

GC-GAT: An integrated approach combining grid calculation and graph attention network for geographic knowledge graph reasoning

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Abstract

Geographic knowledge graph (KG) reasoning enables the inference of missing entities and relations, a fundamental step toward constructing comprehensive geospatial knowledge systems. However, prevailing approaches often struggle with the accurate modeling of complex spatio-temporal dependencies, particularly in the context of large-scale data, and frequently lack interpretability. To address this issue, we present GC-GAT, a hybrid framework that integrates grid-based spatial encoding with a graph attention network to enhance geographic KG reasoning. We benchmark GC-GAT against other 9 models, including TransE, DistMult, ConvE, ComplEx, R-GCN, TANGO-DistMult, RE-NET, CyGNet, and RE-GCN. Our evaluation is conducted on the ICEWS14s dataset. Our framework significantly enhances the performance of the baseline on the spatio-temporal entity reasoning, achieving MRR of 46.11. Our results show that GC-GAT achieves superior accuracy and training efficiency, benefitting from the multiscale spatial aggregation properties of GeoSOT. These findings demonstrate the robustness and scalability of GC-GAT for reasoning over geographic knowledge graphs.

1. Introduction

Knowledge graphs offer a structured and scalable framework for representing information, enabling efficient integration and utilization in advanced computational applications (Chen et al., 2020; Abu-Salih, 2021). Actually, there are two basic elements in knowledge graph: entity and relation (Wang et al., 2019; Zhang et al., 2008). Considering that real geographical scenes are very complex and change in real time, it is difficult to obtain all spatio-temporal information (Pan et al., 2021). Geographic knowledge graph (KG) reasoning can predict missing entities and relations, which is crucial for building a complete geospatial knowledge system (Wang et al., 2019; Chen et al., 2020). However, most existing KG reasoning models have low accuracy in solving complex spatio-temporal relationships and large-scale data (Zhang et al., 2020; Han et al., 2025). Improving the accuracy and interpretability of KG reasoning models remains challenging.

Recently, many KG reasoning models have been proposed including knowledge reasoning methods based on logic rules, representation learning, and neural networks (Tian et al., 2022). Owing to its powerful representation learning capabilities for graph-structured data, Graph Neural Networks (GNNs) are widely adopted for knowledge graph construction. (Sun et al., 2023). Knowledge graphs represent data through graph-structured node-edge architectures. Graph Neural Networks (GNNs) demonstrate superior capability in integrating both structural and attribute features of knowledge graphs (Cai et al., 2018). Through neighborhood information aggregation and node state updating mechanisms, GNNs leverage their exceptional message-passing capacity to capture inter-node semantic relationships and latent patterns (Tian et al., 2022), thereby enabling comprehensive learning of node-level representations, relational dependencies, and global topological characteristics. The precise acquisition of semantically meaningful structural information constitutes a fundamental prerequisite for knowledge graph reasoning (Cao et al., 2015). This explains GNNs' predominant advantages across knowledge

graph processing pipelines, particularly in reasoning tasks. The Graph Convolutional Network (GCN) framework proposed by Kipf & Welling (2016) employs Chebyshev polynomial-approximated spectral filters to encode local graph substructures, establishing itself as a third-generation graph convolutional architecture with demonstrated efficacy in semi-supervised learning scenarios. For instance, the structure aware convolutional network (SACN) (Shang et al., 2019) utilizes one weighted GCN as an encoder and a convolution network ConvTransE as a decoder.

In 2017, Veličković et al. introduced the Graph Attention Network (GAT), a spatially-based graph neural architecture that employs attention mechanisms to dynamically determine edge weight coefficients during neighborhood feature aggregation (Veličković et al., 2017). This innovation extends beyond conventional Graph Convolutional Networks (GCNs) by incorporating adaptive edge weighting (Vaswani et al., 2017), enabling context-aware modulation of neighbor contributions. The GAT framework fundamentally enhances message-passing paradigms through differentiable attention coefficients that assign node-specific propagation weights (Wu et al., 2021; Orji et al., 2025). Subsequent advancements include Zhang et al.'s hierarchical attention-based relational GNN encoder-decoder architecture for knowledge graph completion tasks (Zhang et al., 2020). Notably, Kang et al. developed the Heterogeneous Information Network Embedding framework via Graph Attention Network (HE-GAN), which utilizes stacked GAT layers to capture high-order proximity features of entities, thereby achieving comprehensive semantic representation of knowledge graphs (Kang et al., 2021; Tian et al., 2021).

