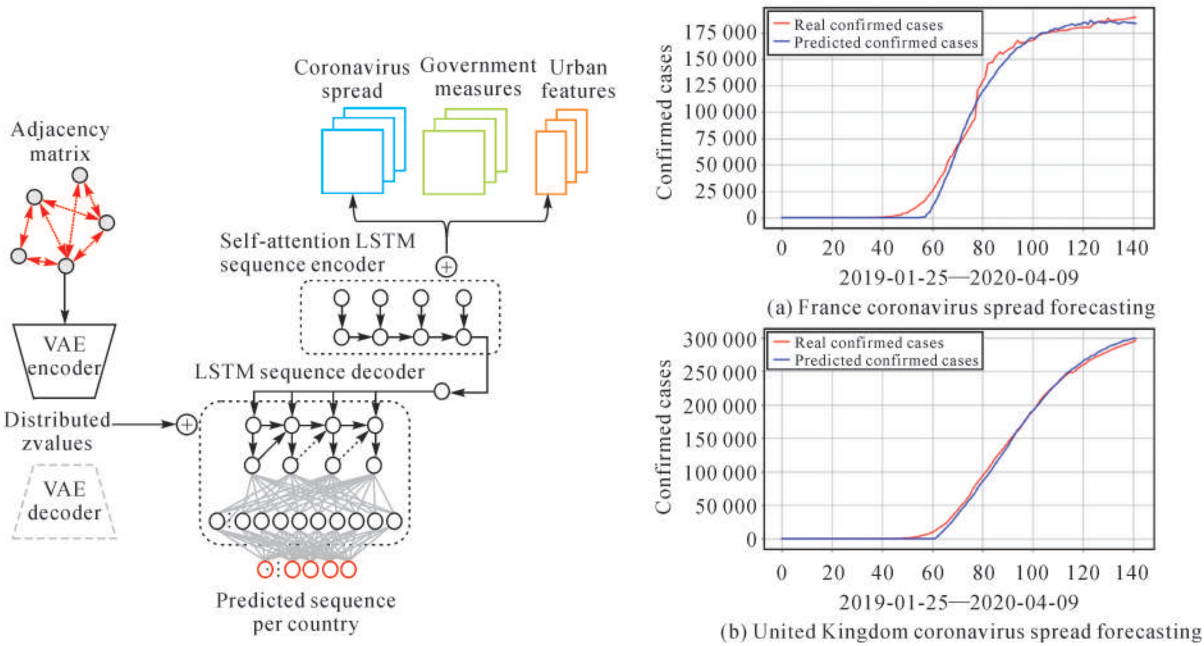


Fig.6 The proposed variational LSTM autoencoder model and prediction results[39]

4 Network-based Clustering and Optimisation

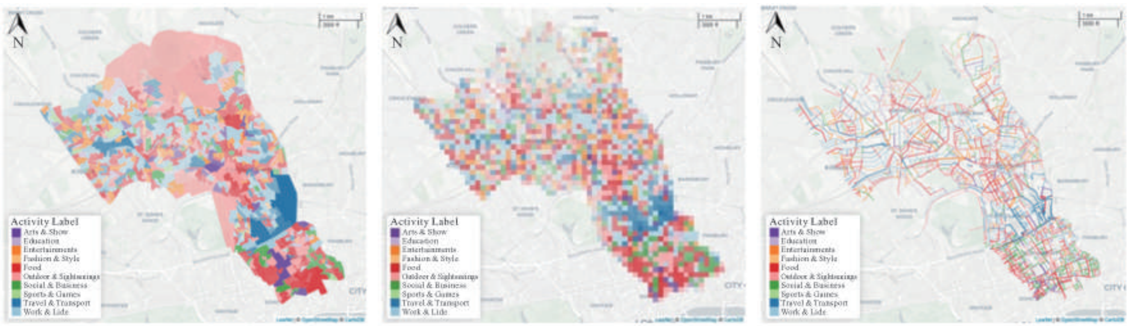
4.1 Network-based clustering of spatial and spatiotemporal hotspots

Region of Interest (RoI) has many synonymous names in activity studies, such as hotspot, interesting place and interesting region. This concept is widely used in travel pattern analysis, criminology, and epidemiology, in which the occurrence of events is represented by point records in space, and hotspots are significant aggregations of the point records. In human dynamics studies, the RoIs are the places that attract high volumes of visits from people. With more and more location-based data generated by modern sensors, such as GPS devices and mobile phone networks, RoIs have become a hot research topic. RoIs are usually detected by finding dense aggregations of stopping behaviours, information posted via telecommunication devices or check-ins with LBS applications.

