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DIMENSIONS OF KNOWLEDGE GRAPH REASONING

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Abstract

Knowledge Graph Reasoning (KGR) is a rapidly expanding field of study that aims to infer new facts from preexisting facts using the mining logic rules that underlie knowledge graphs (KGs). The use of KGs in numerous AI applications, including question-answering and recommendation systems, has been shown to greatly benefit from it. The present KGR models can be broadly classified into three categories based on the graph types: temporal models, multi-modal models, and static models. The majority of early research in this field concentrated on static KGR, while more recent studies have attempted to use temporal and multi-modal information, which is more useful and applicable to real-world scenarios. Nevertheless, there aren't any survey articles or open-source resources that provide a thorough summary and discussion of models in this crucial area. We initially do a survey for knowledge graph reasoning tracing from static to temporal and finally to multi-modal KGs in order to close the gap. In specifics, bi-level taxonomy—that is, top-level (graph kinds) and base-level (techniques and scenarios)—is used to evaluate the models. Additionally, a summary and presentation of the datasets and performances are provided.

INTRODUCTION

Humans acquire skills mostly from two sources: specialized literature and real-world work experiences. For instance, a competent physician must have education from academic institutions and practical experience in hospitals.

A. Knowledge Graph Reasoning (KGR)

Knowledge graph reasoning (KGR) has gained more attention in recent years as a potential solution to the issue. It seeks to deduce missing information from known information in KGs. KGR models are supposed to extract the logic rules (A, father of, B) ∧ (A, husband of, C) → (C, mother of, B) using Figure 1 as the target KG. They should then extrapolate the missing fact (Savannah, mother of, Bronny).

B. Limitations of Current AI Models

Unfortunately, most of the artificial intelligence (AI) models now in use simply mimic the process of learning from experiences; they ignore the prior [1]–[4], which makes them less interpretable and performs poorly.

C. Knowledge Graphs (KGs) as a Solution

Knowledge graphs (KGs) [5] are understandable graphs used to contain human knowledge facts. These days, knowledge graphs (KGs) [5], which store human knowledge facts in logical graph structures [6], are considered as viable remedies.

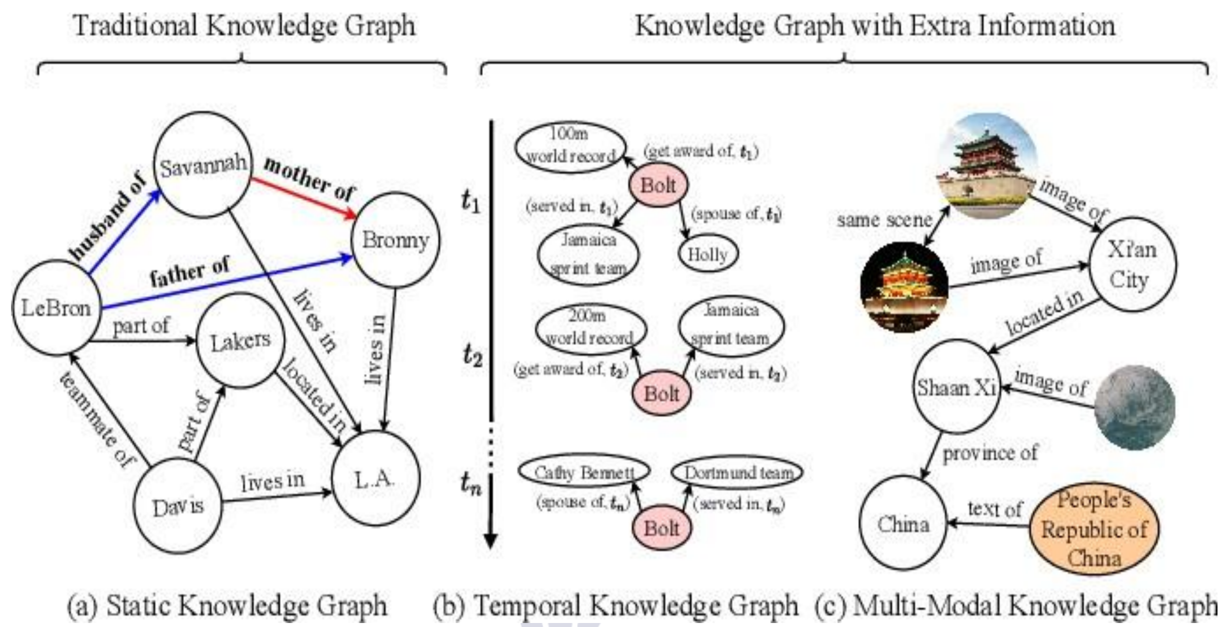

Fig. 1. Shows examples of knowledge graphs in three different categories: multi-modal, temporal, and static.

Since the process of creating KGs is dynamic and ongoing, most KGs have unfinished problems, which reduces their usefulness in KG-assisted applications like recommendation systems [8], question answering [7], and so on.

D. Contributions

This survey:

- Traces the development of KGR models from static to temporal and multi-modal KGs.
- Proposes a bi-level taxonomy of KGR models based on graph types and reasoning techniques.
- Summarizes key datasets and evaluates the performance of KGR models.
- Thorough Examination: Based on a bi-level taxonomy, that is, top-level (graph kinds) and base-level (tech- niques, scenarios), we thoroughly examine common KGR models. Systematic reviews for KGR are provided by the inclusion of fourteen methodologies, four reasoning scenarios, and three graph kinds (static, temporal, and multi-modal KGs).
- Perceptive Evaluation: We evaluate the benefits and drawbacks of the current KGR models as well as their appropriate scope, giving readers helpful direction for choosing the baselines for their own research.
- A possible opening: We provide readers with an overview of the difficulties in knowledge graph reasoning as well as some possible solutions.

I. Related Work

Several previous surveys on KGR focus primarily on static KGs, often categorizing KGR models into statistical reasoning and symbolic reasoning models. For example, [9] divides KGR tasks into statistical and symbolic reasoning categories, while [10] provides a further classification into symbolic, neural, and hybrid models. Temporal and multi-modal KGR models have been less covered in such surveys. In contrast, our survey spans all types of KGR models, including static, temporal, and multimodal.

A. Classification of Knowledge Graphs

As illustrated in Figure 1, modern KGs can be broadly classified into three categories based on the information kinds in KGs: temporal KGs, multi-modal KGs, and static KGs. The development of generic basic KGR models can be accom- plished with ease by using traditional KGs, which only include static uni-modal facts. They are still unable to adequately capture real-world situations, though, since they incorporate data from multiple sources.

B. Advancements in KGs

As a result, more realistic and useful recent KGs (i.e., tem- poral KGs and multi-modal KGs) are created by incorporating additional temporal and multi-modal data based on static KGs. Nonetheless, the incomplete problem persists regardless of the kind of KGs. In order to improve reasoning performance, numerous sophisticated KGR models have been regularly developed and researched throughout the years. Naturally, it is important to remember that the fundamental problems with KGR models vary depending on the type of KG.

C. Focus of Static vs. Temporal and Multi-modal KGR Models

Static KGR models specifically concentrate on the ability to learn representations. However, the secret to the temporal and multi-modal KGR models is in effectively fusing addi- tional data. Additionally, within each graph type, two sub-taxonomies—reasoning strategies and reasoning scenarios— are further examined for a more thorough and systematic review.

II. OVERVIEW OF EARLY DATA

In this part, we first provide formal definitions for static, temporal, and multi-modal knowledge graphs. Subsequently, the reasoning problems pertaining to various KG types and circumstances are developed. Finally, we present the KGR models' taxonomy criterion.

A. Definitions

Knowledge graphs (KGs) are essentially graphical knowl- edge bases that inherit many of the features of classic knowl- edge bases [11], including indexing, storing, and other fea- tures, but in a more user-friendly way. Three categories can be used to loosely categorize existing KGs: temporal, multimodal, and static KGs. In accordance with earlier research, Table II summarizes the notations, and their definitions are stated below.