GeoSOT (Geographic Coordinate Subdividing Grid with One Dimension Integral Coding on 2n Tree), a representative implementation of Discrete Global Grid Systems (DGGs), has exhibited high computational efficiency and strong spatial-temporal organizational capabilities across a range of geospatial applications (Cheng et al., 2012). GeoSOT is a spatial subdivision and encoding system that discretizes the Earth's

surface using a recursive quadtree structure based on the geographic coordinate system of latitude and longitude (Figure 1) (Cheng et al., 2016). Centered at the intersection of the prime meridian and the equator, GeoSOT recursively partitions the Earth's surface into a hierarchical grid system that is continuous, gapless, and non-overlapping. To construct a precise multiscale spatial grid, the Earth's coordinate system is first expanded to a $512^\circ \times 512^\circ$ space. Each degree (1°) is then subdivided into $64'$, and each arcminute ($1'$) is further divided into $64''$. This hierarchical scheme enables the construction of a complete and non-overlapping quadtree structure, ranging from the global scale (level 0) down to centimeter-level resolution (level 32)(Li et al., 2022). GeoSOT is highly suitable for real-world spatio-temporal computing tasks due to its hierarchical structure and efficient spatial indexing capabilities (Zhu et al., 2023). GeoSOT grids can enhance both the training accuracy and computational efficiency of the spatio-temporal knowledge graph reasoning model. For example, the GN-GCN model leverages the multi-scale aggregation capabilities of GeoSOT to improve both the training accuracy and computational efficiency of the model (Han et al., 2025).

Contemporary knowledge graph (KG) reasoning systems exhibit significant limitations in processing complex spatiotemporal dependencies and scaling to voluminous datasets. While graph attention networks (GATs) demonstrate enhanced capability for comprehensive semantic representation in KGs and improved reasoning accuracy/efficiency, their intrinsic architecture remains fundamentally constrained in spatiotemporal relational organization. Therefore, we proposed an integrated approach combining grid calculation and graph attention network (GC-GAT) to enhance geographic KG reasoning.

The main contributions of this study are as followed: (1) The GC-GAT hybrid model, integrating spatial-temporal organizational capabilities of GeoSOT and feature prioritization strengths of GAT. (2) Empirical evaluations show that GC-GAT achieves state-of-the-art performance on geographic KG reasoning benchmarks.

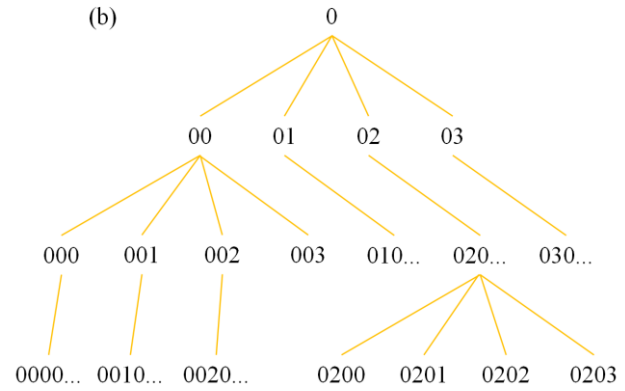
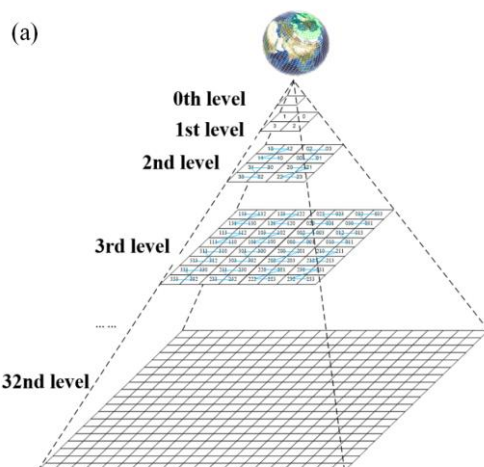


Figure 1. The GeoSOT discrete grid model. (a) GeoSOT subdivision grid. (b) GeoSOT quadtree structure for binary code.

2. Methods

The GC-GAT for spatio-temporal KG reasoning consists of three components including a static GAT module, a neighborhood grid calculation (NGC) module, and a time evolution unit (TEU).

2.1 GAT module

In this study, we use graph attention network (GAT), a novel class of neural architectures designed for graph-structured data, which employ masked self-attention mechanisms to overcome the limitations of traditional graph convolutional approaches and their approximations (Veličković et al., 2017).

