A Schematic Review of Knowledge Reasoning Approaches Based on the Knowledge Graph

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Abstract – In the contemporary world, the Internet technology and its implementation mode are advancing at a swift pace, leading to an exponential growth in the scale of Internet data. This data contains a significant amount of valuable knowledge. The effective organization and articulation of knowledge, as well as the ability to conduct thorough calculations and analyses, have garnered significant attention and developments within a particular environmental context. The utilization of knowledge graphs for knowledge reasoning has emerged as a prominent area of focus within the realm of knowledge graph research. It holds substantial significance in the realm of vertical search, intelligent answering, and various other applications. This article will be centered on fundamental principles of reasoning. The approach of knowledge reasoning oriented towards knowledge graphs is focused on the derivation of novel knowledge or the detection of erroneous knowledge through the utilization of pre-existing knowledge. In contrast to conventional knowledge reasoning approaches, the knowledge reasoning technique employed in knowledge graphs is characterized by greater diversity, owing to the succinct, adaptable, and flexible representation of knowledge.

Keywords – Knowledge Graphs, Knowledge Reasoning, Representation Learning, Visual Representations.

I. INTRODUCTION

The examination of knowledge reasoning has emerged as a prominent area of interest among scholars across various disciplines, including economics, philosophy, and artificial intelligence. Theoretical computer scientists have recently become interested in the utility of reasoning about knowledge for analyzing distributed systems (see relevant literature for an overview and additional references). In numerous domains where knowledge reasoning is applied, it is crucial to possess the ability to engage in probabilistic reasoning alongside the analysis of agents' knowledge. This issue is particularly relevant in the context of distributed systems applications, wherein there is a need to analyze randomly assigned or probabilistic programs. It is not unexpected that scholars have previously examined the relationship between knowledge and financial gain. The literature in economics pertains to the analysis of knowledge, tracing its roots to Nongrum and Jahanara's [1] pioneering paper, incorporates probability as a fundamental component of the model. Nevertheless, the literature does not account for a logical language that expressly enables the process of reasoning about probability. This study examines a language that expands the conventional knowledge logic by enabling explicit analysis of probability, as previously discussed in a related publication.

The field of knowledge reasoning and representation utilizes a knowledge graph (KG) as a means of integrating data within the knowledge based, using a graph-oriented topology or data model. KGs are frequently utilized for the purpose of retaining interconnected explanations of entities, which may include events, abstract concepts, situations or objects. Additionally, they encode the semantics that underlie the utilized terminology. Following the emergence of the Semantic Web, KG have become closely linked with linked open data initiatives, with a particular emphasis on the interrelationships among entities and concepts. Search engines such Bing, Google, Yahoo, and Yext, question-answering and knowledge-engines services such as Apple's Siri, Amazon Alexa, and WolframAlpha, as well as social networking companies such as Facebook and LinkedIn, are widely recognized for their prominent association and usage of these entities.

Knowledge graphs [2] allude to visual representations of a complex network of entities that exist in the real world, such as events, objects, concepts, situations, and demonstrate the interconnections and associations between them. The aforementioned data is commonly stored within a graph database and presented in the form of a graph structure, thus giving rise to the nomenclature "knowledge graph." The fundamental constituents of a knowledge graph comprise of three primary elements, namely nodes, edges, and labels. Nodes can encompass any entity, location, or individual. The relationship between nodes is determined by the presence of an edge. As an illustration, a node may represent a corporate entity, such as IBM, while another node may represent a marketing agency, such as Ogilvy. The categorization of the relationship between IBM and Ogilvy as a customer relationship could be considered an edge.

Knowledge graphs, which are driven by machine learning, apply natural language processing (NLP) to create a holistic representation of edges, labels, and nodes via semantic enrichment. The ingestion of data facilitates the identification of discrete entities and comprehension of inter-entity relationships by knowledge graphs. Subsequently, the practical understanding acquired is juxtaposed and amalgamated with additional sets of data that are pertinent and analogous in character. Upon completion, a knowledge graph enables search systems and question answering to retrieve and reuse comprehensive responses to specified queries. Consumer-oriented products have exhibited their potential to enhance time efficiency. Similarly, these systems can be implemented in a corporate environment to eradicate the need for manual data integration and collection tasks, thereby facilitating informed business decision-making.

During the period of knowledge engineering [3], a multitude of knowledge graphs (KGs) were created, including but not limited to YAGO and Freebase. Knowledge graphs (KGs) possess a substantial volume of pre-existing knowledge and are capable of proficiently structuring information. Question-answering systems, recommendation systems and search engines have been extensively utilized. Knowledge graphs possess the capability to extract, structure, and efficiently administer knowledge from vast amounts of data, thereby enhancing the caliber of data services and furnishing users with more intelligent services. The various aspects mentioned are dependent on the assistance of knowledge reasoning via knowledge graphs, which is considered a fundamental technology in the realm of reasoning. The objective of knowledge reasoning on KGs is to detect inaccuracies and deduce novel inferences from pre-existing information. The process of knowledge reasoning can yield novel associations between entities, which can subsequently enhance the knowledge graphs and facilitate the development of sophisticated applications. The investigation of knowledge reasoning on extensive knowledge graphs has emerged as a significant research area in natural language processing due to the broad range of potential applications for knowledge graphs.

