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Recent advances in Knowledge Graph Completion

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Abstract. Knowledge Graph Completion is dedicated to filling the gaps in knowledge graphs, and this technology has found widespread application in various domains. Traditional knowledge graph completion techniques operate under a closed-world assumption, restricting their analysis to existing content within the same knowledge graph, making it impossible to introduce new entities and relationships. Furthermore, most methods are designed to handle a single type of information, primarily focusing on temporal knowledge graph completion. However, in the real open world, knowledge graphs are dynamic, encompassing multimodal data that evolves over time. As such, traditional knowledge graph completion methods may struggle to address practical needs. To address these limitations, this paper provides an overview of traditional knowledge graph completion research. It highlights the latest advancements in knowledge graph completion methods based on open-world, multimodal, and temporal knowledge. We analyze the enhancements brought about by these new methods in the field of knowledge graph completion, offering a comparative analysis that explores their strengths, weaknesses, application domains, and future development trends to serve as a valuable reference for researchers.

Keywords: Knowledge Graph Completion, Temporal Knowledge Graph Completion, Multimodal Knowledge Graph

1. Introduction

Knowledge graphs serve as repositories for real-world entities and their interconnected relationships, offering an intuitive graphical representation of complex information. Since Google introduced the concept of knowledge graphs in 2012, they have gained widespread adoption in real-world applications, including recommendation systems, information extraction, and natural language understanding.

However, the information contained in most knowledge graphs is incomplete, as it is challenging to encompass all real-world knowledge. Hence, the notion of Knowledge Graph Completion emerged. In the real world, knowledge graph data often undergoes temporal changes, with entities exhibiting different relationships or attributes at various points in time. Additionally, knowledge graphs can house diverse data types, such as text, audio, images, and video data, simultaneously. Conventional closed-world approaches to knowledge graph completion fail to predict new entities and relationships, which are continually added to rapidly evolving real-world knowledge graphs. This paper explores the prediction that knowledge graph completion methods founded on open-world assumptions, multimodal data, and temporal knowledge will shape the future of this field. We examine the key challenges currently faced in knowledge graph completion and evaluate recent advancements in knowledge graph

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completion methods, with a focus on open-world assumptions, temporal knowledge graph completion, and multimodal data. This analysis includes an assessment of their strengths, weaknesses, and application domains, providing valuable insights for researchers.

2. Preliminaries

2.1. Knowledge Graph Completion

A knowledge graph is a structured, multi-relational knowledge base typically containing a set of facts. Each fact within the knowledge graph is stored in the form of triples (s, r, o), with 's' representing the head entity, 'o' representing the tail entity, and 'r' representing the relationship connecting these entities. However, many entities and relationships are often missing.

Knowledge Graph Completion (KGC) is aimed at exploring potential missing relationships and connecting different entities. Given the limited number of entities and relationships within a knowledge graph, there may exist entities and relationships not yet included in the graph, necessitating their discovery. The objective of KGC is to address the issue of incompleteness and sparsity stemming from the absence of certain entities or relationships in knowledge graphs. This is essential for enhancing the quality of knowledge graphs. KGC technology supplements the graph structure by predicting knowledge instances (entities, relationships, attributes, etc.), mining missing entities and relationships, or discovering new facts. Generally, KGC can be categorized into the following three types: (1) predicting the corresponding tail entity when given the head entity and relationship in a triple; (2) predicting the corresponding head entity when given the relationship and tail entity; (3) predicting the relationship between the head and tail entity when both entities are provided. This implies that any two of the elements in a triple can be used to infer the third element.

In most cases, KGC is employed to predict entities or relationships. However, it's worth noting that entities often possess attributes of their own, such as age and gender. Some KGC methods have been proposed to predict missing attribute values for entities [1].

2.2. The Classification of Knowledge Graph Completion

2.2.1. Translation-Based Model. The translation-based model involves embedding a knowledge graph into a continuous vector space while preserving certain attributes of the original graph. This allows for the effective representation of entities and relationships within the knowledge graph. These models typically operate under the assumption that relationships in the knowledge graph can be regarded as translations between entities. In other words, the head entity 'H' plus the relationship vector 'R' should be in proximity to the tail entity 'T'. This assumption enables these models to capture complex patterns within knowledge graphs and perform well in tasks like link prediction. An exemplary model is TransE, as illustrated in Figure 1. This method is straightforward and offers a clear, interpretable modeling of entities and relationships.