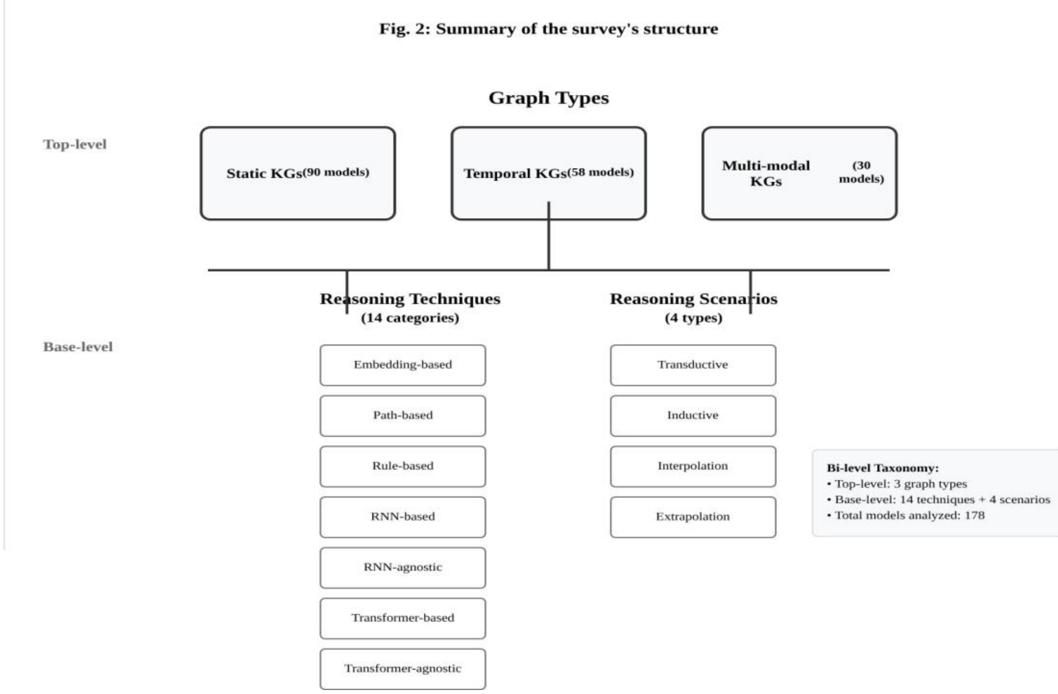

Fig. 2. Summary of the survey's structure.

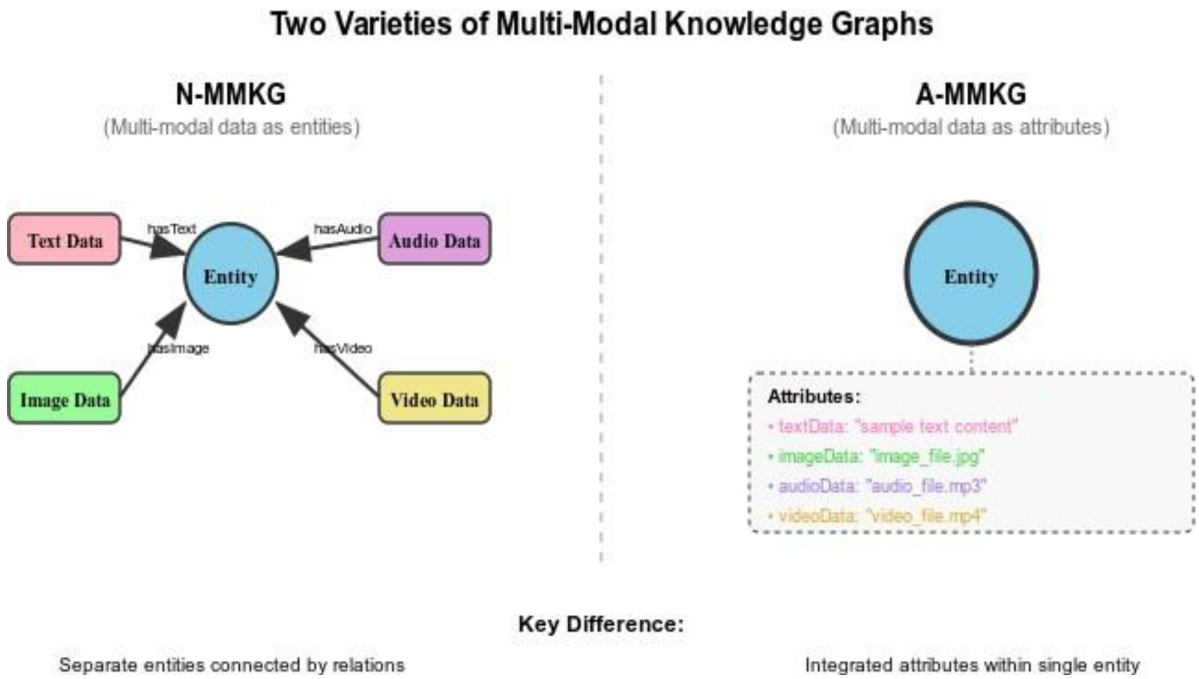

Fig. 3. Two varieties of multi-modal knowledge graphs are compared. The multi-modal data is represented as entities by N-MMKG and as new attributes by A-MMKG.

1) **Static Knowledge Graph:**

Definition 1. The definition of a static knowledge graph (KG) is SKG = {E, R, F}, where E, R, and F stand for the sets of facts, relations, and entities, respectively. The fact is presented in a triplet pattern (e_h, r, e_t) $\in F$, with $r \in R$ and e_h, $e_t \in E$ in between. Take note that in [9], static KGs are referred to as classical KGs. The term" static" is used to set it apart from other KG types.

2) **Temporal Knowledge Graph:**

Definition 2. A se- ries of static knowledge graphs at various timestamps is known as a temporal knowledge graph (KG). TKG = {SKG_1, SKG_2, SKG_3, . . . , SKG_t}. SKG_t = {E, R, F_t} defines the KG snapshot at timestamp t, where E and R are the sets of entities and relations, and F_t is the collection of facts at timestamp $t \in T$. The relation r between head e_h and tail e_t at timestamp t is represented by the quadruple fact (e_h, r, e_t, t).

3) **Multi-Modal Knowledge Graph:**

Definition 3. A multi- modal knowledge graph, or MKG, is made up of knowledge facts that have many modalities. N-MMKG and A-MMKG are the two multi-modal KGs [12] that are represented by the other modal data (See Figure 3).

TABLE I. EVALUATION OF SEVERAL KGR SURVEYS IN COMPARISON

Study Type	[9]	[10]	[11]	[12]	[13]	[14]	[15]	Our Study
Static KG	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Embedding-Based Model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Path-Based Model	Yes	Yes	Yes	Yes	Yes	-	-	Yes
Rule-Based Model	Yes	Yes	Yes	Yes	-	-	-	Yes
Temporal KG	-	-	Yes	Yes	Yes	Yes	Yes	Yes

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Interpolation Scenario	-	-	-	-	-	Yes	-	Yes
Extrapolation Scenario	-	-	-	-	-	Yes	-	Yes
Multi-Modal KGR	-	-	-	-	-	-	Yes	Yes
Non-Transformer Model	-	-	-	-	-	-	Yes	Yes
Transformer Model	-	-	-	-	-	-	-	Yes

TABLE II, KEY NOTATIONS AND MODEL SCENARIOS

Notation	Explanation
SKG TKG	Static knowledge graph Temporal knowledge graph
MKG	Multi-modal knowledge graph Entity set
E	Relation set
R	The set of facts i.e., edges The set of time stamps
F	The set of facts at time *t*
T	
F_t	
Model Scenarios	
Interpolation Scenario	Yes
Extrapolation Scenario	Yes
Multi-Modal KGR	Yes
Non-Transformer Model	Yes
Transformer Model	Yes

B. Formulation of the Task

Knowledge graph reasoning (KGR) uses the generated underlying logic rules to infer new facts from preexisting facts. Based on the types of graphs, KGR may be divided into three tasks: KGR that is multimodal, temporal, and static. Among them, given that more temporal and multimodal KGs incorporate both time and visual information, there are minor task-specific variations.

1) **Static Knowledge Graph:** The process of deriving con- clusions and gleaning insights from a static collection of entities and relationships in a knowledge graph is referred to as reasoning. Static knowledge graphs show a consistent snapshot of the data, in contrast to dynamic knowledge graphs, which may include real-time updates or changing data.

Important Elements include:

- **Relationships and Entities**: The nodes (entities) and edges (relationships) that indicate the connections be- tween the entities make up static knowledge graphs.
- **Inference Techniques**: To infer new information or ver- ify connections that already exist, a variety of reasoning techniques are applied, including logical inference, rule- based reasoning, and graph traversal algorithms.
- **Applications**: Where a clear structure enables effective query processing, such as semantic search, data integra- tion, and question answering, this kind of reasoning is frequently used.

2) **Temporal Knowledge Graph:** The process of deducing and examining connections and occurrences in knowledge networks with a temporal component is known as reasoning. Temporal knowledge graphs show how entities and their interactions change over time, in contrast to static knowledge graphs, which depict information at a particular point in time.

Important Elements include:

- **Temporal Dimension**: Temporal knowledge graphs are characterized by the inclusion of timestamps or intervals that serve as indicators of the timing of events or the holding of particular relationships. This makes it possible to represent knowledge dynamically.
- **Dynamic Relationships**: Understanding how relation- ships between entities change over time is a necessary part of thinking. For instance, an individual might work multiple jobs at various

points in time.