Traditional RoI detection methods only look for aggregated regions in planar space, thereby generating RoIs distributed in 2D Cartesian space, as shown in Figs.7(a) and (b) based on small regions and grid-based active hotspots. In contrast, the network-based activity hotspots in Fig.7(c) provide a finer granularity representation and analysis[40].

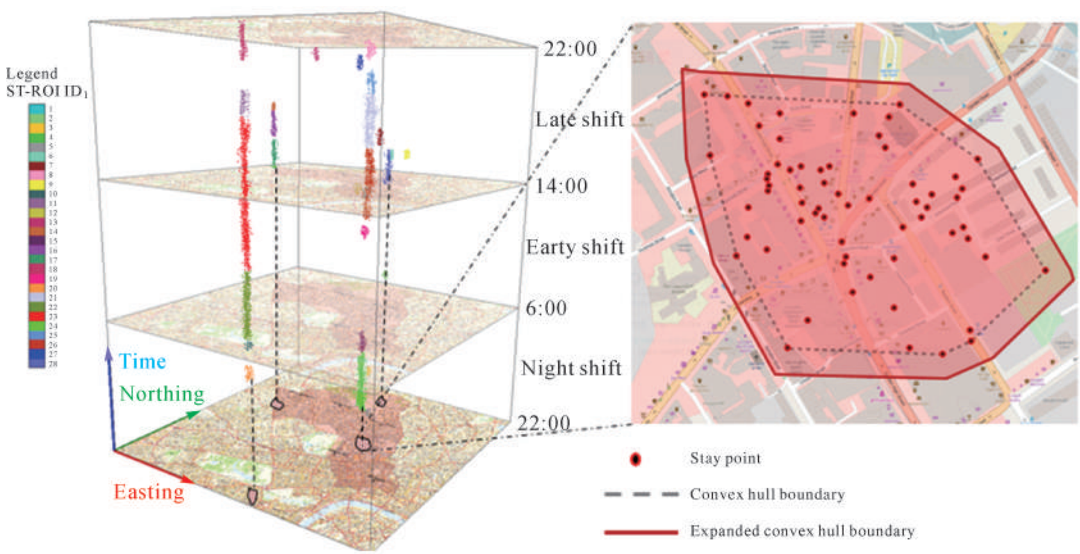
The combination of spatial hotspots and time dimensions leads to the problem of space-time hotspot areas. The commonly used methods in research are Space-Time Scan Statistics and ST-DBSCAN. These methods all add the time dimension to the hot spot detection analysis based on the spatial dimension. This allows not only to detect RoIs in space, but also to find temporal aggregation patterns in other non-spatial properties of events (Fig.8).

Shen developed a network-based RoI detection method named ST-LOI[42].This approach extends spatiotemporal clustering from Cartesian space to network-based space and seamlessly considers both spatial and temporal dimensions (Fig.9). The spatial range of network-based spatiotemporal hotspots is more precise than the range of the spatial convex hull (Fig.8), which is more conducive to combining POIs with specific coordinates (POIs, Point of Interests) and their semantic information to mark the types of active hotspots, so as to facilitate clustering the activity behaviours to profiles individuals.



(a) Output area activity (b) Grid-based activity (c) Street network-based activity