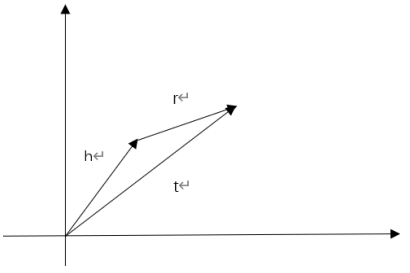


Figure 1. TransE

2.2.2. Graph Neural Network Model. Given that a knowledge graph inherently exhibits a graph structure, graph neural network technology can be more effectively applied to represent the embedding

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of entities and relationships in the knowledge graph. Moreover, in graph neural networks (GNNs), each node is updated and adjusted based on neighboring information. Consequently, GNNs can learn from patterns exhibited by their neighbors, enabling them to appropriately handle unknown but similar nodes and edges.

2.2.3. Information-Enriched Model. The Information-Enriched Model enriches knowledge graph embeddings by incorporating additional information from the knowledge graph. Traditional embedding methods statically embed each entity or relationship, overlooking the attribute information of entities, the textual descriptions of entities and relationships, and the contextual information of entities and relationships within the knowledge graph. Typically, this additional information is integrated into a specific scoring function to enhance the performance of knowledge graph embedding. For instance, Quan Wang et al. introduced a novel knowledge graph embedding paradigm called contextual knowledge graph embedding (CoKE) [2].

Furthermore, Yinyu Lan et al. and others consider the text semantics of symbols in the path and propose MedKGC for completing medical knowledge graphs [3].

2.2.4. Convolutional Network Model. In contrast to other models, those based on convolutional neural networks have the advantage of fully considering additional information and uncovering the deep connections between embedded vectors of entities and relationships. Additionally, these models possess fewer parameters, resulting in lower computational complexity, making them suitable for large-scale knowledge graphs.

3. The Recent Advancements in Knowledge Graph Completion

3.1. Temporal Knowledge Graph Completion

Temporal knowledge graphs have garnered considerable attention in recent years. In contrast to non-temporal knowledge graphs, temporal knowledge graphs introduce a temporal dimension, allowing for the representation of how relationships between different entities change over time, thereby providing a more accurate reflection of real-world dynamics.

3.1.1. Graph Neural Networks. Many knowledge graphs share overlapping content, posing a challenge of aligning *equivalent* entity pairs across different knowledge graphs. In the context of temporal knowledge graphs, a logical solution is to integrate temporal information into the entity alignment model. Existing entity alignment methods, often based on embedded systems, tend to overlook the temporal information frequently found in many large-scale knowledge graphs. The success of Graph Neural Network (GNN) models in entity alignment underscores their significance in temporal knowledge graph completion.

In 2015, Chengjin Xu et al. introduced a novel time-aware entity alignment method known as Time-aware Entity Alignment with Graph Neural Networks (TEA-GNN). This approach leverages GNNs to learn embeddings of entities, relations, and timestamps, all mapped into vector spaces, from different knowledge graphs. Additionally, it incorporates a time-aware attention mechanism, which calculates orthogonal transformation matrices for various nodes by incorporating related relations and timestamps within the neighborhood and assigning different weights. This mechanism effectively integrates relation and temporal information into the GNN structure of the model [4].

The model's loss function comprises two components: the quadruple loss and the temporal regularization term. The total loss function can be expressed as:

$$L_b = \frac{1}{b} \sum_{\omega \in \Omega_b} (L_\omega + \lambda_T L_T)$$

where L_ω represents the quadruple loss, λ_T is the coefficient for the temporal regularization term, L_T is the temporal regularization term, and b corresponds to the size of the training batch Ω_b.

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However, it's important to note that while TEA-GNN is effective at identifying equivalent entity pairs across different knowledge graphs, it does not directly predict unknown entities and relationships.