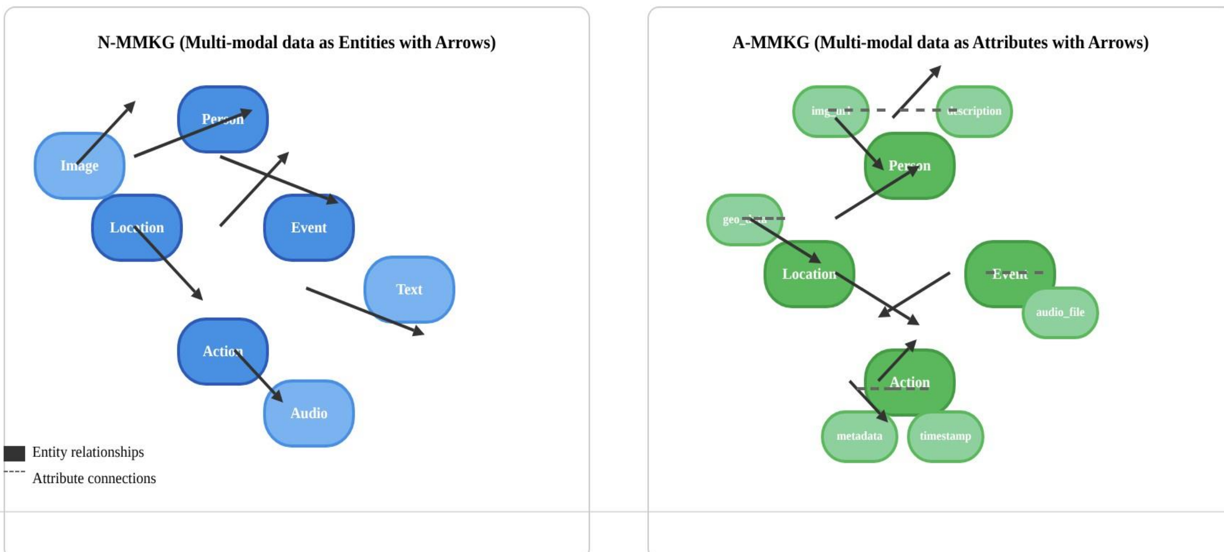
- **Inference Techniques**: To draw new conclusions or patterns based on historical data, temporal reasoning may employ techniques like temporal logic, sequence analysis, and event prediction.

3) **Multimodal Information Graph:** The process of drawing conclusions and drawing inferences from knowledge graphs that include several kinds of data modalities, including text, graphics, audio, and structured data, is known as reasoning. Multi-modal knowledge graphs, which integrate these various data kinds, produce a cohesive representation that improves comprehension depth and context.

C. Example of Transductive Reasoning

Transductive thinking is drawing conclusions from particu- lar cases or occurrences without extrapolating to larger sets of data. Take a social network scenario, for example, where we know that users A and B are buddies. Transductive reasoning

Fig. 3: Two varieties of multi-modal knowledge graphs are compared. The multi-modal data is represented as entities by N-MMKG and as new attributes by A-MMKG.



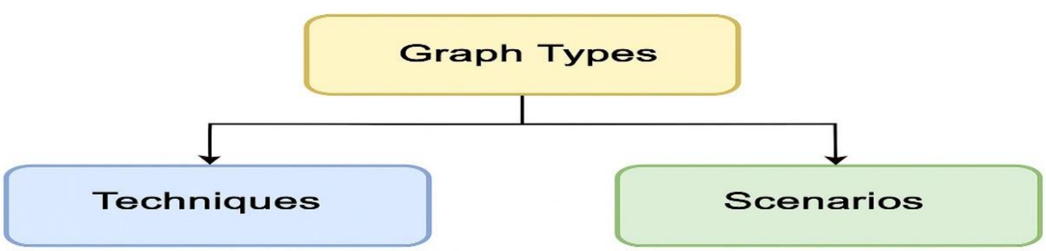


Fig. 4. Example of both inductive and transductive thinking. Entities in test graphs are all visible during the training process in the transductive scenario. Regarding the inductive case, test graphs may contain unobserved entities.

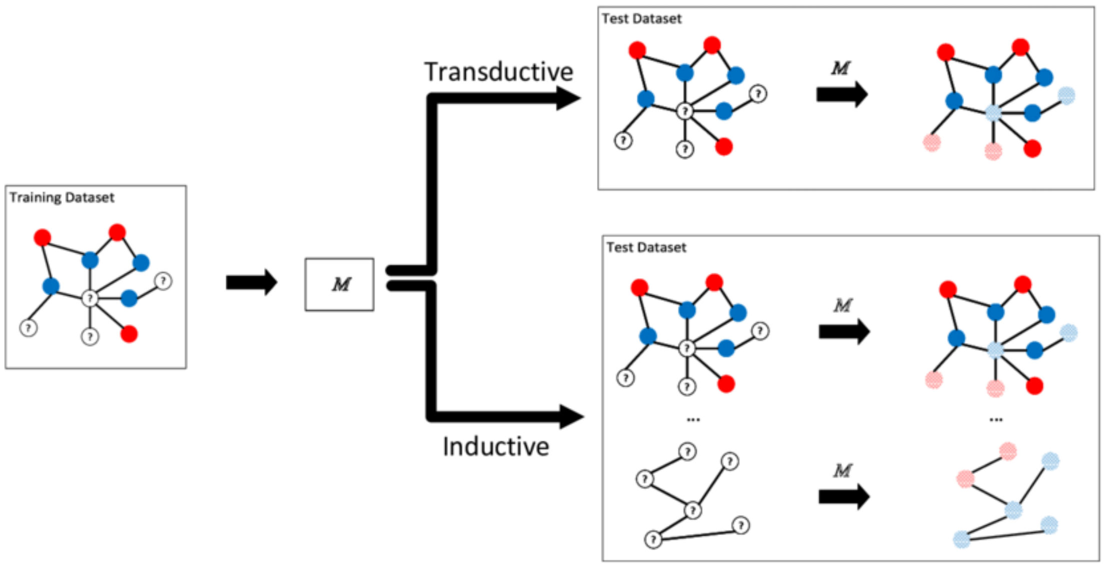


Fig. 7. An example of extrapolation and interpolation reasoning is shown. In the interpolation case, the timestamp t for knowledge graph reasoning is seen in the past ($0 < t < T$). During the extrapolation scenario, the questionedfacts are in the future ($t >= T$).

would only consider the current relationships and traits of users A and B in order to forecast whether or not user A will be friends with user C. In order to reach conclusions that are unique to the available material and do not go beyond it, the reasoning process concentrates on the immediate relationships and context.

D. Inductive Reasoning Scenario

On the other hand, inductive reasoning involves making generalizations based on patterns or trends that have been noticed within a broader set of facts. For example, if we see that every swan we have seen so far is white, we can conclude that all swans are white in an animal collection situation. With this reasoning, we can predict events that haven't happened yet by using the patterns we've seen. In machine learning, inductive reasoning is often applied to train models on a dataset and then utilize the patterns found to classify newly discovered data.

E. Example of Interpolation Reasoning

Estimating unknown values within the range of known data points is the process of interpolation. Take a look at a temperature dataset that was gathered every hour of the day, for instance. The temperature at 11 AM can be estimated with the aid of interpolation if the observed values at 10 AM and 12 PM are 20°C and 25°C, respectively. We may determine that the temperature at 11 AM is probably about 22.5°C by examining the trend between the two known points. Interpolation assumes that the values between known points follow a similar pattern and is useful for filling in gaps in data.

F. Example of Extrapolation Reasoning

In contrast, extrapolation entails guessing values outside of the known data point range. For example, even though the revenue for the upcoming year hasn't been recorded, we may use extrapolation to estimate it if we have a dataset displaying a company's revenue growth over the prior five years and see a constant annual increase. If the revenue has been rising by 10 percent annually on average, we may forecast further increase using this trend. Extrapolation, on the other hand, is riskier since it makes the assumption that current trends will continue, which isn't necessarily the case.

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G. Taxonomy

To systematically review the KGR models that are currently in use for various KGs, we create a bi-level taxonomy. To be more precise, three taxonomy criteria are used to group the examined KGR models: graph kinds, methods, and situations. According to Figure 1, the top-level taxonomy, known as graph types, has three KG types, including as multi-modal, temporal, and static KGs. Furthermore, there are fourteen different categories of approaches in the base-level taxonomy as well as scenarios (four kinds).

III. Knowledge Graph Reasoning (KGR) Model in Static Form

A Static Knowledge Graph Reasoning (KGR) Model is a framework that uses a fixed set of items and relationships represented in a knowledge graph to execute reasoning tasks and extract insights. This model allows for the efficient appli- cation of a variety of reasoning approaches since it functions under the assumption that the underlying network structure stays intact.