Fig.7 The prominent activity derived from Twitter data

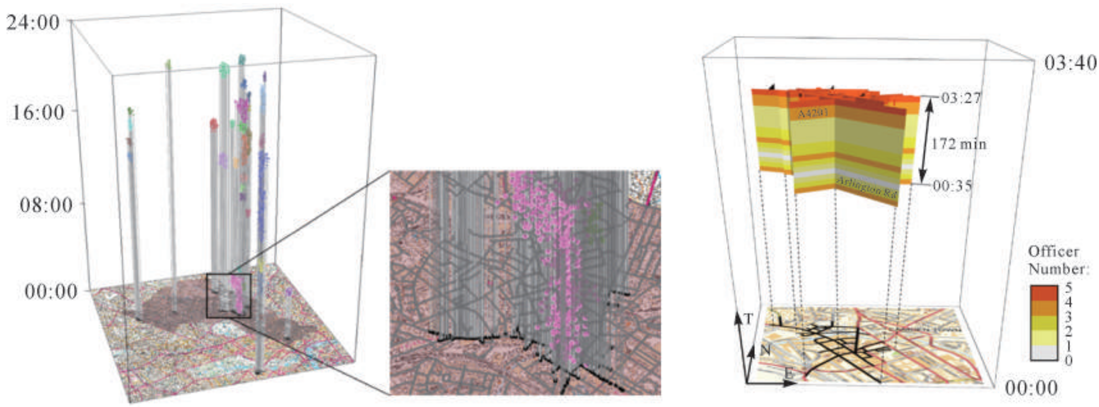


(a) 28 ST-RoIs found by ST-DBSCAN (b) The convex hull and its 20 m buffer area of stay point, which could define the spatial area of ST-RoI [41]

Fig.8 The detection of ST-RoIs based on ST-DBSCAN and the defined spatial area of ST-RoIs

4.2 SpaceTime optimisation-designing efficient and balanced police patrol districts on an urban street network

The Police Districting Problem (PDP) concerns the optimal partition of territory into several patrol sectors with respect to performance attributes such as workload and response time. Traditionally, the police districts were manually drawn by police officers on a road map following the main streets in the area without accomplishing workload balance or geographic compactness[43]. In recent decades, automatic methods for defining police districts have gained increasing attention among researchers and police departments[44]. Following the first study on PDP by Mitchell[45], different mathematical optimisation models for PDP have been developed, focusing on the contiguity of districts and the balanced workload distribution.



(a) Detected ST-LOIs visualised in a space-time cube and their projections on basemap

(b) The 3D wall map visualisation of one ST-LOI in a space-time cube[42]

Fig.9 ST-LOIs detection and visualisation

In formulating a PDP, the first step is to choose the basic units that can be consolidated into districts. Most PDP models use areal units or zones (e.g., grids, census blocks) as basic units[45-46], as shown in Figs.10 (a) and (b). However, considering street networks in PDP is promising for several reasons. The first is simply that the features of street network influence both the long-term crime pattern and the short-term dynamics of crime behaviours, suggesting the importance of street-level crime prevention. Second, as street network fundamentally influences the movement of police officers, network-based models would produce districting plans of better usability than the alternatives. In contrast, as grids or census blocks may intersect physical barriers and contain unconnected street segments, It is less suitable for them to operational deploy PDPs than street segments. Furthermore, as streets are the basic elements of human movement and spatial cognition, the street-based districting solution is able to mitigate the effects of MAUP, which is the inherent issue in the grid-based models. Therefore, Chen proposed a PDP method based on urban road network (Fig.10(c))[47-48]. This method could design efficient and balanced police patrol areas and optimise patrol routings in real-time online, and could reduce emergency response time by 20%. These improvements allow police officers to spend more time patrolling on cirme hotspots. This method could also be employed in the logistics operation of large fleets.

5 Summary and Discussion

This paper proposes the use of networks and graphs as the basic spatial structure for SpaceTimeAI or GeoAI for spatiotemporal analysis. Since people live and travel along the urban road network, this framework is particularly suitable for the study of urban issues. Compared to traditional grid-based representations, network-based structures are more precise and practical. Graphs can express a variety of spatial structures such as points, lines, surfaces/polygons/grids, and networks, by converting these spatial structures into (directed or undirected) graphs and signals on graph vertices, using the spatial domain or spectral domain to model dense and sparse spatiotemporal processes. Taking spatio-temporal prediction, spatio-temporal clustering, and spatio-temporal optimization as examples, this paper introduces network and graph-based spatio-temporal analysis methods and their applications in the fields of transportation, policing, and public health.

