Grid graph convolutional network with neighborhood learning for spatio-temporal prediction

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Abstract

This paper addresses the dual challenges of low accuracy and slow speed in spatio-temporal prediction by proposing a Grid Graph Convolutional Network with Neighborhood Learning (GN-GCN). Leveraging the GeoSOT-4D global grid system for discrete spatio-temporal encoding, the model constructs grid-based knowledge graphs and integrates static graph neural networks, neighborhood grid computation, and temporal evolution units to jointly capture semantic, spatial, and temporal dependencies. Enhanced by a High-level Training and Low-level Testing (HTLT) strategy, GN-GCN achieves state-of-the-art performance in various spatio-temporal tasks, significantly outperforming conventional methods in both accuracy and computational efficiency for complex real-world scenarios.

1. Introduction

Spatio-temporal prediction has emerged as a critical technology in addressing complex real-world challenges across diverse domains. Current applications span spatio-temporal knowledge completion (e.g., inferring missing entities or relations in dynamic environments), low-altitude traffic congestion and trajectory prediction for urban air mobility systems, and meteorological forecasting to support autonomous drone operations (Li et al., 2021). These tasks require models to seamlessly integrate semantic, spatial, and temporal dependencies while handling heterogeneous data structures. Traditional approaches often struggle with the inherent complexity of multi-scale spatio-temporal interactions, particularly in scenarios demanding fine-grained spatial partitioning and long-term temporal reasoning (Huang, Su, and Wang 2024). There are two main issues that need to be addressed in the current spatio-temporal prediction task.

On one hand, the accuracy of spatio-temporal prediction is poor. One is that the scene elements are complex, including environmental factors such as meteorology and hydrology, historical public opinion information, economic and political information, rule libraries, etc. In this special application scenario, traditional vector oriented modeling methods are difficult to achieve unified spatio-temporal level association aggregation and relation calculation (Chen, Deng, and Chen 2017); Secondly, the accuracy of relation extraction is low. Traditional methods focus on all relations related to entities, which have low information value density and do not directly contribute to inference and prediction, often reducing prediction accuracy; Thirdly, information combination is prone to overload, and the explosive growth of big data in intelligence, monitoring, and control can lead spatio-temporal prediction models into the dilemma of information combination overload.

On the other hand, the speed of spatio-temporal prediction is slow. Firstly, the situation changes rapidly, and traditional spatio-temporal prediction theory cannot meet the fast prediction of system intentions in real-time changing situations (Zhang et al., 2020); The second is the influence of multiple forces, and the environment is often in a state of multi-party anxiety. Traditional object-oriented spatio-temporal reasoning requires traversing all force entities, so the prediction time will significantly increase with the increase of forces(Zhang et al., 2024); The third requirement is high response speed, making it particularly important to achieve near real-time completion of spatio-temporal prediction.

Based on the above two main issues, it is more important to quickly organize and extract various elements, and ultimately carry out various spatio-temporal predictions and knowledge learning. In recent years, the emergence of spatio-temporal grids has proposed a new way of knowledge representation and management. The discreteness of grids determines that they can describe spatio-temporal relations in a finite way, which is simpler, more unique, and more limited than objectification methods in describing spatio-temporal, topology, orientation, and distance(Qian et al., 2019).

Therefore, this paper proposes a spatio-temporal prediction architecture based on grid graph convolutional networks. Based on the GeoSOT-4D (GeoSOT-3D+GeoSOT-T) global gird system (Han et al., 2022), all elements in the environment are spatio-temporal encoded, and the grid spatio-temporal knowledge graph is associated with the entities in the system to construct the spatio-temporal and semantic relations of the graph. Subsequently, a Grid graph convolutional network with neighborhood learning was established to perform spatio-temporal prediction tasks in complex spatio-temporal scenarios, such as spatio-temporal knowledge reasoning, airspace congestion prediction, and meteorological risk prediction.