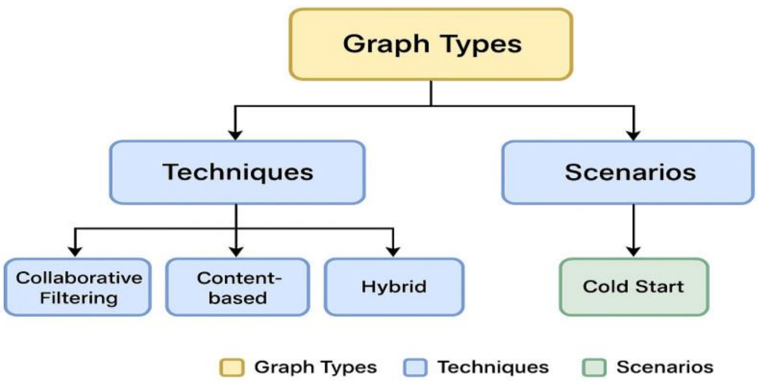

Fig. 9. The timeline of the static KGR embedding-based models.

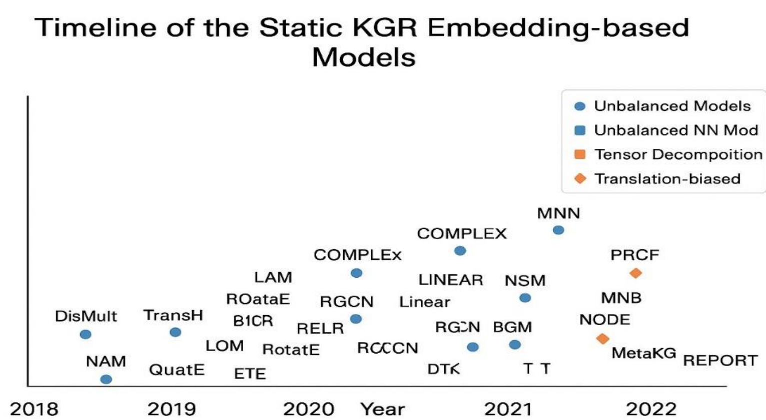

Fig. 10. Chronological distribution of static KGR embedding-based models, highlighting the emergence of different methodological categories between 2018 and 2022

Based on methods and situations, we methodically present 90 static KGR models (See Table III).

A. Review of Techniques for Reasoning

Three types of static KGR models exist: rule-based, path- based, and embedding-based models. The following provides more information.

1) **Embedding-based Model:** Embedding-based models se- lect the top k candidate facts based on the likelihood ascer- tained by scoring functions after learning embedding vectors from existing fact triplets. The three broad categories are neu- ral network, tensor decompositional, and translational models. Due to the overwhelming volume, the timeline of embedding- based models is clearly displayed in Figure 9.

According to translational models, the relation r projects an entity e into a latent space. TransE [13], the first of these models, views relations as basic translation processes, which are expressed by the expressions $\mathbf{e}_h + \mathbf{r} \approx \mathbf{e}_t$.

TransE is efficient, but it has trouble with several relation

types, such as transitive, symmetric, one-to-many, and many- to-one. Numerous sophisticated translational models have been created in order to address these issues.

TransH [14] enhances reasoning for many-to-one and one- to-many relationships by encoding items inside relation- specific hyperplanes. TransR [15] improves expressiveness for transitive relation reasoning by using distinct latent spaces for entities and relations. TransD [16] is appropriate for

larger knowledge graphs since it handles scalability by using independent projection vectors for entities and relations.

Later models use probabilistic techniques to handle ambigu- ity in knowledge graph reasoning. For example, TransG [18] handles one-to-many relations using Bayesian approaches, while KG2E [17] implements Gaussian distribution covari- ance. Adaptive transfer sparser matrices are introduced by TranSparse [19] to address heterogeneity and imbalance con- cerns for enhanced expressiveness.

Other advances are MuRP [20], which uses Mobius matrix- vector addition and multiplication for entity projection, im- proving accuracy and scalability, and TorusE [21], which projects embeddings into a compact Lie group torus. Further- more, TransW [22] improves performance in deducing facts involving unseen entities or relations by enriching entity and relation embeddings with word embeddings.

A rotation-based technique with complex-valued embed- dings is presented by RotatE [23], which successfully infers composition, symmetry, anti-symmetry, and inversion facts.

2) **Overview of the Tensor Decompositional Model:** Knowl- edge graphs (KGs) are represented by tensor decompositional models as three-way tensors, which are further broken down into low-dimensional vectors for entities and relations. The category's first model, RESCAL [24], uses vectors to repre- sent each entity's latent semantics and a matrix to represent pairwise interactions between these latent variables. But this model is complicated, needing $O(d^2)$ parameters in addition to $O(d^2)$.

Bilinear diagonal matrices are used by DistMult [25] to streamline the process and lower the parameter count to $O(d)$ per relation. After then, ComplEx [26] improves the modeling of asymmetric relations by extending DistMult with complex- valued embeddings.

In the meantime, to capture rich relationships between entities, HolE [27] uses circular correlation and holographic reduced representations, while Analogy [28] presents a bilinear scoring function with analogical structural constraints.

The emphasis of later models has moved away from con- ventional decompositional techniques. Two separate entity embeddings are used by SimplE [29] to improve the Canonical Polyadic (CP) decomposition, and Tucker [30] is the first to use Tucker decomposition in this context.

CrossE [31] uses a relation-specific interaction matrix to integrate crossover interactions across entities. By using re- lational rotation quaternion representations, QuatE [32] en- hances semantic matching between head and tail items. Draw- ing inspiration from this, DualE [33] projects embeddings into dual quaternion space, establishing a common structure for rotation and translation functions.

Furthermore, HopfE [34] preserves interpretability by uti- lizing structural and semantic properties in a 4D hyper- sphere space. The emphasis on efficiency has increased in recent years. Based on Tucker decomposition, the LowFER model [35] presents a factorized bilinear pooling technique that is lightweight and efficient.
Additionally, QuatRE [36] uses two innovative processes to learn quaternion embeddings: improving correlations between entities by employing the Hamilton product, and reducing computing load by simplifying translation matrices.

3) **Overview of Neural Network Models:** In knowledge graph (KG) reasoning, neural network (NN) models have demonstrated remarkable progress in recent times. Based on NN approaches, three subtypes—traditional neural networks (NN), convolutional neural networks (CNN), and graph neural networks—are distinguished.

a) **Conventional NN Model:** The SME model [37] was the first to use neural networks to encode things and relations into latent space. After that, neural tensor networks were used by NTN [38] for relation reasoning in KGs. A relational-modulated neural network (RMNN) was presented by the NAM model [39], and ProjE [40] used shared variables to jointly train entity and relation embeddings using a conven- tional loss function.
Even though these conventional NN models show great promise for static KG reasoning, they frequently pick up on richer and more expressive features.

b) **Overview of the CNN Model:** Convolutional neural networks (CNNs) have been used into knowledge graph rea- soning (KGR) models in order to capture deeper features. The first model to use 2D convolutional layers for this purpose was the ConvE model [41].
ConvKB [42] is an improvement over ConvE that may capture global and transitional properties within facts for more informative representations because it does away with the reshaping process. After that, HypER [43] improves per- formance by combining relation-specific convolutional filters with fully connected layers.

c) **Overview of the GNN Model:** Increasingly, graph neural networks (GNNs) are being used for knowledge graph (KG) reasoning, capitalizing on their efficacy in many graph- related applications. Using relation-specific transformations, the Relational Graph Convolutional Network (RGCN) [44] encodes each item as a vector and aggregates neighborhood data.
Based on these entity representations, the decoder, also known as the scoring function, then reconstructs the facts. However, the expressive potential of RGCN is limited because it does not take entity variances into consideration. Many models, like M-GNN [45], KBGAT [46], and [47], include attention techniques to overcome this.
Interestingly, attention-based feature embeddings are used by KBGAT [46] to improve reasoning performance. In the meantime, SACN [48] achieves good results by combining a weighted graph convolutional network (WGCN) as the encoder and a convolutional network named Conv-TransE as the decoder.

B. Path-based Model

A path-based model, in which the items being searched are represented as nodes and the connections as edges, provides
a useful framework for examining the connections and rela- tionships within a network and reveals the logical information underlying the paths between the entities. By examining the relationships between a query's head and tail, these models aid in thinking.
For example, a great deal of research has been done on random walk inferences, and techniques such as the Path- Ranking Algorithm (PRA) [49] have been used to derive path-based logic rules under certain limitations. By combining textual content and space similarity criteria, ProPPR [50] improves PRA and solves feature sparsity problems.
Additionally, neural multi-hop path-based models have been created by composing the implications of relational paths for reasoning using methods like RNN-PRA [51], which makes use of the expressive ability of recurrent neural net- works (RNNs). For logical composition across different ele- ments, LogSumExp [52] presents attention techniques, while DIVA [53] provides a unified variational

inference framework that divides multihop reasoning into two discrete steps: path- reasoning and path-finding.

In recent developments, the use of deep reinforcement learning (DRL) approaches, including the Markov decision process (MDP), has reframed path-finding as a sequential decision-making task. As they identify reasoning paths based on entity interactions, DRL-trained agents employ a range of fine-grained approaches to enhance model performance and efficiency.