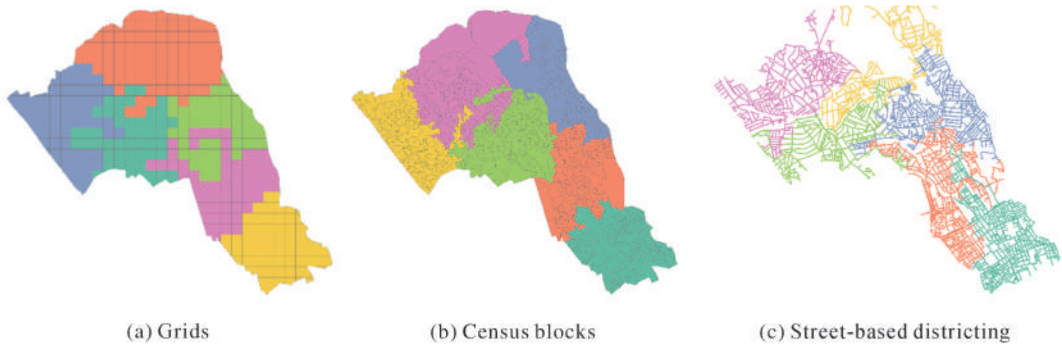


Fig.10 Spatial units in PDP models

This paper aims to provide a theoretical research framework for spatio-temporal intelligence analysis based on networks and graphs, so as not strictly define SpaceTiemAI and GeoAI. This paper introduces a pioneering network-based spatio-temporal analysis method to illustrate spatio-temporal prediction, spatio-temporal clustering, and spatio-temporal optimization. For the subsequent application and development of related models, other related literatures can be referred to.

The development of graph-based deep learning and spatio-temporal prediction is in full swing, but most of them are based on the static graph structure, that is, the graph structure is fixed and invariant. If the network structure changes (nodes or links between nodes are lost and increased), none of the existing models can make spatio-temporal predictions for such dynamic graph structures. The development of this type of dynamic graph model will help to study traffic accidents, road network optimization and other issues. Due to the lack of historical data to train the model, the development of transfer learning or reinforcement learning may help to solve this problem. In addition, spatio-temporal optimization using reinforcement learning of multi-agents is also a current hot direction, such as matching taxis and user needs[49].

Despite the rapid development of graph theory-related research, its application in geographic information science is still limited to navigation and route searching. Therefore, graph-based knowledge and matrix-based computing capabilities still need to be improved to further assist the application of graph structures in geographic information science and promote the development of SpaceTiemAI and GeoAI. In addition, more graph-based analysis and database management tools need to be developed and applied, which will strongly promote the development of digital twins and metaverses. For example, the graph database Neo4J can flexibly link geometric and semantic information, and its route search is fast, showing outstanding superiority in the study of connecting indoor and outdoor paths[50].

Since the 1980s, the study of network complexity has been in the ascendant, but it is still limited to single-layer networks in geographic information science research, such as roads, power grids or social networks. As the core functions of each city are increasingly interconnected, the interactions between each network are closer, such as transportation, telecommunications and energy. Multilayer networks and related models have also become an important direction to promote the development of SpaceTiemAI and GeoAI, as well as to study practical problems in the geospatial and real world.

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References

[1] IBRAHIM M R, HAWORTH J, CHENG Tao. Understanding cities with machine eyes:a review of deep computer vision in urban analytics[J]. Cities, 2020, 96:102481.

[2] ZHANG Fan, WU Lun, ZHU Di, et al. Social sensing from street-level imagery:a case study in learning spatio-temporal urban mobility patterns[J]. ISPRS Journal of Photogrammetry and Remote Sensing, 2019, 153:48-58.

[3] ZHANG Junbo, ZHENG Yu, QI Dekang, et al. Predicting city-wide crowd flows using deep spatio-temporal residual networks [J]. Artificial Intelligence, 2018, 259:147-166.

[4] WANG B, ZHANG D, BRANTINGHAM P.J., et al.Deep learning for real time crime forecasting [EB/OL]. [2022-05-25]. https://arxiv.org/abs/1707.03340.

[5] OPENSHAW S, TAYLOR P. The modifiable areal unit problem [M]//WRIGLEY N, BENNETT R J. Quantitative Geography:A British View. London:Routledge, 1981:60-69.

[6] ROSSER G, DAVIES T, BOWERS K J, et al. Predictive crime mapping: arbitrary grids or street networks? [J]. Journal of Quantitative Criminology, 2017, 33(3):569-594.

[7] CHENG Tao, HAWORTH J, WANG Jiaqiu. Spatio-temporal autocorrelation of road network data[J]. Journal of Geographical Systems, 2012, 14(4):389-413.