2. Grid graph convolutional network

2.1 GeoSOT-4D

GeoSOT-4D is mainly composed of GeoSOT-3D and GeoSOT-T, which discretize space and time respectively (Han, and Qu 2025). In this paper, GeoSOT-3D (Geographic Coordinate Subdividing Grid with One Dimension Integrated Coding on 2^n Tree-3D) is selected as the coding scheme for 3D subdivision framework to establish an abstract environment (Zhai et al., 2021), as shown in Figure 1. The subdivision of GeoSOT-3D is

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to expand the latitude and longitude to a space of 512 °× 512 °, and use the equal latitude and longitude recursive quadtree partitioning method to perform multi-scale subdivision on the expanded space. The altitude is mapped to 512 degrees, corresponding to the airspace range from an altitude of 50000 kilometers to the center of the earth (Han et al., 2023). The GeoSOT-3D is a 32 level multi-scale octree solid grid that uniquely identifies and stores internal information for each discrete element in the spatial domain through grid encoding (Liu et al., 2022).

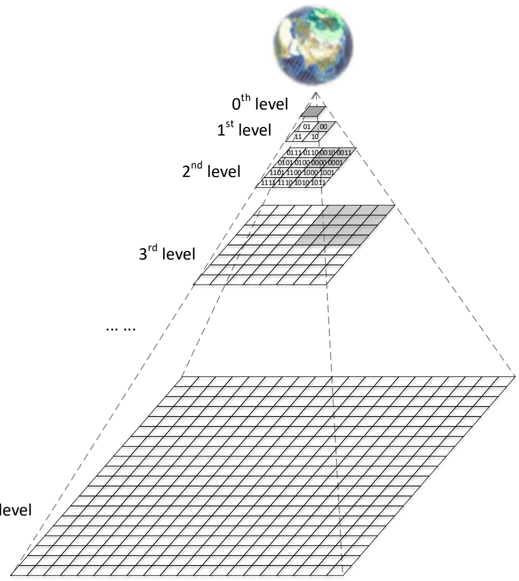

Figure 1. GeoSOT-3D earth subdivision grid for spatio-temporal prediction (Han et al., 2022).

The time subdivision of spatio-temporal knowledge mainly focuses on the time adverbials in the quadruple, encoding the time slices in time. The time encoding adopts the GeoSOT-T time discretization architecture, which discretizes time into time intervals of different lengths and assigns a unique binary encoding to discretize time into longer "time periods". Compared with time point labels in string form, GeoSOT-T can reduce storage capacity and serve as an easily recognizable encoding scheme for computers to identify time periods. Based on the GeoSOT-T time partitioning model, the time information of entities and relations can be uniquely and discretely represented by time encoding. Through GeoSOT-T time partitioning encoding, spatio-temporal knowledge can effectively incorporate temporal neighborhoods into the computational system and construct temporal logical relations through multi-scale temporal hierarchies.

2.2 Grid Spatio-temporal knowledge graph

Grid spatio-temporal knowledge graph simplifies multiple layers into a grid map, and integrates political, economic, and environmental information from the perspective of global strategy and dynamics through the grid. As shown in Figure 2, a unified grid diagram is used to horizontally correlate the grids through spatial knowledge and vertically correlate them through temporal knowledge. By using grid coding, the computational complexity is much lower than that of latitude and longitude vector coordinate maps, making calculations more efficient and faster, with speeds up to tens or even hundreds of times faster, and independent of the number of entities. When an entity enters another grid spatio-temporal region, it can also synchronize the environmental properties of the grid where the entity is located for updates, thereby completing subsequent spatio-temporal predictions.