For example, DeepPath [54] leverages DRL for relational path learning by utilizing incentive structures and creative action spaces. Path discovery is treated as a sequential op- timization problem by MINERVA [55], which ignores target answer entities and maximizes expected rewards in order to improve reasoning skills.

MultiHop [56] offers a soft reward technique to improve path discovery in addition to traditional binary rewards. Addi- tionally, CPL [57] emphasizes collaborative policy learning for path-finding and fact extraction by using relevant text corpora, whereas M-Walk [58] creates routes using Monte Carlo Tree Search (MCTS).

CURL [59] proposes a dual-agent system with a DWARF AGENT at the entity level and a GIANT AGENT at the cluster level to get the best reasoning performance. These advancements show how flexible and effective path-based models are in a variety of reasoning-related applications.

C. Rule-based Model

A rule-based model is a systematic method that is frequently applied in domains such as data mining, expert systems, and artificial intelligence to support decision-making and derive results from a predetermined set of rules. These models use ”if-then” statements, in which the condition is stated in the ”if” section and the subsequent action or result is specified in the ”then” section.

Using the symbolic qualities found in logic rules—which are usually represented in the form $B \rightarrow A$, where A is a fact and B is a collection of facts—is the main objective of rule-based models. Knowledge graphs (KG) can be used to extract logical rules using rule mining tools like AMIE [60] and RuleN [61].

More scalable rule mining methods have been developed recently; one example is RLvLR [62], which uses algorithms for rule finding and pruning. Using joint learning or iterative training techniques, there is also growing interest in embed- ding logical rules to improve reasoning performance.

For example, RUGE [63] uses soft rules for embedding adjustment, while KALE [64] implements a unified joint model that uses t-norm fuzzy logical connectives between compatible facts and rule embeddings. Axiom injection, axiom induction, and embedding learning are three components of the iterative training approach used by the IterE model [65].

Additionally, to address issues with low expressiveness and excessive resource consumption, researchers have incorporated neural network approaches into rule-based models. Using a specially constructed radial kernel, Neural Theorem Provers (NTP) [66] extract logical rules, and NeuralLP [67] optimizes the rule mining process by utilizing attention processes and auxiliary memory.

This is further improved by Neural-Num-LP [68], which combines dynamic programming with NeuralLP for learning numerical rules, and cumulative sum operations. Additionally, pLogicNet [69] creates a probabilistic logic neural network that is excellent at first-order logic mining, while DRUM [70] presents an end-to-end differentiable rule-based model.

These ideas are further upon by ExpressGNN [71], which optimizes graph neural network models for reasoning that is more effective, and GCR [72], which performs well in reasoning and recommendation by analyzing the neighborhood information surrounding facts that are asked.

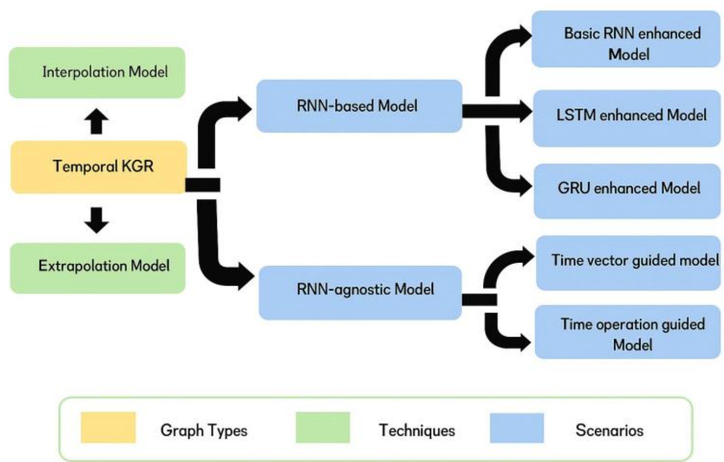

Fig. 11. Taxonomy of the temporal KGR models

IV. TEMPORAL KGR MODEL

We present 58 temporal KGR models in a methodical manner based on their methods, that is, on how they include scenarios and time information (refer to Table 2).

A. Review of Techniques for Reasoning

RNN-based models and RNN-agnostic models are the two primary groups into which temporal knowledge graph reason- ing (KGR) models fall. These categories' specifics are listed below.

1) **Models Based on RNNs**: Recurrent neural networks are used by RNN-based models for temporal knowledge graph reasoning to record changes across time, which makes them ideal for mining temporal data. As such, RNNs are directly used in a large number of temporal KGR models to describe these temporal dynamics.

These models can be divided into three groups depend- ing on distinct RNN variants: basic RNN enhanced models, LSTM-enhanced models, and GRU-enhanced models. RNN- based models make use of these architectures' advantages to manage variable-length sequences and preserve contextual information—both of which are critical for comprehending temporal linkages in knowledge graphs.

a) **Fundamental RNN-Enhanced Models:** The fundamen- tal architectures for temporal knowledge graph reasoning are basic RNN augmented models. These models learn patterns and correlations over time by utilizing the recurrent neural network framework to capture sequential dependencies in the data.

Certain temporal KGR models model temporal information by utilizing simple RNNs in an efficient manner. One classical temporal KGR model that produces non-linear entity embed- dings over time is Know-Evolve [73]. Similarly, to capture the developing dynamics of temporal knowledge graphs in response to queries, RE-NET [74] combines RNNs and graph convolutional networks (GCNs).

In EvoKG [75], neighborhood data is integrated into entity interaction models, and RNNs are used to mine dynamic struc- ture information. Although the vanishing gradient problem limits the temporal information that basic RNN augmented models can gather, it can hinder learning in longer sequences.

b) **LSTM Enhanced Models:** By resolving the short- comings of simple RNNs, LSTM augmented models offer a significant leap in temporal knowledge graph reasoning. Many temporal KGR models employ long short-term memory (LSTM) networks for temporal feature mining.

These networks are very useful for simulating sequences with intricate temporal dynamics because of their ability to capture long-range dependencies and handle the vanishing gradient problem well.

Because LSTMs have memory cells, they can learn complex patterns in temporal data by retaining information over extended periods of time.

To increase performance, a number of temporal KGR mod- els make use of LSTM augmented architectures. For instance, temporal restrictions are added to the TransE model by TTransE [76], which encodes time information as translations with functions akin to relationships. This process shifts the head representation inside the embedded space.

Furthermore, expanded versions of TransE and DistMult that incorporate temporal embeddings are called TA-TransE and TA-DistMult [76]. Moreover, EvolveGCN [77] uses LSTM (or GRU) models to evolve the GCN parameters over time while using graph convolutional networks (GCNs) to describe the graph topology in each static image.

c) **GRU Enhanced Models:** Recent years have seen a notable increase in the adoption of GRU enhanced models due to their superior performance in temporal knowledge graph reasoning. One prominent example is TeMP [78], which learns entity representations at each timestamp by using message- passing graph neural networks (MPNNs) and combines them with an encoder.

By modeling sequences from recent timestamps, RE- GCN [79] creates entity embeddings with an emphasis on the evolution of temporal knowledge graphs. Other models are the HIP network [80], which studies the graph's dynamic evolution and event interactions from several angles, and TPmod [81], which combines attributes of entities and relations while learning dynamic weights for different events.

2) **RNN-agnostic Model:** Traditional static KGR (Knowl- edge Graph Representation) models are extended by RNN- agnostic models, which incorporate temporal information without depending on RNNs. Time-vector guided models and time-operation guided models are the two primary categories into which these models fall.

Additional temporal embeddings (t) are generated by time- vector guided models and fused with fact embeddings. Famous instances are TComplEx and TNTComplEx, which are models of a fourth-order tensor space that take temporal information into account and are derived from ComplEx [82].

When building subgraphs, the xERTE model uses temporal embeddings to compute weighted probabilities [83], whereas T-GAP encodes Temporal KGs' query-specific structural pat- terns to enable path-based reasoning [84].

In order to solve entity prediction tasks, CyGNet generates a time-indexing vector by encoding historical information pertaining to the subject entity [85]. By linking relation and time embeddings to produce an overall rotation embedding for final entity embeddings, ChronoR builds upon RotatE [86].

V. MULTI-MODAL KGR MODELS

Thirty multi-modal KGR models are presented here in a methodical manner, grouped by approach (Figure 12).

A. Review of Reasoning Methodologies

Because fusion modules that may integrate additional mul- timodal data, such text and graphics, are usually missing, applying static KGR models directly to multi-modal settings frequently leads to less-than-optimal performance. To ad- dress this problem, we separate the multi-modal KGR models into two main groups, defined by their fusion approaches: transformer-based models and transformer-agnostic models.