To address this limitation, Z. Han et al. proposed the Graph Hawkes Neural Network (GHNN). This model, which captures the probability of events occurring over continuous time, can capture the dynamics of evolving graph sequences. Consequently, GHNN can predict the probability of an event occurring at any given time and anticipate the likelihood of future events [5].

GHNN excels at predicting the likelihood of events at different times and changes in various entities and their relationships that were previously unaccounted for in the knowledge graph.

3.1.2. Non-Graph Neural Network Methods. Given the incompleteness of temporal knowledge graphs, various approaches for completing them have been proposed, with many relying on embedding methods.

Chengjin Xu, for example, explored the impact of the temporal granularity of time datasets on the completion of temporal knowledge graphs. He introduced a new time-aware knowledge graph embedding method, TeLM, which employs a linear temporal regularizer and multi-vector embedding to perform fourth-order tensor decomposition on temporal knowledge graphs [6].

Furthermore, Rishab Goel et al. introduced a diachronic entity embedding function capable of transforming static models into new time-aware knowledge graph completion models. This function provides entity features at all time points and imposes no restrictions on the embedding model, potentially allowing integration with any static model [7]. Their diachronic word embedding (DE) method offers entity characteristics at any given time and is highly versatile [7].

Johannes Messner et al. proposed a model for Temporal Knowledge Graph Completion (TKGC) named BoxTE, building upon the static knowledge graph embedding model BoxE. BoxTE demonstrated strong inductive capabilities in temporal settings [8].

While most existing knowledge graph completion methods rely on embeddings, many of these models lack interpretability and transparent reasoning chains. To address this, logical rules have been leveraged to enhance embedding methods. Logical rules not only offer a means of understanding and explaining model predictions intuitively but also provide an inductive bias for improved model induction. Moreover, logical rules can capture structured knowledge within the knowledge graph, a challenge for many other model types.

Yushan Liu introduced an interpretable framework based on time random walk extraction of temporal logic rules, TLogic. This model can learn temporal logic rules from the temporal knowledge graph (TKG) and apply these rules to the link prediction task[9].

Additionally, some scholars employ path reasoning as an approach to address the challenges associated with completing temporal knowledge graphs.

Jaehun Jung and his colleagues introduced an innovative Temporal Knowledge Graph Completion (TKGC) model known as T-GAP. T-GAP is designed to maximize the utilization of temporal information and the underlying graph structure through its encoder and decoder. It meticulously encodes query-specific elements of TKGC, with particular emphasis on the time difference between each event and the query timestamp. T-GAP employs reasoning based on paths, systematically distributing attention throughout the graph. This approach enables T-GAP to effectively harness both temporal and structural information within the knowledge graph [10].

The loss function for T-GAP is defined as:

$$L = -\prod_{i \in_{\text{train}}} \log a_{u_i}^{(T)}$$

Yi Xu and their team have proposed a novel model that utilizes a unique training framework referred to as Comparative Event Network (CENET). CENET is applied in the context of event prediction. It involves learning from past events and identifying potential dependencies between entities to distinguish highly related entities. Through comparative learning, combined with the distribution of two events, CENET trains the query's expression form to determine which event is more dependent on the present moment [11].

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3.2. Multimodal Knowledge Graph Completion

Many existing knowledge graphs are unimodal, primarily focusing on a single type of data, often limited to text and structured data. However, in the real world, entities contain rich multimodal information, including images, videos, audio, and more. Utilizing multimodal information in knowledge graphs can provide additional insights, such as enhancing entity descriptions by combining images with text data. Moreover, incorporating information from various modes is invaluable for understanding abstract concepts. To enable machines to better understand abstract concepts, it is crucial to rely on both abstract and related concrete concepts [12]. Multimodal semantic associations enable machines to capture semantic features of abstract concepts effectively. Therefore, leveraging multimodal information as a data source to build a multimodal knowledge graph is essential.

Furthermore, to meet practical needs, several large multimodal models like MMEKG have been developed [13]. However, most Multimodal Knowledge Graphs (MKGs) have room for improvement. Hence, the concept of completing multimodal knowledge graphs is introduced, aiming to extract knowledge from multimodal data to fill in missing facts in knowledge graphs.