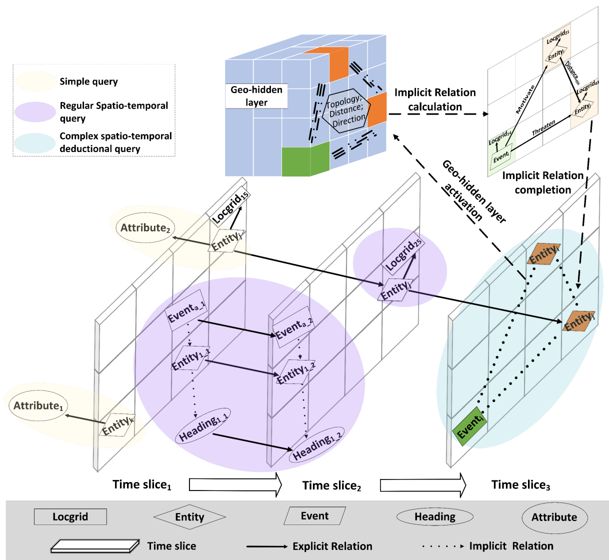

Figure 2. The framework of grid Spatio-temporal knowledge graph (Han et al., 2023).

2.3 Grid graph convolutional network with neighborhood learning

Because of the difficulty of utilizing hidden spatio-temporal information, spatio-temporal knowledge graph (KG) reasoning tasks in real geographic environments suffer from low accuracy and poor interpretability(Chen, Jia, and Xiang 2020). Our proposed grid graph convolutional network architecture incorporates neighborhood learning for spatio-temporal KG reasoning, achieving superior performance in knowledge completion tasks compared to conventional graph neural networks. The grid neighborhood mechanism addresses sparse connectivity in traditional graph structures by leveraging GeoSOT-3D subdivision's inherent regularity.

As shown in Figure 3, the grid graph convolutional network (GN-GCN) comprises three components: a static graph neural network for semantic knowledge, a neighborhood grid calculation module for spatial knowledge, and a time evolution unit for temporal knowledge (Han, Qu, and Jiang 2025). Temporal information and spatial topological relations are representable through grid coding, where spatio-temporal grid neighborhoods exhibit graph-like semantics. This enables learning structural dependencies within temporal and spatial relations.

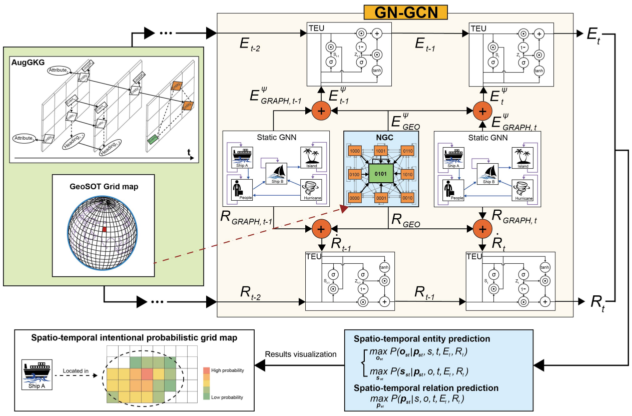

Figure 3. The framework of Grid graph convolutional network with neighborhood learning (GN-GCN) (Han, Qu, and Jiang 2025).

3. Grid graph convolutional network for spatio-temporal knowledge reasoning

Spatio-temporal geographic scenarios encompass numerous spatio-temporal facts. Unlike semantic facts, these exhibit characteristics such as high sparsity and a multitude of relations (Shbita et al., 2023). Spatio-temporal knowledge reasoning involves inferring missing spatio-temporal entities or relations within these facts (Sioutis, and Long 2022).

3.1 HTLT algorithm

The grid graph convolutional network (GN-GCN) leverages the multi-scale aggregation property of the GeoSOT grid system to enhance model training accuracy and efficiency. Its core principle, Hierarchical Training and Low-level Testing (HTLT), operates across multiple GeoSOT grid scales. Training occurs at higher (coarser) grid levels to meet the computational and structural demands of spatio-temporal scenes and graphs. Information learned at these higher levels is then transferred, utilizing the inherent recursive coding topology of GeoSOT, for faster testing and inference at the original (finer) data resolution level. This approach fully exploits the GeoSOT multi-scale discrete grid model.