Transformer-Based Models: Transformer-based models are a unified solution for multi-modal problems because of their well-known excellent cross-modal scaling capabilities. ViLBERT [87] and VisualBERT [88] are examples of general multi-modal pretrained transformer models that can be utilized straight to multi-modal knowledge graph reasoning (MKGR), however they may not perform as well.

They can be applied to multi-modal KGR instead. This is primarily due to the differences between multi-modal knowl- edge graphs and other types of multi-modal data. Because of this, researchers have made great strides in developing transformer-

based multimodal KGR models over the past two years.
For example, VBKGC [89] encodes multi-modal features by combining a pretrained transformer with a multi-modal scoring function for optimization. In a similar vein, Knowledge- CLIP [90] enhances the pre-trained model by considering the semantic links between multi-modal concepts using the CLIP model [91].
Furthermore, a model-agnostic reasoning framework that use transformers for analogical reasoning is presented by MarT [92]. A hybrid transformer with multi-level fusion that integrates learning paradigms into a single framework for a range of downstream applications is also provided by MKGformer [93].

1) **Transformer-agnostic Models:** An alternative to multi- modal knowledge graph reasoning is provided by transformer- agnostic models, which emphasize the integration of various data kinds without depending on transformer frameworks. Generally, these models build upon the original unimodal KGR models, like TransE [13], by encoding additional modal information through a variety of techniques.
Consequently, these models are categorized as transformer- agnostic. A noteworthy instance is CKE [94], the first model to concurrently execute collaborative filtering and reasoning. It can produce representations and capture implicit rules in knowledge graphs thanks to this dual methodology.
After that, DKRL [95] uses language neural networks in conjunction with entity descriptions from knowledge graphs to produce more expressive semantics for reasoning tasks. Motivated by this idea, IKRL [96] presents an attention-based neural network, which TransAE [97] also uses, to integrate visual information from entity images.

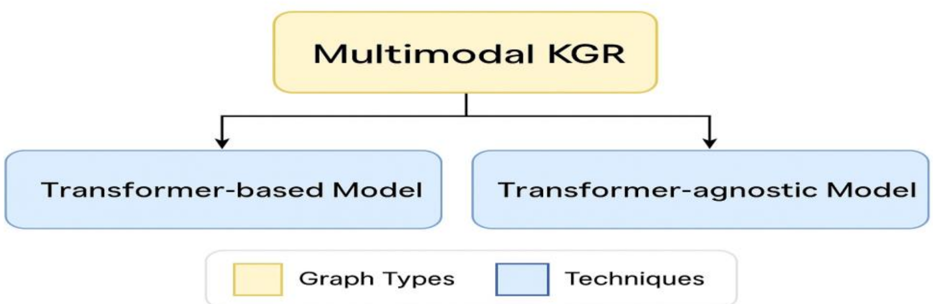

Fig. 12. Taxonomy of the multi-modal KGR models

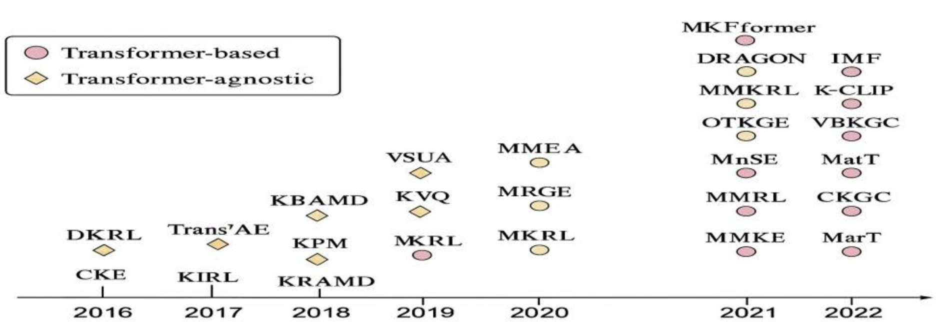

Fig. 13. Fig. 11: Timeline of the multi-modal KGR models

In order to accommodate latent, relational, and numerical information, KBLRN [98] pioneers an end-to-end reasoning framework that combines neural network approaches with expert models. Building on this foundation, textual data is used as auxiliary information by KR-AMD [99] and MKRL [100] to improve reasoning performance.

Furthermore, MTRL [101] proposes a model with three energy functions corresponding to visual, linguistic, and structural information, drawing influence from translation- based static KGR models. Furthermore, relational models are integrated with different neural encoders and decoders by MKBE [102] and MRCGN [103] to effectively embed learning and reasoning across multi-modal data.

VI. DATASETS

With a specific emphasis on temporal and multi-modal knowledge graphs, we present an extensive overview of com- mon knowledge graph reasoning (KGR) datasets. We provide an overview of these datasets and pertinent information below. Furthermore, the datasets have been arranged in our GitHub repository to facilitate community access.

A. Static KGR Datasets

We provide an overview of common static knowledge graph reasoning (KGR) datasets, which consist of 15 inductive and 38 transductive datasets. Tables IV offer the pertinent statistics, and the complete explanations are given below.

Important datasets include:

- **ATOMIC** [104]: This knowledge graph includes descrip- tions of each thing and includes reactions, affects, and intents related to human behaviors. It is intended for use in everyday, commonsense thinking.
- **Countries** [105]: Based on publicly available geographic data, this dataset presents links between various countries.
- **CoDEX** [106]: Three different sub-knowledge graph sizes (CoDEX-S, CoDEX-M, and CoDEX-L) are in- cluded in this collection of completion datasets that were taken from Wikipedia and Wikidata.
- **ConceptNet** [107]: This dataset improves the comprehen- sion of word meanings by connecting words and phrases with tagged edges in AI applications. There are 100,000 training triplets in the subset ConceptNet100K [124].
- **DBpedia** : Sourced from organized material in a number of Wikimedia projects, DBpedia enables the construction of many subsets according to the size of the entity set, such as DBpedia50 [108], DBpedia500 [108], and DB100K [109].
- **FAMILY** [110]: This dataset describes the interactions between members of a family.
- **Freebase**: A sizable information repository assembled from numerous sources, including Wikipedia and differ- ent directories, is Freebase [113]. FB13 [38], FB122 [64], FB15k [13], FB15k-237 [111] are some of the subsets that are based on the size of the entity set.
- **WordNet** [114]: A lexical database called WordNet de- scribes the semantic relationships between words, includ- ing synonyms, hyponyms, and meronyms. WN18 [111] and WN18RR [111] are a few of the subsets.
- **YAGO** [115]: A WordNet-integrated, extendable, and light ontology constructed from Wikidata. The subsets YAGO3-10 [112] are determined by relation sizes.

B. Temporal KGR Datasets

We provide an overview of eighteen noteworthy temporal knowledge graph reasoning (KGR) datasets, which are critical for identifying and deriving conclusions regarding relation- ships that change over time. Table V presents the statistics for these datasets, and the descriptions are further upon below:

Key temporal datasets include:

- **GDELT** : A thorough knowledge graph based on the Global Database of Events, Language, and Tone. GDELT- m10 [121] and GDELT-small [120], which concentrate on particular event datasets, are noteworthy subsets.
- **ICEWS** [116]: A database of political events with pre- cise timestamps is provided by the Integrated Crisis Early Warning System (ICEWS). ICEWS05-15 [76], ICEWS14 [83], and ICEWS18 [83] are some of the important temporal KGs that are obtained from ICEWS.
- **Wikidata** [117]: Compared to the static

version of Wiki- data, this dataset for temporal KGR includes more time- related information. Variants produced during varying time periods include WIKI/Wikidata12k [122] and Wiki-data11k [84].

C. Multi-Modal KGR Datasets

Eleven noteworthy multi-modal knowledge graph reasoning (KGR) datasets are compiled in this section. Table VI displays the statistics, while the following lists the descriptions of each dataset:

Important multi-modal datasets include:

- **FB-IMG-TXT** [101]: This dataset is a subset of the traditional KG dataset FB15k [13], and it includes both textual descriptions and photos. ImageNet [118] is the source of the pictures. On the other hand, the triplet scope is adjusted to FB15k-237 [111] by FB15K-237-IMG [93].
- **MKG** [123]: Web search engine-generated visual enti- ties are found in both of the dataset's subsets, MKG- Wikipedia and MKG-YAGO. The triplet components are taken from YAGO and Wikipedia, in that order.
- **WN9-IMG-TXT** [101]: This dataset, whose triple section is a subset of the traditional KG dataset WN18 [111],

combines textual descriptions with photos. By contrast, WN18-IMG [93] covers the entirety of WN18.

VII. Challenges and Opportunities in Current KGR Models

Based on prior evaluations of the current KGR models, we identify a number of interesting areas for further research. The capacity of a model to draw conclusions or make predictions is essential for advancing the field.

A. Large-scale Reasoning

Knowledge graph representation (KGR) relies on large- scale reasoning to manage large datasets with a large number of entities, relationships, and characteristics. The increasing complexity and scale of knowledge graphs pose difficulties for conventional reasoning models in terms of accuracy and efficiency. Consequently, building models that can efficiently interpret and draw conclusions from large-scale knowledge graphs is crucial.