[8] CHENG Xingyi, ZHANG Ruiqing, ZHOU Jie, et al. Deeptransport: learning spatial-temporal dependency for traffic condition forecasting[C]//Proceedings of 2018 International Joint Conference on Neural Networks. Rio de Janeiro:IEEE, 2018.

[9] SHIODE S. Street-level spatial scan statistic and STAC for analysing street crime concentrations[J]. Transactions in GIS, 2011, 15(3):365-383.

[10] CHEN Huanfa, CHENG Tao, SHAWE-TAYLOR J. A balanced route design for min-max Multiple-Depot Rural Postman Problem (MMMDRPP):a police patrolling case[J]. International Journal of Geographical Information Science, 2018, 32(1):169-190.

[11] CHENG Tao, HAWORTH J, ANBAROGLU B, et al. Spatiotemporal data mining [M] // FISCHER M, NIJKAMP P. Handbook of Regional Science. Berlin:Springer, 2019.

[12] BOLLOBÁS B. Modern graph theory[M]. New York:Springer, 2019.

[13] ORTEGA A, FROSSARD P, KOVAČEVIC'J, et al. Graph signal processing: overview, challenges, and applications [J]. Proceedings of the IEEE, 2018, 106(5):808-828.

[14] ESTRADA E. Graph and network theory[J]. Developments in Water Science, 1988, 32:317-339.

[15] HASHEMI H, ABDELGHANY K. End-to-end deep learning methodology for real-time traffic network management[J]. Computer-Aided Civil and Infrastructure Engineering, 2018, 33(10): 849-863.

[16] ZHANG Yang, CHENG Tao. Graph deep learning model for network-based predictive hotspot mapping of sparse spatio-temporal events[J]. Computers, Environment and Urban Systems, 2020, 79:101403.

[17] HOPFIELD J J. Neural networks and physical systems with emergent collective computational abilities[J]. Proceedings of the National Academy of Sciences of the United States of America, 1982, 79(8):2554-2558.

[18] HOCHREITER S, SCHMIDHUBER J. Long short-term memory [J]. Neural Computation, 1997, 9(8):1735-1780.

[19] GRAVES A. Generating sequences with recurrent neural networks [EB/OL]. [2022-05-25].https://arxiv.org/abs/1308.0850.

[20] CHO K, VAN MERRIËNBOER B, BAHDANAU D, et al. On the properties of neural machine translation:encoder-decoder approaches[C]//Proceedings of the 8th Workshop on Syntax, Semantics and Structure in Statistical Translation. Doha:Association for Computational Linguistics, 2014:103-111.

[21] LECUN Y, BENGIO Y. Convolutional networks for images, speech, and time-series [M] // ARBIB M A. The Handbook of Brain Theory and Neural Networks. Cambridge:MIT Press, 1995.

[22] MONTI F, OTNESS K, BRONSTEIN M M. Motifnet: a motif-based graph convolutional network for directed graphs[C]//Proceedings of 2018 IEEE Data Science Workshop. Lausanne: IEEE, 2018:225-228.

[23] HENAFF M, BRUNA J, LECUN Y. Deep convolutional networks on graph-structured data [EB/OL]. [2022-05-25]. https://arxiv.org/abs/1506.05163.

[24] KIPF T N, WELLING M. Semi-supervised classification with graph convolutional networks[C]//Proceedings of the 5th International Conference on Learning Representations. Toulon: OpenReview, 2017:1-14.

[25] ZHANG Yang. Graph deep learning models for network-based spatio-temporal data forecasting: from dense to sparse[D]. London: University College London, 2020.

[26] SHI Xingjian, CHEN Zhourong, WANG Hao, et al. Convolutional LSTM network: a machine learning approach for precipitation nowcasting[C]//Proceedings of Annual Conference on Neural Information Processing Systems 2015. Montreal: [s.n.], 2015.

[27] LIANG Ming, HU Xiaolin. Recurrent convolutional neural network for object recognition[C]//Proceedings of 2015 IEEE Conference on Computer Vision and Pattern Recognition. Boston: IEEE, 2015:3367-3375.

[28] XU Zhenqi, LI Shan, DENG Weihong. Learning temporal features using LSTM-CNN architecture for face anti-spoofing[C]//Proceedings of the 2015 3rd IAPR Asian Conference on Pattern Recognition, Kuala Lumpur: IEEE, 2015:141-145.