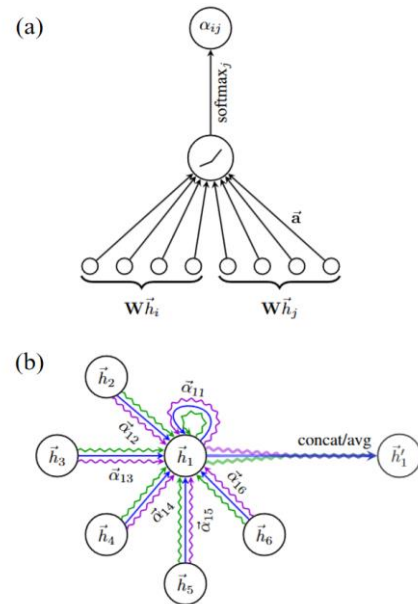


Figure 2. The GAT module (Veličković et al., 2017).

2.2 NGC module

The NGC module is based on the GeoSOT Grid map, which can build a spatial neighbourhood learning network. The architecture of the NGC module is presented in Figure 3. The

architecture of NGC has been described in a previous study (Han et al., 2025).

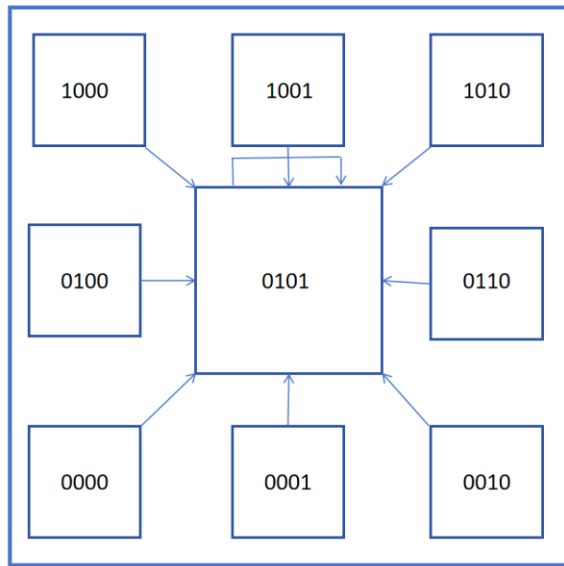


Figure 3. The NGC module.

2.3 TEU module

The TEU module is a type of gated recurrent unit method, which can achieve spatiotemporal KG reasoning. The spatiotemporal entity prediction architecture of the TEU module is presented in Figure 4. The architecture of TEU has been described in a previous study (Han et al., 2025).

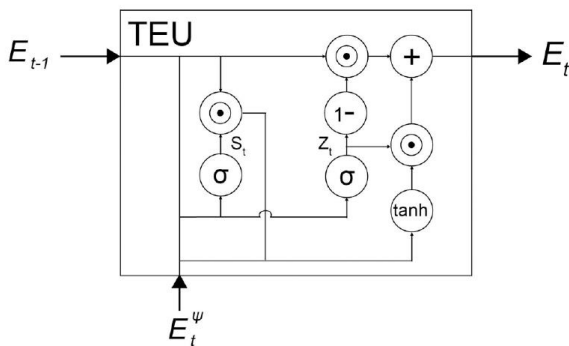


Figure 4. Architecture of the TEU module (Han et al., 2025).

3. Experiments and Results

3.1 Datasets

In this paper, our evaluation is conducted on the universal temporal benchmark dataset: ICEWS14 (García-Durón et al., 2018), sourced from the Integrated Crisis Early Warning System. Detailed statistics of the three datasets are shown in Tables 1.

Datasets	ICEWS14
Train	74,845
Valid	8,514
Test	7,371
Time gap	24 hours

Table 1. The statistics of ICEWS14 dataset.

3.2 Experimental Setup

In this study, we carried out the experiments in a high performance computing environment. We selected the hyperparameters used in the model, with details provided in Table 2.

Parameter	Value
Epoch	100
Attention heads	1
Dropout	0.2
Batch-size	1
Learning rate	0.001

Table 2. Description of model parameters.

We benchmark GC-GAT against 9 other models, including TransE (Bordes et al., 2013), DisMult (Yang, 2014), ConvE (Dettmers et al., 2018), ComplEx (Trouillon et al., 2016), R-GCN (Schlichtkrull et al., 2018), TANGO-DistMult (García-Durán et al., 2018), RE-NET (Jin et al., 2019), CyGNet (Zhu et al., 2021) and RE-GCN (Li et al., 2021).