The present article offers a scholarly examination of knowledge reasoning that is grounded on the knowledge graph. The subsequent sections of the article have been arranged in the following manner: Section II provides a critical analysis of knowledge reasons in the context of KG reasoning on logic rules, KG reasoning on representation learning, and KG reasoning on neural network. Section III is the last section providing brief remarks and directions for future research.

II. CRITICAL ANALYSIS

The process of knowledge-based reasoning utilizing a knowledge graph involves the utilization of established facts within the graph to deduce new information or detect erroneous data. An instance of a knowledge graph that is widely used is DBpedia. The presence of known triples (X, birthplace, Y) can significantly aid in deducing the absence of a particular triple. In academic discourse, it is customary to express that a knowledge graph typically employs triples consisting of head entities, relationships, and end entities to represent attributes and semantic relations between entities and attribute values. This is achieved by organizing them into a ternary group within the relationship, as supported by He, Feng, and Zhao [4]. The process of knowledge graph completion involves inferring a missing element within a triad, given any two known elements. Stated differently, the task at hand involves identifying the optimal tail entity, or entity, within a given set of entities and relationships (comprising relations and the head entity). Similarly, one must determine the relationship between the formation of effective triples, or the relationship between prediction, given the head and tail entities of a given entity. Both entity and relationship forecasting, which involve selecting a final element to form a ternary group, are more likely to yield effective results when used as a means of reasoning. Validity can be established through the application of rules or a scoring function to a derivation that is based on specific assumptions.

The process of knowledge graph denoising involves the assessment of the accuracy of triples. While knowledge graph completion is primarily concerned with expanding the knowledge graph, knowledge graph denoising is focused on accurately assessing the correctness of the triad within the knowledge graph. Essentially, it involves evaluating the effectiveness of the triad. The Knowledge Graph can be classified as a type of semantic network that enables the formal description of real-world entities and their interrelationships. It is a directed graph that incorporates tags, attributes, and visual representations to depict the semantic connections between entities. This facilitates the identification of knowledge and production-related nodes. The utilization of a structured approach to represent knowledge through knowledge graphs involves the explicit representation of semantic relationships between attributes and entities. In contrast to structured expression forms like frames and scripts, knowledge graphs represent relationships between properties and characterizations of things in a more concise, intuitive, flexible, and rich manner through the use of triples. The utilization of a flexible framework is not mandatory.

Knowledge Graphs (KGs) often encounter the issue of incomplete knowledge triples owing to the constraints of KGs construction and the swift evolution of data. Furthermore, the execution of subsequent assignments may experience significant deterioration. Hence, the process of utilizing knowledge reasoning to forecast the absent connections within KGs holds significant academic and practical significance. The following section provides an exposition of knowledge reasoning techniques that rely on representation learning, neural networks, and logic rules.

KG Reasoning on Logic Rules

The process of knowledge reasoning through logical rules involves the utilization of basic rules and features within knowledge graphs to uncover novel pieces of information. The utilization of symbolic representations of knowledge can be effectively employed by these methods. Under such circumstances, they have the ability to achieve a high level of precision in their performance and offer clear justifications for their reasoning outcomes. This section presents an overview of three distinct types of knowledge graph (KG) reasoning methodologies that rely on logical rules, namely graph structure-based reasoning, statistics-based reasoning, and logic-based reasoning.

Reasoning on Logic

Knowledge reasoning process on the basis of logic involves the utilization of description logic and first-order logic (FOL) [5] to explicitly articulate the protocols established by domain professionals. The classification of logic-based reasoning approaches could be established on the representation methods of rules, wherein two distinct categories emerge: reasoning based on First-Order Logic (FOL) and reasoning based on Description Logic. The utilization of First-Order Logic (FOL) in representing expert-defined rules and performing reasoning tasks through the use of propositions as fundamental units characterizes knowledge reasoning based on FOL. The utilization of first-order logic (FOL) in reasoning processes results in a level of interpretability that closely resembles natural human language, thereby enabling increased accuracy on small-scaled KGs. Propositions consist of two components, namely predicates and individuals. Entities and relations in KG are respectively represented by individuals and predicates. As illustrated in **Fig 1**, the individual identified as "Carl" exhibits a preference for the director "Roland Emmerich", who happens to be the director of the film "The Day after Tomorrow". There may be a correlation between the "Like" relationship of "Carl" and "The Day after Tomorrow". Consequently, it is possible to derive a rule in First-Order Logic (FOL).

$$(Carl, Like, The\ Day\ after\ Tomorrow) = A\ Rolan\ Emmerich, The\ Day\ after\ Tomorrow, Direct, (Carl, Like, Rolan\ Emmerich)$$

where A refers to the conjunction operator, which forms the Boolean-valued element, becoming true only when different proportions are considered true.