Optimizing computing resources while maintaining model scalability is one of the primary issues. Scientists are investi- gating a range of methods, including as distributed computing and optimization strategies, to improve the effectiveness of cognitive processes. Using cloud-based systems, for example, enables data to be processed in parallel, greatly cutting down on the amount of time needed for inference jobs.

Another crucial component is incorporating several data sources into a cohesive reasoning framework. To do this, models must be able to reliably and smoothly merge data from different knowledge graphs while maintaining data integrity. With the ability to supply richer information for inference tasks, multi-modal reasoning approaches—which integrate tex- tual, visual, and structured data—are becoming more and more significant.

Due to the large-scale nature of industrial knowledge graphs, more effective KGR models are needed. In order to achieve this, a few current works attempt to gradually optimize the propagation techniques [59]. For example, in GNN-based KGR models, NBF-net incorporates the Bellman- Ford algorithm to replace the original depth-first search (DFS) aggregation process [125].

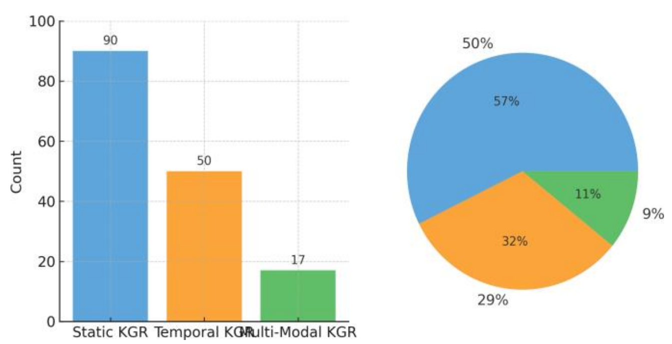

Fig. 14. Models' statistical comparison over different KG kinds.

B. Out-of-Distribution Reasoning

The capacity of a model to draw conclusions or make pre- dictions from data that is different from its training distribution is known as out-of-distribution (OOD) reasoning. Knowledge graphs (KGs) in real-world contexts are dynamic, with new entities and relations appearing on a regular basis. It is difficult to reason about these unexplored components within KGs, which increases the demands on knowledge graph reasoning (KGR) model construction.

The need for reasoning about unseen entities—often re- ferred to as inductive reasoning models—has been effectively addressed by recent techniques. These models show promising results when mining the logical rules underlying network structures without being constrained by the particular mean- ings of entities, as demonstrated by references [126]–[129].

Few-shot KGR models [130]–[132] seek to improve the generalization capacity of KGR systems for unseen relation inference. These models allow the taught system to learn new tasks based on previously learned knowledge, successfully adapting to unforeseen relations with only a small amount of data.

Furthermore, to solve OOD reasoning tasks, models such as BERTRL [133] utilize textual semantics obtained from language models. But when these language models are not sufficiently trained, their performance usually starts to drasti- cally deteriorate.

C. Multi-relational Reasoning

In knowledge graphs (KGs), multi-relational reasoning en- tails determining relationships between things across different kinds of connections. Applications such as natural language processing, recommendation systems, and semantic search depend on this intricacy.

The diversity of relationships in KGs grows with their size, making the application of sophisticated reasoning techniques necessary to extract valuable insights. Multi-relational facts between two entities are frequently encountered in KGs, as Figure 15 illustrates.

As seen in the figure, these multi-relational facts have more structural diversity and semantic complexity than the uni- and bi-relational facts. The majority of KGR models currently in use concentrate mostly on uni- and bi-relational facts, frequently handling multi-relational facts crudely by leaving out specific relationships. This method reduces the expressive capability of the models and hinders their ability to accurately represent real-world circumstances.

Recent developments have demonstrated promise in tackling these issues, especially with regard to graph neural networks (GNNs). GNNs facilitate sophisticated reasoning over multi- relational data by modeling the complex dependencies and relationships found in KGs. Model performance in multi- relational databases is improved by techniques like relation- aware embeddings, which aid in differentiating between rela- tionships.

Multi-relational thinking challenges are increasingly incor- porating attention strategies. By enabling models to concen- trate on the most important links during inference, these strate- gies enhance the interpretability and accuracy of predictions. Overfitting is still a serious problem, though, particularly in relational settings that are complex and have little data.

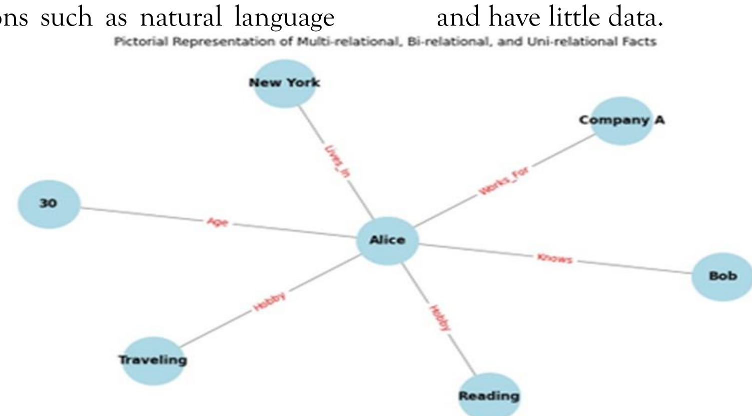

Fig. 15. Comparing multi-, bi-, and uni-relational facts

D. Multi-modal Reasoning

Integrating and evaluating material from several modalities—such as text, graphics, and structured data— within knowledge graphs (KGs) is known as multi-modal reasoning. Making informed decisions requires the capacity to synthesis information from numerous sources, which is becoming more and more important as real-world data gets more diversified.

By fusing verbal descriptions with visual representations, this reasoning technique improves our comprehension of en- tities and their interactions, which results in more precise predictions and insights. However, because of their inherent variations in data structures and representation approaches, merging diverse modalities poses major hurdles.

Recent developments in multimodal KGR models have taken different approaches to overcome these difficulties. Deep learning frameworks, particularly neural networks, are used in many methods to learn joint representations of multi-modal input. Effective alignment of information from several modal- ities has been achieved through the development of techniques such as cross-modal embeddings and attention mechanisms.

To handle multi-modal data, for example, models like VisualBERT [88] and CLIP [91] have made use of pre- trained transformers, yielding state-of-the-art performance on a variety of applications. These models allow for thorough reasoning that takes into account both aspects by recording visual elements in addition to textual information.

Through the incorporation of text corpora or other infor- mation from other modalities, knowledge reasoning that fuses multi-source information can lessen the disconnectedness and sparsity of KGs. The advantages of each modality are en-hanced by this multimodal fusion, which raises reasoning performance as a whole. Nonetheless, there is still much room for research and growth in this field because multi-modal KGR models are still in their infancy.

E. Explainable Reasoning

In many domains, explainability is a crucial problem for deep learning models. Even though KGR models—especially those based on neural networks like GNNs—generally provide greater transparency, additional research is required in this area, especially for embedding-based KGR models [1].

Neural networks are used in many contemporary KGR systems; although expressive, they frequently lack enough explainability. On the other hand, whereas rule-based and path- based KGR models are less expressive and typically need a lot of computing power, they are easier to understand.

Aiming to merge rule-based and path-based frameworks with embedding-based models, some initiatives have attempted to achieve a compromise between explainability and expres- siveness. To improve the interpretability of path-based models, ARGCN [134] for instance, develops a reward function based on embeddings generated by Relational Graph Convolutional Networks (RGCN) [44].

Many of these initiatives are still in the exploratory stage, though. In conclusion, KGR's explainable reasoning is essen- tial to building confidence and comprehension of AI-driven judgments. Future research should focus on creating user- friendly interfaces and efficient explanation strategies while making sure the models offer insightful information about how they reason and strike a suitable balance between expressive- ness and explainability.

F. Knowledge Graph Reasoning Applications

Even with the substantial progress made in Knowledge Graph Reasoning (KGR) techniques, more research is still needed to determine how they may be used in real-world scenarios. Knowledge graphs are becoming more and more popular in a number of fields, such as financial, medical, and plagiarism detection.

KGR models are used in the medical field to help doctors diagnose patients by using electronic medical records. Studies have demonstrated that diagnosing accuracy can be improved by reasoning over knowledge graphs created from electronic medical databases. As an illustration of the possibilities of multimodal KGR techniques, studies [135], [136] use pre- trained language models such as BERT to produce efficient textual embeddings for entities.

KGR is essential to the financial industry's anti-fraud detec- tion process. A noteworthy technique [137] uses case-based reasoning to assist users with information verification and proactive fraud detection. Furthermore, KGR techniques are used in plagiarism detection, where the accuracy of identifying copied text is improved by the use of continuous learning techniques [138].