For each dataset, we used 80% of the sequences as the training set, 10% as the test set, and 10% as the valid set. To evaluate the results on these datasets, we used the mean reciprocal rank (MRR) and Hits@{1, 3, 10} (the proportions of correct predictions ranked within the top 1/3/10) as evaluation metrics.

MRR and Hits@{1, 3, 10} are two commonly used performance evaluation indicators in knowledge graph embedding models, mainly used to measure the accuracy of link prediction tasks. MRR is the average of the reciprocal rankings of correct facts, reflecting the model's ability to rank correct facts in the top positions. The larger the MRR value, the better the model performance. Hits@n refers to the average proportion of triples ranked less than n in link prediction. Generally, n is taken to be 1, 3 or 10. The larger the indicator, the better. For example, Hits@3 refers to the proportion of triples predicted to rank in the top 3 to the actual correct triples. If there are 100 triples, 50 of which rank in the top 3 in the prediction, then Hits@3 is 50%. The larger the indicator, the higher the proportion of correct predictions of the model in the top three.

We conducted two types of spatiotemporal reasoning comparison experiments, namely spatiotemporal entity reasoning and spatiotemporal relation reasoning.

3.3 Experimental results

Spatiotemporal knowledge graph (KG) reasoning involves predicting missing elements in quadruples within spatiotemporal contexts. This task extends traditional semantic reasoning by incorporating both temporal and spatial dimensions, thereby enhancing the expressiveness and generalizability of the model.

We evaluate the performance of GC-GAT by comparing it against nine representative KG reasoning models: TransE, DisMult, ConvE, ComplEx, R-GCN, TANGO-DistMult, RE-NET, CyGNet, and RE-GCN. All baseline models are implemented using their recommended configurations. It is important to note that most of these models are designed primarily for semantic reasoning and have not been specifically adapted for spatiotemporal scenarios. Therefore, the comparison highlights GC-GAT's ability to handle spatio-

temporal reasoning, supplemented by representative results from traditional semantic models.

3.3.1 Spatio-temporal entity reasoning: Spatio-temporal entity prediction results are presented in Figure 5 and Table 3. Figure 5 demonstrates that GC-GAT consistently outperforms the baselines on the ICEWS14s+* dataset. In the entity prediction based on the ICEWS14s+* dataset, the MRR values of TransE, DistMult, ConvE, ComplEx, R-GCN, TANGO-DistMult, RE-NET, CyGNet, RE-GCN and GC-GAT are 10.49, 18.78, 28.55, 23.64, 25.41, 45.63, 35.35, 40.35, 46.11, respectively. The Hits@1 values of TransE, DistMult, ConvE, ComplEx, R-GCN, TANGO-DistMult, RE-NET, CyGNet, RE-GCN and GC-GAT are 6.10, 10.10, 16.83, 13.73, 20.01, 16.22, 34.42, 26.42, 29.80, 35.72, respectively. The Hits@3 values of TransE, DistMult, ConvE, ComplEx, R-GCN, TANGO-DistMult, RE-NET, CyGNet, RE-GCN and GC-GAT are 13.98, 22.99, 28.92, 27.99, 31.89, 30.86, 49.10, 36.83, 45.20, 51.22, respectively. The Hits@10 values of TransE, DistMult, ConvE, ComplEx, R-GCN, TANGO-DistMult, RE-NET, CyGNet, RE-GCN and GC-GAT are 32.34, 44.75, 42.68, 43.61, 44.51, 46.36, 58.47, 53.05, 60.98, 66.18, respectively.