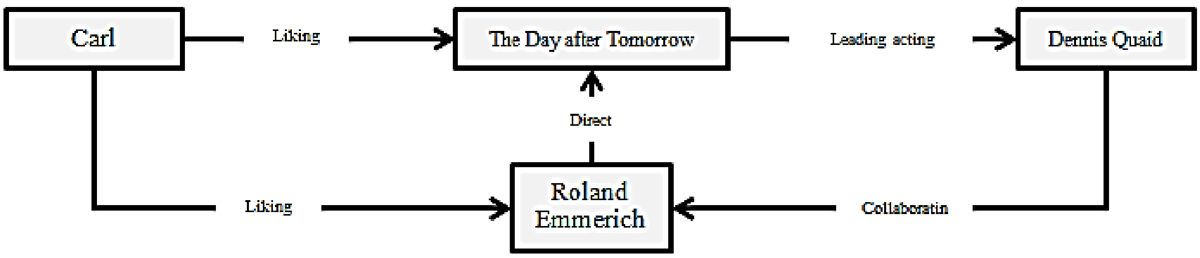

Fig 1. An Illustration of Knowledge Reasoning Techniques that Rely on Logical Rules

The objective of reasoning utilizing description logic is to convert intricate reasoning involving entities and relationships into a problem of detecting consistency. The aforementioned approach successfully mitigates the cognitive burden associated with reasoning over knowledge graphs, while simultaneously striking a balance between the capacity to express information and the level of reasoning complexity required. The KG, which is represented using description logic, comprises of two fundamental components, namely assertional sets (ABoxes) and terminological axioms (TBoxes). TBoxes comprise a set of axioms that delineate concepts and their relationships, while ABoxes consist of instances of concepts that are defined in TBoxes. This approach employs logical consistency as a criterion for evaluating the validity of a statement or description.

Reasoning on Statistics

The application of machine learning techniques to excerpt implicit logical procedures from knowledge graphs (KGs) and subsequently utilize them for reasoning purposes is known as statistical knowledge reasoning. The aforementioned techniques are rule-independent and possess the ability to automatically deduce logical rules to interpret the outcomes of the reasoning process. The application of statistical reasoning methods can be categorized into two distinct subtypes, namely inductive logic programming and association rule mining.

Inductive Logic Programming

Inductive Logic Programming (ILP) [6] is a novel field of study that explores the inductive development of first-order clausal theories through the utilization of examples and background knowledge. The term ILP is situated at the logic programming intersection and data mining or machine learning. ILP endeavors to identify patterns within data that can be utilized to construct predictive models or to acquire a deeper understanding of the data. Additionally, it explores the inductive development of first-order clausal theories through the use of examples and background knowledge. The domain of ILP exhibits a close association with logic programming, owing to the shared utilization of clausal first-order logic as a means of representing both data and hypotheses. The theoretical framework of ILP is founded on the principles of proof theory and model theory as applied to the first-order predicate calculus. The process of forming inductive hypotheses is marked by the utilization of various techniques such as inverse resolution, inverse implication, inverse entailment, and relative least general generalizations.

Inductive Logic Programming (ILP) is a specialized field within the realm of Artificial Intelligence (AI) that focuses on the process of inducing hypothesized predicate definitions from a given background knowledge and a set of examples. Logic programs are observed as unified representations, encompassing both hypotheses and background knowledge. ILP is differentiated from other machine learning types by its application of increasingly-expressive representation language and its capabilities to utilize logically encoded background knowledge. Effective ILP application has been evident in two critical areas, such as natural language and molecular biology. Both domains possess abundant sources of foundational knowledge and derive advantages from the utilization of expressive languages for representing concepts. The ILP model identified as Progol has been employed to yield comprehensible descriptions for 23 highly populated-fold proteins classes. Preceding this application, no such definition has been manually framed.

In the natural language domain, ILP has not exhibited superior levels of accuracy compared to several other machine learning methodologies in acquiring the past tense of English. However, it has demonstrated enhanced abilities in acquiring precise grammar that can convert different sentences into queries of deductive databases. In recent times, Learning Language in Logic (LLL) approach has presented various challenges to the current theory and implementations of ILP. The utilization of ILP in language applications necessitates the modification and expansion of a set of predicates that are hierarchically defined. It is noteworthy that examples are typically equipped for predicates founded on hierarchy apex. The creation of novel predicates frequently necessitates the development of intricate recursive processes. The progress made in ILP application and theory with regards to the difficulties posed by LLL has resulted in advantageous developments in other ILP applications that involve sequences.

During its initial stages, ILP was utilized for the purpose of generating functional or logic programs that could perform a variety of tasks, integrating but not limited to the structure of data and its manipulation (e.g. sorting or reversing a list). The conducted investigations have demonstrated the feasibility of synthesizing small programs based on a limited number of input/output examples. The contemporary technological revolution has generated tangible prospects for additional methodologies and implementations. Presently, a majority of computer users lack programming skills and are restricted to a passive role as consumers of available software. The utilization of ILP has the potential to enhance the ability of users to efficiently utilize computers for the purpose of automating their routine tasks. The utilization of Inductive Logic Programming is prevalent in the domains of End-user Programming and Education.

Attribute-based learning offers several benefits, including simplicity, efficiency, and the availability of effective techniques for managing large datasets. The scope of attribute-based learning is restricted to non-relational depictions of objects, as the acquired descriptions do not delineate the interconnections among the constituent components of the objects. The utilization of attribute-based learning is constrained by two significant limitations. Firstly, the expression of background knowledge is confined to a rather limited form. Secondly, the absence of relations renders the concept description language unsuitable for certain domains.