Nevertheless, compared to unimodal knowledge graph completion, multimodal knowledge graph completion presents more challenges. The multimodal information associated with entities is often imbalanced, with different multimodal knowledge graphs placing varying emphasis on different types of information. For instance, a knowledge graph about movies may contain numerous images and videos, while a knowledge graph about theoretical research may predominantly contain text and symbolic data. Additionally, relationships between different modes often coexist, leading to potential conflicts between different modal relations during training. This is because for a pair of entities, the relationship in one mode may contradict that in another mode. Furthermore, constructing a suitable model architecture for multimodal knowledge graph completion poses higher demands, as different tasks require different knowledge graph architectures. To address these challenges and accommodate multiple modes, a universal model architecture is needed.

Yu Zhao et al. proposed a novel framework known as MoSE, designed for Modality Split representation learning and Ensemble inference, tailored specifically for Multimodal Knowledge Graph Completion (MKGC). During training, the focus was on embedding modal split relations for each individual modality. These embeddings were subsequently employed in the inference phase, where modality-split predictions were generated. Different ensemble methods were used to obtain prediction results with varying weights, facilitating dynamic simulation of modalities [14]. The loss function for MoSE is defined as a multi-class cross-entropy (CE) loss. Specifically, for each mode 'm', the CE loss can be calculated as:

$$L_m = -\sum_{t \in |E|} \log\left(p_m\left(t \mid (h,r)\right)\right) = CE\left(p_m\left(t \mid (h,r)\right)\right)$$

However, it's worth noting that while MoSE has made advancements in processing different modal information, it has certain limitations, particularly in cases where information about other related entities is scarce, and it heavily depends on entity relationships.

Xiang Chen et al. introduced a hybrid transformer with multi-level fusion. Specifically, they adopted a hybrid transformer that incorporates multi-level fusion, integrating visual and text representations through a coarse-grained prefix-guided interaction process. They also employed fine-grained correlation-aware fusion modules for further integration [15]. Their fusion strategy combines visual and text features, encoding them into the same embedded space, allowing for modeling multimodal representations of descriptive text and images.

Another approach involves using the architecture of graph neural networks to transform the original knowledge graph into a super-node graph network.

Shuang Liang et al. proposed a Hyper-node Relational Graph Attention (HRGAT) network capable of processing diverse modal information and integrating it with graph structural information. HRGAT leverages low-rank multimodal fusion to transform traditional knowledge graphs and associated multimodal information into hyper-node graphs. Subsequently, using the Relational Graph Attention

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(RGAT) network, it achieves multimodal knowledge graph embedding by capturing graph structural information [16].

Multimodal KGC also proven effective in completing knowledge graphs with limited samples. Traditional knowledge graph completion with few samples relies heavily on limited training data from entity neighbors. However, the strategic use of multimodal context can extract more valuable information for knowledge graph completion.

Xuan Zhang et al. introduced a multi-modal few-shot relation learning framework capable of connecting a few instances to a knowledge graph using the multimodal context of entities. Their encoding encompasses entity images, text descriptions, and neighborhood information. Based on a matching metric learned within their framework, they match query triples with a few reference examples [17].

Additionally, an effective negative sampling strategy can alleviate the vanishing gradient problem in Knowledge Graph Completion (KGC). However, the typical negative sampling approach of uniform sampling is not suitable for multimodal knowledge graphs. Completing a multimodal knowledge graph requires considering both traditional structural knowledge negative sampling and the exploitation of complementary semantics between multiple patterns as additional context.

Derong Xu et al. proposed a Multimodal Relationship Enhanced Negative Sampling (MMRNS) framework. They designed a cross-modal attention (KCA) mechanism providing bidirectional attention for visual and textual features. Their contrasting semantic sampler is better suited for learning representations between positive and negative samples simultaneously [18].

Furthermore, Yichi Zhang et al. introduced a VisualBERT-enhanced Knowledge Graph Completion model called VisualBERT for Knowledge Graph Completion (VBKGC). It aims to deeply fuse multimodal information about entities and incorporate it into the KGC model. They also presented a new negative sampling strategy suitable for multimodal scenarios, known as Twin Negative Sampling, which aligns different embeddings of each entity, improving efficiency [19].