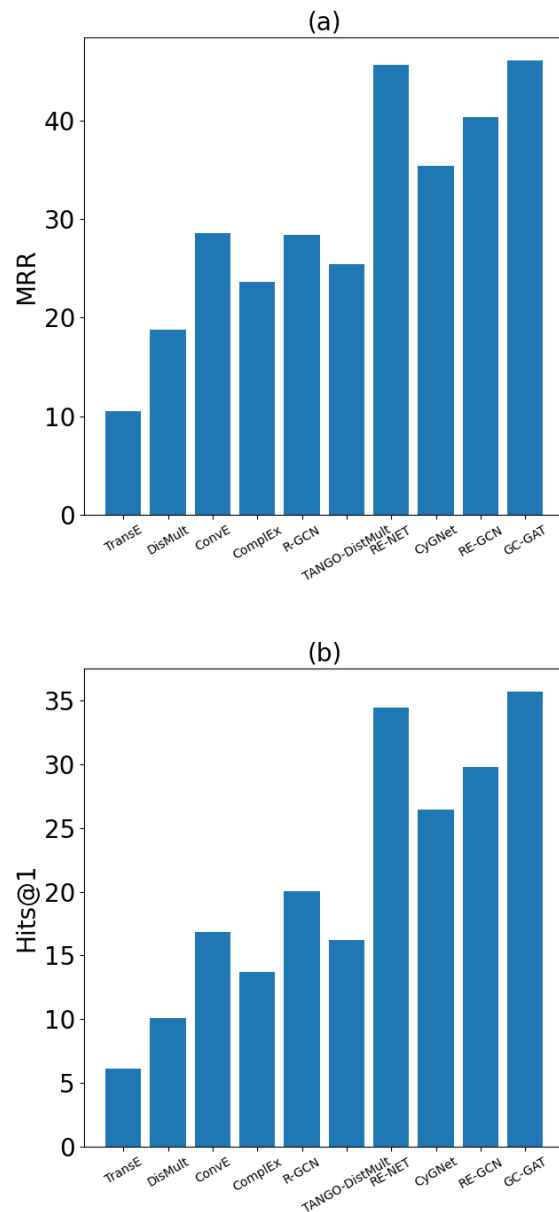
Static embedding models such as TransE, DistMult, ConvE and ComplEx perform poorly due to their limited capacity to capture complex entity and relation structures. Specifically, TransE, DistMult, and ConvE struggle with datasets characterized by a large number of relation types and high sparsity. DistMult, a simplified version of RESCAL, is limited to modeling symmetric relations. Although TANGO-DistMult integrates features from both TANGO and DistMult, its inference performance remains suboptimal. R-GCN performs relatively well among static semantic models but fails to effectively capture temporal and spatial dependencies, resulting in a mean reciprocal rank (MRR) below state-of-the-art (SOTA) levels.

Several temporal reasoning models demonstrate competitive performance. For instance, RE-NET performs well on the ICEWS14s dataset; however, its effectiveness diminishes on other datasets, likely due to the limited number of entities and relations in ICEWS14s. RE-GCN incorporates a time-gating mechanism that enhances its ability to model temporal neighborhoods, but it lacks the capacity to analyze spatial neighborhoods in an interpretable manner. CyGNet, inspired by the replication mechanism in natural language generation, suffers from long training times and delivers inferior predictive performance compared to other temporal models.

Overall, GC-GAT achieves superior spatio-temporal reasoning performance compared to all baseline models, particularly in terms of mean reciprocal rank (MRR). It demonstrates the largest performance gains and effectively captures more precise and comprehensive spatio-temporal dependencies. The entity prediction experiments confirm the high accuracy and robustness of GC-GAT in spatio-temporal settings.

RE-GCN	40.35	29.80	45.20	60.98
GC-GAT	46.11	35.72	51.22	66.18

Table 3. Results of spatio-temporal entity prediction experiments conducted on ICEWS14s+* dataset.



Model	MRR	Hits@1	Hits@3	Hits@10
TransE	10.49	6.10	13.98	32.34
DisMult	18.78	10.10	22.99	44.75
ConvE	28.55	16.83	28.92	42.68
ComplEx	23.64	13.73	27.99	43.61
R-GCN	28.42	20.01	31.89	44.51
TANGO-DistMult	25.41	16.22	30.86	46.36
RE-NET	45.63	34.42	49.10	58.47
CyGNet	35.35	26.42	36.83	53.05