Frequently, computer users necessitate the creation of concise and singular scripts to mechanize recurring duties. The efficacy of ILP has been demonstrated in aiding these particular users. As an illustration, let us contemplate the realm of data manipulation. Different kinds of documents, including text/log files, Excel spreadsheets, and internet pages, provide creators with a high degree of flexibility in arranging hierarchical data by integrating presentation and modifying with the fundamental information model. Nonetheless, this poses a significant challenge for users who intend to retrieve the fundamental data for routine activities such as data manipulation, retrieval, modification of the display format, or conversion of data to an alternative storage configuration. Several programmatic solutions are available for data manipulation, including Excel macro language, standard expression libraries in Perl/Python, and the JQuery library for Javascript. However, these solutions have certain limitations.

Initially, it should be noted that the solutions are specific to a particular domain and necessitate pre-existing knowledge or expertise. Secondly, it is imperative for the user to possess a comprehensive comprehension of the complete foundational document framework, encompassing the various data fields. Consequently, a majority of users opt for the manual method of copying and pasting, which is both a laborious and error-prone task. The utilization of inductive synthesis has the potential to facilitate a diverse range of data manipulation techniques. The process of retrieving information from partially organized documents, encompassing textual files, web pages, and spreadsheets, involves the conversion of fundamental data categories such as strings or numerical values, as well as the conversion of complex data categories such as tables and XML. Additionally, the formatting of data is a crucial aspect of this process. The integration of these technologies in a sequential process of extraction, conversion, and formatting has the potential to enable users to execute advanced data manipulation operations.

The process of human learning and communication frequently involves the utilization of examples. This may manifest in a student endeavoring to comprehend a particular concept or a trainer devising strategies to assist the student in rectifying any misunderstandings, or offering beneficial feedback on their written work. The utilization of an ILP illustration within computer-based training holds practical value for a diverse range of students. The inductive synthesis community has developed example-based reasoning techniques that can be utilized to automate various repetitive and structured tasks in the field of education. These tasks include solution generation, feedback generation, and problem generation. The automation of tasks is applicable to a diverse range of STEM subject areas, automata theory, encompassing logic, programming, algebra, arithmetic, and geometry. Additional ILP methodologies and implementations encompass acquiring knowledge of structure-activity regulations for pharmaceutical development, finite-element mesh evaluation design standards, primary-secondary expectation of the protein system, and fault diagnosis standards for satellites. ILP has become a widely researched area of interest due to the implementation of ILP systems such as Aleph and Progol, as well as the exploration of hyper-parameter optimization, and optimal search theory.

Association Rule Mining

Market basket analysis (MBA): Market basket analysis (MBA) [7] is a widely used application of ARM, which aims to uncover the relationships between items purchased by clients in a particular database. The development of data technology has allowed retailers to access normal transactional data at a significantly reduced cost. Hence, significant quantities of valuable data that can aid in the management of retail operations can be derived from extensive transactional databases. The process of data mining (DM) is utilized to extract significant insights from extensive databases. The key purpose of ARM analysis is to effectively depict the most noteworthy patterns. The ARM evaluation, also known as MBA, is a technique utilized to identify patterns obtained from customer transactions by extracting associations from the retailer's database. In contemporary times, it is commonplace for every product to be equipped with a bar code. The business community is swiftly recognizing the significant potential value of this data in the realm of marketing.

Commercial firms are presently interested in identifying "association rules" that reveal purchase patterns. These rules enable the identification of additional items that are likely to be present in a basket when one item is already present. The identification of such patterns is a detailed process that is of great importance to commercial organizations. The outcome of the "market basket analysis" can be utilized to suggest product combinations for exclusive sales or promotion, develop a more contemporary store arrangement, and provide insight into co-branding and brand loyalty. This will additionally guide executives and managers towards authentic and effective strategic decision-making process. Data mining techniques are employed to identify the set of items that are frequently purchased together. Strategic product placement on store shelves can significantly enhance sales performance by facilitating the identification of complementary products that are best positioned to be displayed together.

Construction Intelligent Transportation System: The Intelligent Transportation System (ITS) is a novel integration of data technology, switch technology, processor technology, and beam technology that is implemented throughout the whole transportation structure. The ITS is constructed to encompass a multifaceted function, precise and up-to-date real-time capabilities, and an efficient integrated transport management structure. Advanced traffic data ITS is constructed on an information network and is developed using data from traffic participants on roads, weather center sensors, parking, transfer stations, transmission equipment to relay data to traffic data centers. The structure necessitates essential data via real-time system for processing road traffic data, parking data, and other essential traffic data. This information is then utilized to determine the optimal route selection for traffic participants. If the vehicle is outfitted with a navigation system, it has the capability to assist the driver in automatically selecting the optimal route for their intended destination. The implementation of an ITS has the potential to effectively mitigate traffic congestion and reduce environmental pollution. The fundamental objective is to verify the safety of traffic and enhance the efficiency of transportation.