Crucially, GeoSOT enables parameter and information sharing between different grid levels within the same spatial region, making it highly suitable for multi-scale spatial structure learning. The HTLT algorithm thus leverages the advantages of coarse grids (improved prediction accuracy) while maintaining the flexibility of the original fine grid size without information loss. Furthermore, it reduces GPU memory requirements during testing, enhancing overall efficiency.

3.2 Loss function

For spatio-temporal knowledge reasoning, grid graph convolutional network employs a customized loss function to evaluate prediction performance:

$$F_O^e = \sum_{t=1}^{T} \sum_{i=1}^{E} hits(s,p,i,t) Decoder(s,p), \quad (1)$$

where $hits(s,p,i,t)$ = binary validation operator ensuring data integrity

$Decoder(s,p)$ = the decoder calculation component of the likelihood of spatio-temporal entity

3.3 Results

Compared to existing models (e.g., RE-GCN, CyGNet, RE-NET), GN-GCN achieves state-of-the-art (SOTA) performance in spatio-temporal reasoning. Specifically, its Mean Reciprocal Rank (MRR) reaches 48.33 for spatio-temporal entity prediction and 54.06 for relation prediction. These results represent improvements of 6.32 (18.16%) and 6.64 (15.67%) over the best-performing baselines, respectively. Experimental analysis indicates that GN-GCN's superior performance primarily stems from incorporating dedicated temporal and spatial dependency modules and effectively capturing regional associations via GeoSOT grid domain coordinates.

4. Grid graph convolutional network for airspace congestion prediction

Airspace congestion prediction is a critical challenge in modern air traffic management systems (Alharbi, Petrunin, and Panagiotakopoulos 2023). With the rapid growth of the aviation industry, air traffic density continues to increase, particularly near busy routes and hub airports, leading to more frequent congestion phenomena (Xiang, Liu, and Luo 2016). Airspace congestion prediction aims to integrate event data, traffic sentiment, meteorological conditions, airspace utilization, and spatio-temporal relations to rapidly identify congestion points and regions in large-scale spatio-temporal scenarios, providing early warnings for flight operators and airspace managers to enable proactive mitigation (Sudarsanan, and Kostiuk 2024). Congestion not only reduces flight punctuality and transportation efficiency but also elevates safety risks (Watkins et al., 2021). Therefore, accurate prediction of future congestion is essential for optimizing air traffic management, improving flow distribution, and enhancing operational efficiency (Wu et al., 2024).

The rapid expansion of urban areas and the gradual opening of low-altitude airspace have intensified congestion challenges, with unmanned and manned aerial vehicle densities projected to surge dramatically (Cummings, and Mahmassani 2024). For instance, China's *Low-Altitude Economy Development Report (2024)* predicts that its low-altitude economy will exceed 10.6446 trillion RMB by 2026 (Huang, Su, and Wang 2024), with over 1.987 million registered drones as of August 2024 (LIAO, XU, and YE 2024). In large-scale low-altitude operations, uneven spatiotemporal resource allocation inevitably leads to congestion at high-traffic origins/destinations and peak hours (Stuive, and Gzara 2024). Unlike ground vehicles, low-altitude congestion cannot be fully resolved through manual intervention, and relying solely on heterogeneous onboard collision avoidance systems may fail to rapidly resolve conflicts, increasing collision risks, which is shown in Figure 4 (Zhang et al., 2024). Thus, proactive congestion prediction and early warnings are imperative for urban airspace safety (She, and Ouyang 2021).

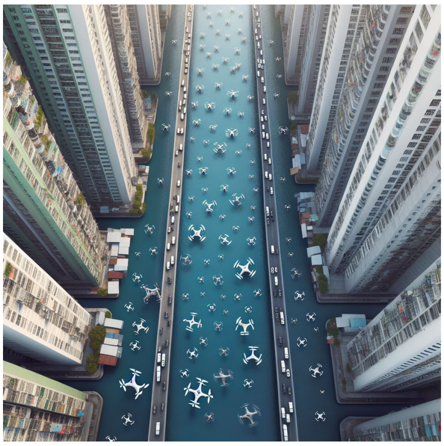

Figure 4. Possible scenarios of congestion in low altitude airspace.