All things considered, even though KGR approaches have demonstrated a lot of promise in theoretical settings, their real-world applications in a variety of industries are still developing, underscoring the necessity of ongoing study and advancement.

G. Knowledge Graph and Large Language Model

Large Language Models (LLMs) have become increasingly popular because of their remarkable generalizability and rea- soning powers, as demonstrated by ChatGPT and GPT-4 [139]. Nevertheless, they encounter significant obstacles, such as restricted explainability and scalability when handling novel data, which can be resolved by means of efficient integration with Knowledge Graph Reasoning (KGR) models.

For example, QA-GNN uses KGs to guide the reasoning process and LLMs for text preparation [140]. Furthermore, an LLM-guided logical reasoning approach is specifically used by DRAGON for multi-modal KGR [141].

Some researchers suggest that LLMs may develop into a more generalized version of KGs that can do tasks like indexing, reasoning, and storing as the amount of data in- creases. There are a number of hypotheses regarding the relationship between KGs and LLMs, but it's not apparent which framework is more useful.

However, investigating how they interact is set to become a major field of study in the future, emphasizing how crucial it is to use both LLMs and KGs to advance AI capabilities [142].

VIII. CONCLUSION

This survey offers a thorough analysis of current Knowledge Graph Reasoning (KGR) models by classifying them accord- ing to different reasoning scenarios, methodologies, and graph kinds (static, temporal, and multi-modal). We explore fourteen different approaches and four logic cases, providing a well- organized summary of the KGR environment.

In order to assist readers in their investigation of knowledge graph reasoning, we also list the main obstacles that need to be overcome and indicate possible directions for further study. The comprehensive taxonomy we present serves as a foundation for understanding the current state of KGR research and identifying promising areas for future development.

Our analysis reveals several key insights:

- **Static KGR models** have reached considerable maturity, with embedding-based approaches dominating the field, though challenges remain in explainability and large-scale reasoning.
- **Temporal KGR models** represent a growing area of research, with RNN-based and RNN-agnostic ap- proaches showing promise for handling dynamic knowl- edge graphs.
- **Multi-modal KGR models** are still in their infancy but show tremendous potential for real-world applications by incorporating diverse data modalities.
- The field faces significant challenges in **scalability**, **out- of-distribution reasoning**, and **explainability**, requiring continued research efforts.
- Integration with **Large Language Models** presents new opportunities for advancing KGR capabilities and real- world applications.

We hope this comprehensive survey will serve as a valuable resource for researchers and practitioners in the knowledge graph reasoning community, providing both a thorough un- derstanding of current approaches and guidance for future research directions.

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TABLE III
SUMMARY OF MODELS, SCENARIOS, AND TECHNIQUES

Year	Model	Scenario	Technique
2022	LogCo	Inductive	Graph Neural Networks
2022	REPORT	Inductive	Graph Neural Networks
2022	RED-GNN	Inductive	Graph Neural Networks
2022	ConGLR	Inductive	Graph Neural Networks
2022	TripleRE	Transductive	Translational
2022	InterHT	Transductive	Translational
2022	HousE	Transductive	Translational
2022	BERTRL	Inductive	Graph Neural Networks
2022	SNRI	Inductive	Graph Neural Networks
2022	TEMP	Inductive	Graph Neural Networks
2022	RMPI	Inductive	Graph Neural Networks
2022	Meta-iKG	Inductive	Graph Neural Networks
2022	CSR	Inductive	Graph Neural Networks
2022	CURL	Transductive	Relation Path
2022	GCR	Inductive	Logic Rule
2021	PairRE	Transductive	Translational

2021	HopfE	Transductive	Tensor Decompositional
2021	DualE	Transductive	Tensor Decompositional
2021	ConEx	Transductive	Convolutional Neural Networks
2021	KE-GCN	Transductive	Graph Neural Networks
2021	HRFN	Inductive	Graph Neural Networks
2021	GEN	Inductive	Graph Neural Networks
2021	INDIGO	Inductive	Graph Neural Networks
2021	NBF-Net	Inductive	Graph Neural Networks
2021	CoMPILE	Inductive	Graph Neural Networks
2021	TACT	Inductive	Graph Neural Networks
2021	RPC-IR	Inductive	Graph Neural Networks
2020	HAKE	Transductive	Translational
2020	TransRHS	Transductive	Translational
2020	LowFER	Transductive	Tensor Decompositional
2020	InteractE	Transductive	Convolutional Neural Networks
2020	DPMPN	Transductive	Graph Neural Networks
2020	RGHAT	Transductive	Graph Neural Networks
2020	COMPGCN	Transductive	Graph Neural Networks
2020	GraIL	Inductive	Graph Neural Networks
2020	ExpressGNN	Inductive	Logic Rule
2020	pGAT	Inductive	Graph Neural Networks
2019	RotatE	Transductive	Translational
2019	TransW	Inductive	Translational
2019	MuRP	Transductive	Translational
2019	QuatE	Transductive	Tensor Decompositional
2019	TuckER	Transductive	Tensor Decompositional
2019	CrossE	Transductive	Tensor Decompositional
2019	ConvR	Transductive	Convolutional Neural Networks
2019	HypER	Transductive	Convolutional Neural Networks

TABLE IV
STANDARD BENCHMARK DATASETS FOR STATIC TRANSDUCTIVE KNOWLEDGE GRAPH REASONING.

Dataset	# Ent.	# Rel.	# Train Facts	# Val. Facts	# Test Facts
ATOMIC [104]	304,388	9	610,536	87,700	87,701
Countries [105]	271	2	1,110	24	24
CoDEX-S [106]	2,034	42	32,888	3,654	3,656
CoDEX-M [106]	17,050	51	185,584	20,620	20,622
CoDEX-L [106]	77,951	69	551,193	30,622	30,622
ConceptNet [107]	78,334	50	100,000	3,407,492	3,407,492
ConceptNet100K [124]	78,334	34	100,000	1,200	1,200
DBpedia50 [108]	49,900	654	32,388	399	10,969
DBpedia500 [108]	517,475	654	3,102,677	10,000	1,155,937
DB100K [109]	99,604	470	597,482	49,997	50,000
FAMILY [110]	3,007	12	23,483	2,038	2,835
FB13 [38]	75,043	13	316,232	11,816	47,464
FB122 [64]	9,738	122	91,638	9,595	11,243

FB15k [13]	14,951	1,345	483,142	50,000	59,071
FB15k-237 [111]	14,505	237	272,115	17,535	20,466
WN18 [111]	40,943	18	141,442	5,000	5,000
WN18RR [111]	40,559	11	86,835	2,924	2,824
YAGO3-10 [112]	123,143	37	1,079,040	4,978	4,982

TABLE V
TEMPORAL KNOWLEDGE GRAPH REASONING BENCHMARK DATASETS.

Dataset Name	Type	# Entities	# Relations	# Timestamps	# Training	# Validation	# Testing
DBpedia-3SP [119]	Knowledge Graph	66,967	968	3	103,211	3,000	-
GDELT [119]	Temporal Event Dataset	7,691	240	8,925	1,033,270	238,765	305,241
GDELT-small [120]	Temporal Event Dataset	500	20	366	2,735,685	341,961	341,961
GDELT-m10 [121]	Temporal Event Dataset	50	20	30	221,132	27,608	27,926
ICEWS05-15 [76]	Event Forecasting	10,488	251	4,017	386,962	46,092	46,275
ICEWS14 [83]	Event Forecasting	7,128	230	365	63,685	13,823	13,222
ICEWS18 [83]	Event Forecasting	23,033	256	7,272	373,018	45,995	49,545
WIKI/Wikidata12k [122]	Knowledge Graph	12,554	24	232	2,735,685	341,961	341,961
Wikidata11k [84]	Knowledge Graph	11,134	95	328	242,844	28,748	14,283

TABLE VI
TYPICAL MULTI-MODAL KNOWLEDGE GRAPH REASONING BENCHMARK DATASETS.

Dataset	Modality	# Ent.	# Rel.	# Train Facts	# Val. Facts	# Test Facts
FB-IMG-TXT [101]	KG	11,757	1,231	285,850	34,863	29,580
	TXT	11,757	-	-	-	-
	IMG	175,700	-	-	-	-
FB15k-237-IMG [93]	KG	14,541	237	272,115	17,535	20,466
	IMG	145,410	-	-	-	-
MKG-Wikipedia [123]	KG	15,000	169	34,196	4,274	4,276
	TXT	14,123	-	-	-	-
	IMG	14,463	-	-	-	-
MKG-YAGO [123]	KG	15,000	28	21,310	2,663	2,665
	TXT	12,305	-	-	-	-
	IMG	14,244	-	-	-	-
WN9-IMG-TXT [101]	KG	6,555	9	11,741	1,319	1,337
	TXT	6,555	-	-	-	-
	IMG	63,225	-	-	-	-
WN18-IMG [93]	KG	14,541	18	141,442	5,000	5,000
	IMG	145,410	-	-	-	-