The areas of ITS encompass a range of systems, including progressive public transport systems, advanced traveler data systems, emergency organization systems, electronic toll group systems and innovative vehicle control systems. The utilization of ITS necessitates adherence to certain prerequisites. Firstly, the road and traffic information gathered must be precise, comprehensive, and contemporaneous. Secondly, the exchange of data between road management and traffic management facilities should be effective and prompt. Lastly, the toll management centers and traffic management centers ought to possess self-learning computer structures. CDMA is a sophisticated system for controlling traffic. The system is comprised of three distinct components, specifically traffic management centers, wireless routers, and various features such as electronic police, vehicle detection, and signal control. The CDMA wireless router serves the purpose of facilitating the transfer of data in both directions, while the site equipment is responsible for the acquisition of real-time traffic data and the management of traffic signals.

Web Log Data: Web log file analysis and automated knowledge extraction are now complete thanks to the widespread use of the internet. Information providers are keen on any methods that may be used to investigate the information requirements and tastes of internet users. It may be used to make websites more effective by tailoring their information architecture to individual visitors' preferences. Finding the right tools for analyzing the little online log data to get the relevant and actionable information may be challenging, though. There are now several basic web log research programs; however, most users find them to be too sluggish, too stringent, too costly, too difficult to maintain, or too partial in their conclusions to be of any real value. Web log mining, also known as web use mining, is a relatively new data mining methodology for uncovering procedural patterns from Web data, which indicates that such methods are now available as an alternative to conventional approaches to decision-making. In the vast literature on data mining, the application of popular pattern finding techniques on Web log data is one of the most discussed topics.

Identification of Frequent Illness: In order to describe or extract valuable information, data, or data patterns within big database, a technique known as "data mining" is used. Data mining is a broad term for a set of methods used to discover insights and patterns in large datasets. Data mining techniques are utilized to make informed treatment decisions in the medical industry. The healthcare industry collects data, but in case the data is not mined, it will not provide anything useful for making decisions. Health care managers may utilize the gleaned information to restore high-quality service. The researchers had used an association rule (AR) based aproiri Procedure to determine which illnesses were prevalent in a certain location at a given period. In terms of the extraction of information, association rules are the most dynamic and crucial models.Association rules center on the relationship between the quality domain and the ability to foresee specific requirements. All the simultaneous occurrences are laid bare by the patterns. It offers a streamlined approach to identifying patterns and assigning credit to models.

Computer-Assisted Diagnostic System of Breast Cancer: The quantity of data created by several fields has rapidly grown as a result of the widespread use of computers and knowledge. Data mining (DM) techniques are reused to get insight from this information. Positive outcomes in fields such as illness diagnosis, organ transplantation, therapy, image analysis, medication development, scientific investigation, etc. have been achieved employing data reduction methods. The Spine Hospital at the University of Southern California has used data removal methods in a variety of medical specialties, including cancer, liver pathology, gynecology, thyroid disease diagnosis, urology, and neuropsychology.

Falk et al. [8] expounded on the challenges of data presentation in the area of Deoxyribonucleic Acid (DNA) data inspection, touching on topics such comparing DNA sequence resemblance, semantic incorporation of dispersed data, disease-causing genes, and more. Camargo, Nusspaumer, Abia, Briceño, Remacha, and Ballesta [9] suggested assembling proteins according to the order of their amino acids. Mohebbanaaz, Kumari, and Sai [9] devised a decision tree based on ECG readings in order to reboot the brain. Authors of [11] suggested neural network technology for studying the development of protein drugs. Using data extraction techniques, Nikku, Myöhänen, Ritvanen, and Hyppänen [12] figured out a hematologic misrepresentations evaluation system with powerful data evaluation and removal capabilities. Data mining applications in the health sector have their own advantages due to the fact that the collected data is generally genuine and trustworthy and is not accomplished by other concerns. The size of a medical database is quite staggering. In the case of a patient exhibiting symptoms associated with a certain illness, for instance, the laboratory testing and therapy associated with that condition may be same.

The term "ILP-based reasoning" [13] describes the process of automatically summarizing abstract rule sets through logic programming and machine learning technologies. Good reasoning ability across small-scale KGs is achieved without resorting to manually set rules using this approach. Association rule mining is the foundation of inductive reasoning since it can automatically extract and use high-confidence rules. Association rule mining-based reasoning outperforms conventional ILP techniques in terms of speed and scalability, and can deal with KGs of greater complexity and size.

Reasoning on Graph System

To reason based on the graph's structure is called "graph structure-based reasoning." Paths connecting entities are the most common kind of structure in KG and play a crucial part in KG reasoning. Graph-based reasoning is effective and understandable because of its visual nature. In **Fig 1**, for instance, the route "DirectLeading actor" from the "Roland Emmerich" node suggests that "Dennis Quaid" and "Roland Emmerich" might have a "Collaborate" interconnection. The global structure-oriented and local structure-oriented models are two categories into which graph structure-based reasoning techniques fall. Extraction of complete KG routes for use as features in determining the presence of a target relation is the crux of global structure-based reasoning. KG reasoning is carried out using the reasoning with the local structure method, which makes use of the highly relevant local graph structure as features. This approach prioritizes characteristics at a finer granularity than global structure-based reasoning and requires less processing power.