For trajectory and congestion prediction tasks in low-altitude airspace, the grid graph convolutional network with neighborhood learning architecture demonstrates exceptional capability in learning complex motion patterns (Wu et al., 2024). By modeling airspace trajectories as temporal sequences of grid transitions, the network captures both micro-scale movement characteristics (through grid-level features) and macro-scale traffic trends (via hierarchical grid aggregation). The neighborhood convolution operator adaptively weights adjacent grids based on their historical transition probabilities and current traffic states, effectively encoding congestion propagation patterns.

4.1 Airspace congestion analysis formula

Upon completing parameter learning, the grid graph convolutional network model acquires the capability to predict aircraft trajectories during target prediction periods. By integrating these trajectory predictions with airspace attributes, it ultimately aggregates congestion forecasts for critical airspace sectors within designated regions. This aggregation process systematically combines spatial-temporal trajectory distributions with airspace capacity constraints, enabling multi-scale congestion evaluation through probabilistic fusion and rule-based reasoning mechanisms.

To operationalize airspace congestion prediction using the GN-GCN model, this paper aggregates predicted trajectories across temporal intervals and spatial grids. Adaptive congestion thresholds are established for each 3D spatial grid cell coordinate (*i*,*j*,*z*) by integrating meteorological impacts and airspace class constraints, which is formalized as:

$$T_{ijz} = B \cdot C_{category}^{ijz} \cdot \prod_{k=1}^{n}(1 - W_{weather}^{k} M_{ijz}^{k}), \tag{2}$$

where T_{ijz} = maximum tolerable aircraft count for spatial grid (*i*,*j*,*z*) under congestion
B = baseline threshold (maximum aircraft capacity under standard conditions)

After consulting with aviation experts, $C_{category}^{ijz} \in \{C_{unrestricted} = 1, C_{minor} = 0.8, C_{major} = 0.5\}$ represents airspace class coefficient; $W_{weather}^{k} \in \{W_{weather}^{thunder} = 0.5, W_{weather}^{wind} = 0.2, W_{weather}^{rain} = 0.1\}$ denotes weather impact coefficients; M_{ijz}^{k} is intensity level of weather type k in spatial grid (*i*,*j*,*z*). By the calculation of T_{ijz}, the airspace congestion severity S_{ijz} in grid (*i*,*j*,*z*) is quantified via a piecewise function:

$$S_{ijz} = \begin{cases} 0, if\ N_{ijz} \le 0.5T_{ijz} \\ \frac{N_{ijz} - 0.5T_{ijz}}{0.5T_{ijz}}, if\ 0.5T_{ijz} < N_{ijz} \le T_{ijz}, \\ 1,\ if\ N_{ijz} > T_{ijz} \end{cases} \tag{3}$$

where N_{ijz} = predicted aircraft count by GN-GCN model
$S_{ijz} \in [0,1]$ = normalized congestion severity (0 means complete airspace freedom,1 means critical congestion)

4.2 Probability grid map

In airspace congestion prediction, GN-GCN can visualize different probabilities in a spatio-temporal probabilistic grid map. Based on the intention of the system entity in the global environment, the spatio-temporal probability grid map uses grids as the basic unit to display the impact range of airspace congestion through different color intensities. In this paper, an airspace congestion probability grid map is also established based on the airspace predicted congestion severity S_{ijz} to dynamically display the congestion prediction of each airspace grid, as shown in Figure 5.

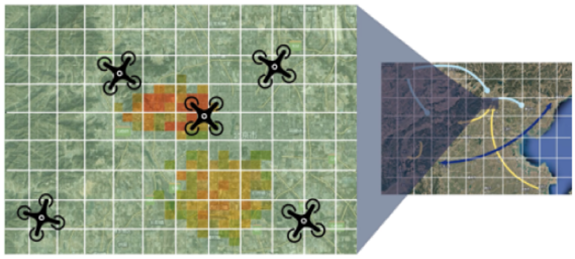

Figure 5. The representation of spatio-temporal congestion probability grid map.