The loss function for VBKGC is defined as:

$$L = \sum_{(h,r,t)\epsilon T} \max(\gamma - \mathrm{F(h,r,t)} + \frac{1}{k} \sum_{(h_i,r_i',t_i')\in T} F(h_i, r_i', t_i'), 0)$$

4. Open Environment Knowledge Graph Embedding (KGE)

Under the prevailing closed-world hypothesis, most knowledge graph completion models predominantly employ embedding methods. Based on whether the content of the knowledge graph changes over time, this can be broadly categorized into dynamic knowledge graph completion and static knowledge graph completion.

While most research on knowledge graph completion is grounded in the closed-world hypothesis, knowledge graph completion technology under the open-world hypothesis is anticipated to offer more extensive functionality, better suited for practical knowledge graphs.

In the open-world knowledge graph completion approach, there is no fixed knowledge graph content, allowing for the addition of new entities and relationships. Given the rapid growth of existing large-scale knowledge graphs, this approach is instrumental for their ongoing enhancement. Moreover, in an open environment, completing the knowledge graph can leverage external data sources, resulting in richer information and improved accuracy. This open-world knowledge graph is rich with unknown information.

Graph neural networks (GNNs) are considered a crucial method for knowledge graph completion due to their capacity to handle inherent graph structures and effectively embed entities and relationships. GNNs are adept at utilizing multi-relationship information through intricate aggregation strategies on neighboring nodes, updating node features via information aggregation on the graph, and collecting and transforming features from their neighbors. GNNs also exhibit inductive abilities, adapting to unknown yet similar nodes and edges by learning from their neighbors' patterns [20].

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Moreover, Shuwen Liu et al. have introduced an innovative approach that directly encodes knowledge graphs into Graph Neural Networks (GNNs). Notably, this method can read predicted triples directly from the final layer of the GNN without requiring additional components or scoring functions. This transparent encoding approach maximizes the utilization of GNN capabilities and eliminates the need for heuristic or specially designed scoring functions. This approach has outperformed state-of-the-art methods in inductive knowledge graph completion benchmarks, highlighting its powerful performance and potential [21].

However, GNNs tend to overlook the inequality of neighboring nodes when gathering information from domain nodes. Therefore, some researchers have combined GNNs with attention mechanisms.

Additionally, researchers like Xiaojiun Chen et al. have integrated attention mechanisms with graph neural networks, proposing an attention-based aggregator designed for real-world scenarios. The effectiveness of this approach has been successfully demonstrated [22].

Jingchao Wang et al. have introduced an innovative model called Structural Attention Graph Neural Network (SAGNN), capable of discovering new relationships outside the knowledge graph without relying on extensive external resources. This model leverages structural information to extract potential related features. Furthermore, it combines attention with graph neural networks, assigning varying weights to different nodes in the neighborhood to obtain embeddings with advanced semantic features, even in the absence of embedding representation [23].

In open-world knowledge graph completion, inferring unknown entities often requires additional information beyond triples. While some methods solely employ entity description information to represent invisible entities, they may neglect the rich hierarchical type information contained within entities.

Xiaojun Chen et al. have introduced a new model specifically for open-world Knowledge Graph Representation (KGR) tasks. This model can produce a more robust knowledge graph by integrating information such as entity structure, entity descriptions, and hierarchical type information within a unified framework. For entity descriptions, they use a continuous word bag and a convolutional neural network model to encode the semantics of entity representation. They construct layered projection matrices using recursive layered encoders and weighted layered encoders for layered processing [24].

The loss function for this model is defined as:

$$L = \sum_{(h,r,t)\in S} \sum_{(h',r,t')\in S'} \max\left(\gamma + E_{SDT}(h,r,t) - E_{SDT}(h',r,t'),0\right)$$

Certain researchers have developed a logical framework encompassing a wide array of functions. Dyuman Aditya et al. have proposed PyReason, a software framework based on generalized annotation logic. PyReason can handle logical problems, support time and open-world reasoning, and provides transparent reasoning traces. It also includes practical functions such as type checking and efficient memory implementation [25].

Additionally, some researchers have introduced a case-based reasoning approach. Case-based Reasoning (CBR) systems solve new problems by retrieving "cases" similar to a given problem. This approach is often simpler and more extensible compared to other methods.