[29] HUANG C J, KUO P H. A deep CNN-LSTM model for particulate matter ($PM_{2.5}$) forecasting in smart cities[J]. Sensors, 2018, 18(7):2220.

[30] LIU Yipeng, ZHENG Haifeng, FENG Xinxin, et al. Short-term traffic flow prediction with conv-LSTM[C]//Proceedings of the 2017 9th International Conference on Wireless Communications and Signal Processing (WCSP). Nanjing: IEEE, 2017:1-6.

[31] ADEPEJU M, ROSSER G, CHENG Tao. Novel evaluation metrics for sparse spatio-temporal point process hotspot predictions-a crime case study[J]. International Journal of Geographical Information Science, 2016, 30(11):2133-2154.

[32] REN Yibin, CHENG Tao, ZHANG Yang. Deep spatio-temporal residual neural networks for road-network-based data modeling [J]. International Journal of Geographical Information Science, 2019, 33(9):1894-1912.

[33] REN Yibin, CHEN Hao, HAN Yong, et al. A hybrid integrated deep learning model for the prediction of citywide spatio-temporal flow volumes [J]. International Journal of Geographical Information Science, 2020, 34(4):802-823.

[34] ZHANG Yang, CHENG Tao, REN Yibin. A graph deep learning method for short-term traffic forecasting on large road networks [J]. Computer-Aided Civil and Infrastructure Engineering, 2019, 34(10):877-896.

[35] MHASKAR H N, POGGIO T. Deep vs. shallow networks: an approximation theory perspective[J]. Analysis and Applications, 2016, 14(6):829-848.

[36] KRAWCZYK B. Learning from imbalanced data: open challenges and future directions[J]. Progress in Artificial Intelligence, 2016, 5(4):221-232.

[37] BOTHA A E, DEDNAMW. A simple iterative map forecast of the COVID-19 pandemic [EB/OL]. [2022-05-25]. https://arxiv.org/abs/2003.10532.

[38] Z HU Q GE, S LI, et al. Forecasting and evaluating intervention of COVID-19 in the world. [EB/OL]. [2022-05-25].https://arxiv.org/abs/2003.09800.

[39] IBRAHIM M R, HAWORTH J, LIPANI A, et al. Variational-LSTM autoencoder to forecast the spread of coronavirus across the globe[J]. PLoS One, 2021, 16(1):e0246120.

[40] LAI Juntao. Urban place profiling using geo-referenced social media data[D]. London: University College London, 2019.

[41] CHENG Tao, SHEN Jianan. Grouping people in cities: from space-time to place-time based profiling[M]//SHAW S L, SUI D. Human Dynamics Research in Smart and Connected Communities. Cham: Springer, 2018:181-201.

[42] SHEN Jianan. Profiling and grouping space-time activity patterns of urban individuals[D]. London: University College London, 2017.

[43] BRUCE C. Districting and resource allocation: a question of balance[J]. Geography&Public Safety, 2009, 1(4):1-3.

[44] WANG Fahui. Why police and policing need GIS: an overview[J]. Annals of GIS, 2012, 18(3):159-171.

[45] MITCHELL P S. Optimal selection of police patrol beats[J]. The Journal of Criminal Law, Criminology, and Police Science, 1972, 63(4):577-584.

[46] ZHANG Yue, BROWN D E. Police patrol districting method and simulation evaluation using agent-based model&GIS[J]. Security Informatics, 2013, 2(1):7.

[47] CHEN Huanfa, CHENG Tao, YE Xinyue. Designing efficient and balanced police patrol districts on an urban street network[J]. International Journal of Geographical Information Science, 2019, 33(2):269-290.

[48] CHEN Huanfa. Developing police patrol strategies based on the urban street network[D]. London: University College London, 2019.

[49] ZHOU Ming, JIN Jiarui, ZHANG Weinan, et al. Multi-agent reinforcement learning for order-dispatching via order-vehicle distribution matching[C]//Proceedings of the 28th ACM International Conference on Information and Knowledge Management. Beijing: ACM, 2019:2645-2653.

[50] PARK S. ISPRS WG IV/8(GeoComputation and GeoSimulation) webinar[EB/OL].[2022-03-01].https://www.isprs.org/news/announcements/details.aspx? ID=277.