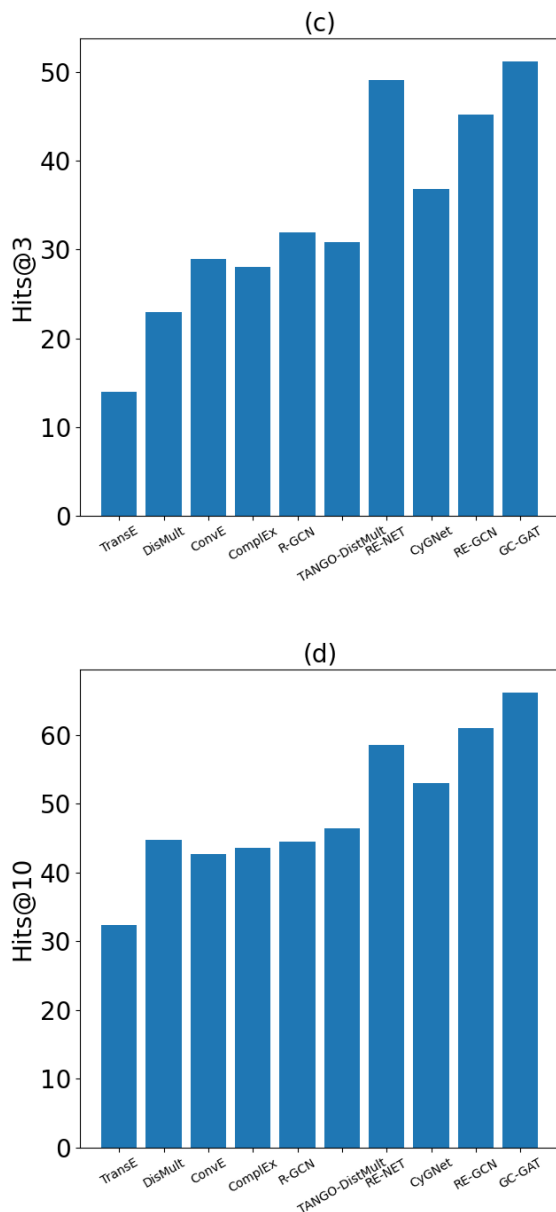


Figure 5. Results of spatio-temporal entity prediction experiments conducted on ICEWS14s+* dataset.

3.3.2 Spatio-temporal relation reasoning: We also evaluate spatio-temporal relation prediction, with the results presented in Table 4. Since not all models support relation prediction, a subset of representative models is selected as baselines. In the relation prediction based on the ICEWS14s+* dataset, the MRR values of TransE, ConvE, R-GCN, RE-GCN and GC-GAT are 32.66, 34.88, 40.44, 46.69, 52.72, respectively.

As shown in Table 4 and Figure 6, static embedding models such as TransE and ConvE perform poorly on spatio-temporal relation prediction tasks. In contrast, R-GCN and RE-GCN highlight the strengths of graph convolutional networks (GCNs) in modeling temporal relations. However, when spatial relations are introduced, both models tend to treat them as standard semantic relations, limiting their effectiveness. In comparison, GC-GAT achieves the best

performance among all models, demonstrating superior capability in capturing and reasoning over spatio-temporal relations.

Model	ICEWS14s+ * dataset
TransE	32.66
ConvE	34.88
R-GCN	40.44
RE-GCN	46.69
GC-GAT	52.72

Table 4. MRR scores produced for the spatio-temporal relation prediction results obtained on three spatio-temporal datasets.

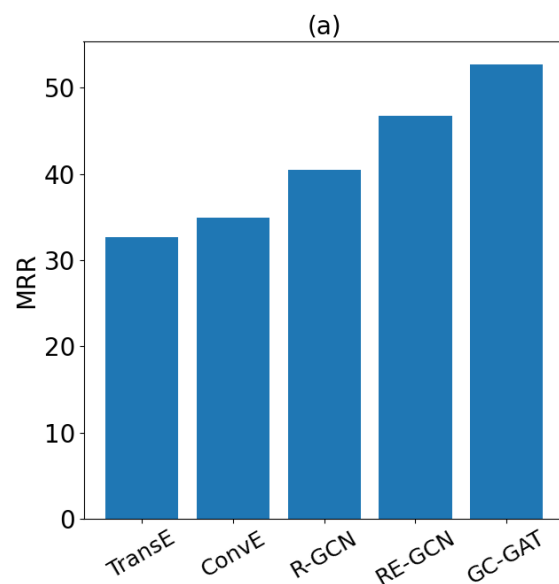


Figure 6. Results of spatio-temporal relation prediction experiments conducted on ICEWS14s+* dataset.

4. Conclusions and Future Works

Geographic knowledge graph (KG) reasoning facilitates the inference of missing entities and relations, serving as a foundational step in building comprehensive geospatial knowledge systems. However, existing methods often struggle to model complex spatio-temporal dependencies effectively, especially at large scales, and typically lack interpretability. In this work, we propose GC-GAT, a hybrid framework that combines grid-based spatial encoding with a graph attention network to improve geographic KG reasoning. We evaluate GC-GAT against several baseline models using a widely adopted temporal benchmark dataset. Compared with state-of-the-art methods, our method achieves superior accuracy and training efficiency, owing to the multiscale spatial aggregation capabilities of the GeoSOT-based encoding. These findings underscore the robustness and scalability of GC-GAT in geographic knowledge graph reasoning tasks.

Acknowledgements

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