R. Das et al. have proposed a new reasoning knowledge base (KBs) that utilizes a probability model to predict entity attributes. It does so by collecting reasoning paths of similar entities from the knowledge base and evaluating the effectiveness of these paths in answering queries for given entities. The parameters of this model can be efficiently calculated using simple path statistics without iterative optimization. This model is nonparametric and can dynamically grow with the addition of new entities and relationships. It combines the probability model with information from the knowledge base to predict entity attributes and can adapt to new entities and relationships dynamically [26].

In open-world knowledge graph completion, some methods obtain the representation of the target entity through the text description of the target entity and derive text-based embeddings.

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J. Villmow et al. have proposed a simple yet effective method for completing open-world knowledge graphs. Their model learns a transformation function that can convert the text-based embedded space into the graph-based embedded space, directly linking it to the prediction model in the closed world. Furthermore, this model not only accounts for open-world entities but also considers the relationships of target triples, learning specific graph embeddings for different relationships [27].

Y. Wang et al. have introduced a knowledge graph representation learning model called Caps-OWKG, which leverages capsule networks to obtain triples with or without knowledge graphs. This model combines descriptive text with knowledge graphs to simultaneously learn descriptive and structural embeddings, enabling the learning of potential features [28].

Completing knowledge graphs in an open environment often necessitates the use of entities and associated text descriptions from various knowledge graphs. Thus, entity alignment becomes a critical task. The objective of entity alignment is to identify entities across different knowledge graphs that describe the same real-world objects. These knowledge graphs may use different languages and data sources, but they might contain overlapping and complementary knowledge.

To address entity alignment challenges, a joint learning approach called FOlK (Open-World KG embedding Framework) has been proposed. It generates embeddings based on entity descriptions and the knowledge graph structure of open-world knowledge graphs, enhancing knowledge graph completion in open environments [29].

Furthermore, when dealing with multi-source information, multi-source noise data with varying quality may impact the accuracy of knowledge graph completion.

Jiacheng Huang et al. have introduced a new method for processing multi-source noise data and making the most of facts within the knowledge graph. Their approach comprises four main components: a graph neural network to evaluate the credibility of facts, a value alignment network to handle heterogeneity between values, a truth reasoning model to incorporate the quality of data sources into fact scoring, and a semi-supervised learning method to infer truth from heterogeneous values. These methods together form a comprehensive framework that allows for more accurate processing and utilization of information within the knowledge graph [30].

5. Future Challenges and Directions

As knowledge graphs continue to evolve, it is clear that traditional knowledge graph completion techniques are no longer sufficient to meet the growing demands. Therefore, the future development trend in knowledge graph completion is likely to revolve around Open-World, multimodal, and temporal knowledge.

Multi-modal knowledge graph completion technology has the capacity to integrate information from various modes. This means that, in addition to entities, different types of information associated with entities can be fully harnessed to enhance the prediction of missing tuples. Temporal knowledge graphs introduce a temporal dimension, allowing for the representation of different relationships and attributes of entities at different points in time. This better reflects the dynamic nature of real-world relationships. Open-environment knowledge graph completion techniques can systematically analyze and mine unknown entities and relationships. Moreover, by incorporating a broader range of data sources, they can significantly enhance accuracy through the utilization of external information.

6. Outlook and Conclusion

Knowledge graphing serves as an effective means to represent real-world concepts and relationships, and it stands as a crucial branch of artificial intelligence. Consequently, completing incomplete knowledge graphs is of paramount importance. However, traditional knowledge graph completion methods are no longer adequate to meet the demands of contemporary knowledge graphs. Therefore, this paper has provided a summary of recent advancements in knowledge graph completion, focusing on Open-World, multimodal, and temporal knowledge.

While some challenges persist, such as addressing the differing emphases within different multimodal knowledge graphs and managing noise or redundant information originating from

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unstructured texts in open-environment knowledge graph completion, researchers are actively addressing these issues and proposing solutions. It is anticipated that in the future, methods for Open-World, multimodal, and temporal knowledge graph completion will emerge as a new developmental trend, further enhancing the field.

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