KG Reasoning on Representation Learning

An essential method in machine learning is representation learning, which simplifies complex data structures into numerical vectors. Based on this large-scale data condition, the modern single-hot embedment of relational data meets the difficulty of feature sparsity. Knowledge reasoning's imprecision prevents us from including semantic information in our entity and relation type representations. Consequently, improved reasoning quality necessitates representations with a higher density of semantic information. KRL ensures a stable semantic space by accurately capturing the interrelationships between entities and relation types inside the learnt distributed embeddings.

These semantically rich, distributed embeddings have the potential to improve the efficiency of knowledge reasoning by making it easier to represent relationships expressively. In order to reveal previously concealed relationships in graphs, KRL maps this information into a low-dimensional space. When compared to many other methods, representation learning clearly shines. As a result, research on KG reasoning that makes use of representation learning has blossomed in recent years. This section presents the technique known as tensor decomposition, the semantic matching model, and the distance model, three kinds of KG reasoning technique on the aspect of representation learning, and contrasts them.

Tensor decomposition approach

A low-dimensional KG embedding may be built by decomposing its related tensor into many matrices, which is what is meant by "tensor decomposition-based KG reasoning." Training a decentralized representation of KG is accomplished by adapting and using already fundamental tensor decomposition methods. RESCAL is the most popular tensor decomposition-based KG reasoning method presently in use. The paradigm of entity-relation-entity interactions that KG employs is represented as a three-way tensor. To create entity and relation representations, RESCAL solves a straightforward tensor decomposition issue. RESCAL's low-dimensional embedding accurately depicts the neighborhood structure homogeneity of the original KG's entities and connection types. KG is illustrated in **Fig 2**, which displays a relational graph. Both "2012" and "The Day After Tomorrow" composed of a similar director, "Roland Emmerich," and the same screenwriter, "Harald Kloser," but they feature different actors in the major roles. Both "2012" and "The Day After Tomorrow" have a similar neighborhood structure, which contributes to their shared embeddings. If "The Day After Tomorrow" is classified as "Science fiction," then "2012" must also fall within that category, as determined by RESCAL.

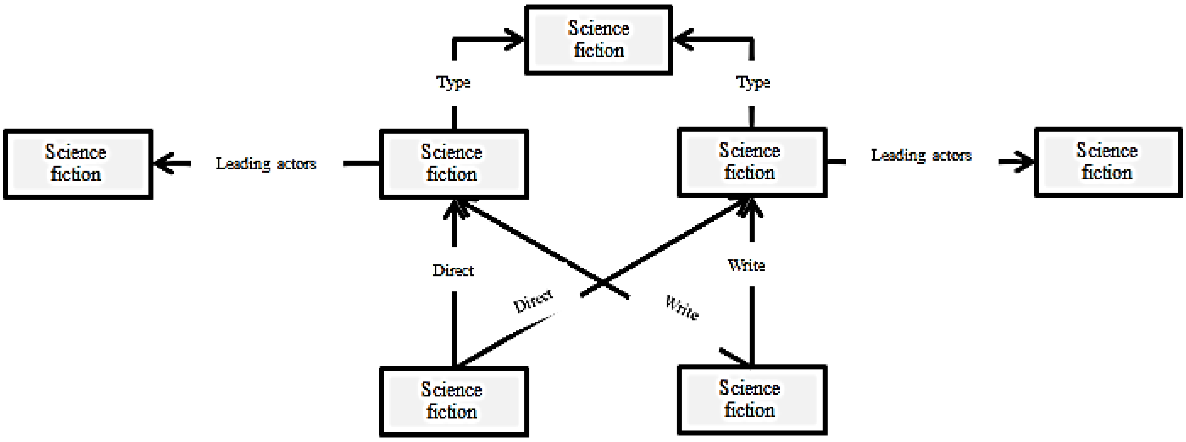

Fig 2. A Sample of a Knowledge Reasoning Challenge

For representation learning, RESCAL is an old standby tensor decomposition framework. Nonetheless, RESCAL is not directly applicable in complicated settings due to its simplicity and lack of interpretability. In order to improve the efficiency of representation learning, several tensor decomposition models have been created. Three further KG representation learning strategies were suggested by Montero Quispe, Utyiama, Dos Santos, Oliveira, and Souto [14], all of which target more complex application scenarios.

Distance model

In the distance model, a relation between two KG entities is seen as a linear mapping from one embedding space to another. All the different entity and types of relations in KG are taught low-dimensional embeddings by these models by reducing the transformation error. TransE and its variations serve as the prototypical distance model. In order to learn distributed representations of the various relation types and entities, the popular translational framework TransE mandates that all triples of relations in KG satisfy the equation $r + h = t$, where r, h, and t stand for the embeddings of the relation type, entity in subject, and the object entity, respectively.