The airspace congestion probability grid can summarize the reasoning of the movement trends of aircrafts based on GN-GCN, and finally conduct congestion risk assessment and prediction for the airspace scenarios. In the grid map, the darker the color of the grid, the higher the congestion risk S_{ijz} of the area during the predicted time interval. If $S_{ijz} > 0.6$, it is necessary to provide congestion warnings to nearby aircraft for pre-evacuation to relieve local risks. This paper can help to achieve proactive airspace traffic management through early warning dissemination by airspace congestion probability grid map.

4.3 Results

After comparative experiments with other time-series models, this paper further evaluates the GN-GCN model across extended temporal intervals for airspace trajectory prediction. As detailed in Table 1, short-term predictions achieve lower MSE and MAE values, while both metrics exhibit a gradual yet acceptable increase as the prediction horizon extends, reflecting the inherent challenges of long-term forecasting common to time-series models. Results confirm that GN-GCN maintains reliable trajectory prediction accuracy within a five-hour horizon, with MSE and MAE deviations remaining within operational tolerances. Across all intervals, the model achieves an MRR of 0.8318, with Hit@1, Hit@3, and Hit@10 scores of 73.60%, 92.43%, and 97.63%, respectively. These metrics indicate that the ground-truth trajectory positions are consistently ranked within the top-three predicted spatial grids in over 92% of cases, demonstrating the GN-GCN model's practical applicability for airspace decision support.

Predict time period		MSE	MAE
Short-term	$\tau = 1$	0.0057	0.0207
	$\tau = 2$	0.0073	0.0264
	$\tau = 3$	0.0064	0.0244
	$\tau = 4$	0.0052	0.0196
	$\tau = 5$	0.0053	0.0202
	$\tau = 6$	0.0099	0.0358
	Average	**0.0066**	**0.0245**
Long-term	$\tau = 7$	0.0056	0.0226
	$\tau = 8$	0.0092	0.0333
	$\tau = 9$	0.0100	0.0358
	$\tau = 10$	0.0099	0.0356
	$\tau = 11$	0.0085	0.0314
	$\tau = 12$	0.0098	0.0354
	Average	**0.0089**	**0.0324**

Table 1. The result indicators of airspace congestion prediction using grid graph convolution network model.

5. Grid graph convolutional network for meteorological prediction

The grid graph convolutional network framework further proves effective in meteorological prediction by learning the temporal evolution of weather elements (e.g., wind, precipitation, turbulence) across grid hierarchies. The model successfully generates dynamic meteorological knowledge graphs that encode spatio-temporal relatios between weather phenomena at different altitudes and resolutions (Han et al., 2023). This capability enables predictive risk assessment for low-altitude flight operations through probabilistic reasoning over the learned graph structure. By integrating real-time sensor data with historical weather patterns, the system demonstrates high accuracy in predicting hazardous meteorological conditions 30 minutes in advance, significantly outperforming conventional numerical weather prediction models in localized scenarios. The grid-based knowledge representation naturally supports the fusion of heterogeneous data sources, including satellite observations, ground station reports, and flight trajectory data, establishing a robust foundation for safety-critical decision-making in urban air mobility systems. In the future, this paper will conduct more in-depth research on meteorological risks based on grid graph convolutional neural networks.

6. Conclusions

The GN-GCN framework resolves critical spatio-temporal prediction limitations by unifying GeoSOT-4D grid encoding with neighborhood-driven graph convolutions, effectively addressing accuracy bottlenecks through multi-scale dependency learning and accelerating computation via grid-based topological optimization. Experimental validation demonstrates superior performance: achieving SOTA MRR in spatio-temporal knowledge reasoning, reliable trajectory and meteorological forecasting for airspace management. This work establishes a versatile foundation for safety-critical applications in urban air mobility and emergency response, with future research directed toward enhancing dynamic grid adaptation and cross-domain generalization capabilities.

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