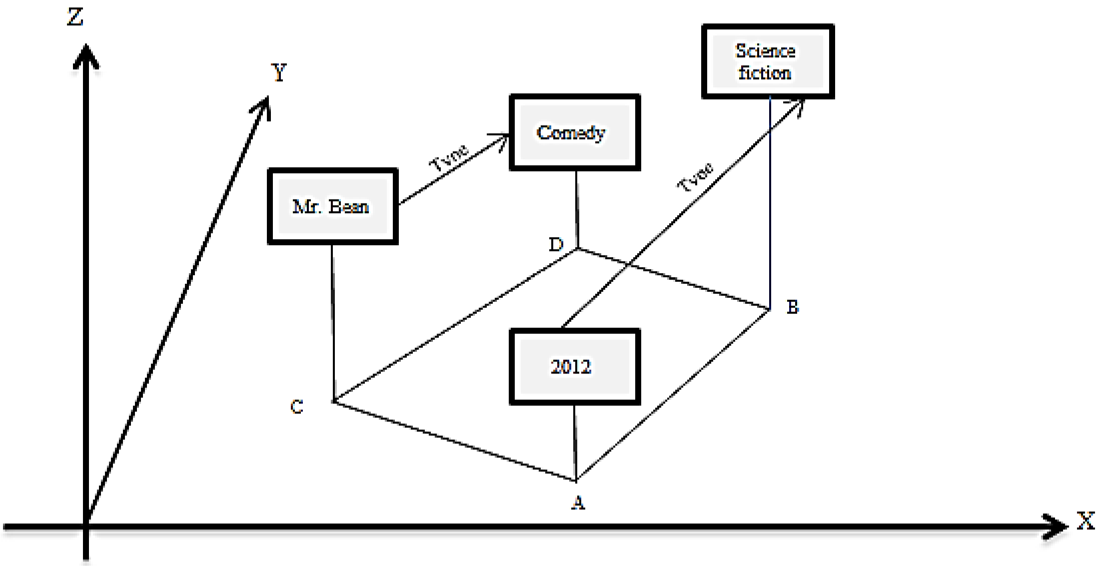

Fig 3. A Relation and Entity Mapping Example of TransE

Using the previously described example, **Fig 3** explains how TransE works. TransE projects represent the various entities on a lower dimensional space to determine whether "Science fiction" and "2012" have the connection "Type," as shown by the dotted line. Both "2012" and "Science fiction" are real things that have been extrapolated to some future year, and these years happen to be A and B. Mr. Bean and Comedy are two more entities that are subsequently sent to Point D, and Point C. Having established the connection "Type," they may map this onto embedding spaces as the vector of transition between the "Mr. Bean" (Point C) and "Comedy" (Point D) embedding points. After obtaining all of these embeddings, we can test for the presence of (2012, Type, Science fiction) relation by visualizing if the 2012 embedding of Point A could be considered as Point B's Science fiction embeddings via the embeddings of "Type" Only under these circumstances can the connection between (2012, Type, Science fiction) hold.

TransE is easily interpretable since the issue is expressed clearly. However, TransE does have two restrictions. The rigidity of the translation rule limits the system's adaptability and reliability. In order to deal with the noise present in real-world data, many relaxed translational models are developed. Another restriction that severely restricts TransE's practical use is that it cannot handle N-to-N, N-to-1, or 1-to-N relationships. Setting aside an entity space from its relations space in order to depict their connections in a particular space is an approach used by several studies. Stochastic distance framework, rotation frameworks, including other distance frameworks are only a few examples of the many publications that address issues unrelated to these two derivatives.

Semantic matching model

The semantic matching approach employs a scoring function to evaluate the veracity of relationship triples by finding hidden semantic matches between relation types and entities in a lower dimensional space. The models compare relations described in KG to one another and treat those described elsewhere as different. In KG, matching three-way and two-way semantics is where the majority of existing models, such as three- and two-way embeddings combinations (TATECs), excel. In this context, a linear scoring function is used to assess the reliability of relationships. First, TATEC proposes a scoring element for three-way connections like (The Day After Tomorrow, Direct, Roland Emmerich), given a relational graph like the one illustrated in **Fig 3**. Similarly, TATEC proposes scoring procedures to assess the validity of two-way relationships e.g., (Roland Emmerich, Directs,), (The Day After Tomorrow, Roland Emmerich), and (Direct, The Day After Tomorrow).

A three-way score of 0.35 would represent (Roland Emmerich, Direct, The Day After Tomorrow), whereas (Directs, Roland Emmerich), (The Day After Tomorrow, Roland Emmerich), and (The Day After Tomorrow, Direct) each have scores of 0.25, 0.12, and 0.18, respectively. A combined score of 0.90 seems reasonable for the trio of Roland Emmerich, Direct and The Day After Tomorrow. The training procedure improves the quality of both the three-way and two-way interactions in KG. TATEC merely determine the triple's score (Science fiction, Type, 2012) to determine whether "Science fiction" and "2012" have the connection "Type," and in case the score appear to be larger than the experimental threshold, like 0.75, the relation is established. The many configuration options available in TATEC contribute to its prohibitive computational complexity. As a result, a number of bilinear and linear models attempt to strike a compromise between the two extremes of its performance and complexity. Many models have been developed that use neural networks to train representations based on semantic matching, with the goal of better capturing non-linear patterns of interactions. Relationship scores are computed by these models using deep neural networks.

KG Reasoning on Neural Network

Despite the increasing number of proposed KG reasoning methods, the challenge of multi-hop and complex relation reasoning remains unresolved. The utilization of neural networks for the purpose of analyzing such relations has been found to be a more potent approach as compared to other reasoning techniques that rely on representation learning or logic rules. Following representation learning via neural networks such as RNN or CNN, a precise comprehension of knowledge semantics may prove advantageous for subsequent reasoning processes utilizing softmax layer and completely connected layer. In addition, these methods have the potential to enable automated reasoning on knowledge graphs without the need for theoretical modelling, or logical inference. The ubiquitous conditions of different structure as well as their reasoning aspect have led to a proliferation of neural network-based KG reasoning techniques. This subsection provides a detailed introduction to knowledge reasoning methods that are based on Deep Reinforcement Learning (DRL), CNN, RNN, and GNN.

With reference to the knowledge subgraphs depicted in **Fig 4**, the RNN algorithm selects the green, blue and red pathways as inputs for determining the target connection between "Life Story" and "Spider-Man". In the context of the red path, the Recurrent Neural Network (RNN) selectively attends to lexemes such as "background" and "hope" and holds them within the memory cell, thereby augmenting the likelihood of the "main feature" association. Regarding the blue pathway, RNN identifies the involvement of "Captain America" within the "Vietnamese War" and subsequently recognizes the portrayal of "Captain America" within the "Life Stories" narrative. The analysis further infers the existence of a relation between "Captain America" and "Spider-Man". In the context of the green path, it can be observed that the Recurrent Neural Network (RNN) exhibits a certain degree of forgetfulness towards the "create" relation, owing to the uniformity of all the relations. Finally, the Recurrent Neural Network (RNN) amalgamates all data from 3 pathways and attains a high likelihood of the "main feature" association between the "Spider-Man" and the Life Story" entities. The decision to augment the knowledge subgraph with a novel triple (Life Story, Spider-Man, main character,) was made by the RNN model, based on the ultimate logical conclusion reached regarding the relation between "Captain America" and "Spider-Man" in the aforementioned work.

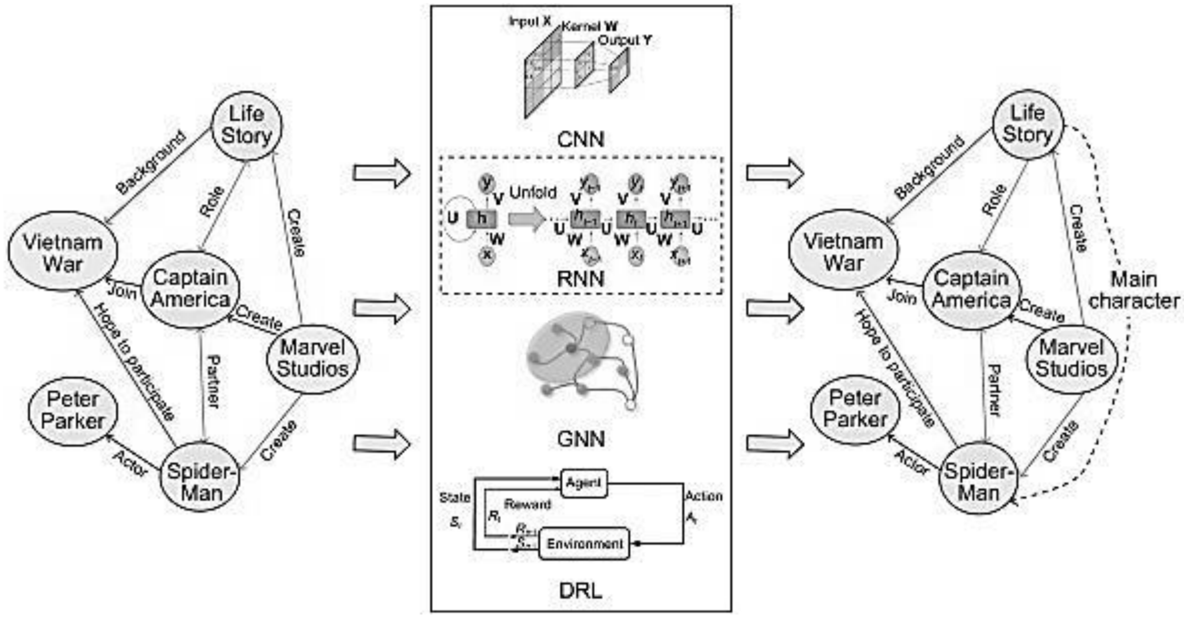

Fig 4. KG Reasoning Techniques in RNNs

The Convolutional Neural Network (CNN) has been utilized for knowledge reasoning in the early stages due to its ability to capture the local features of Knowledge Graphs (KG). The utilization of knowledge triples may serve as an optimal instructional tool. ConvE utilizes a 2D convolution on a 2D entity relationship embedding matrix to effectively capture interactive characteristics between relations and entities, as reported by Beelen and van Dooren [15]. Moreover, textual descriptions of entities offer additional insights pertaining to entities available within knowledge triples. One commonly cited instance is the learning of knowledge representation through description embodiment, or DKRL. This approach involves the use of CBOW (Continuous Bag of Words) and convolutional neural networks (CNN) to separately train the unordered elements and the word-order characteristics of text definitions. Subsequently, the fused element facilitates efficient identification of novel entities.

Moreover, restricting the attention solely to individual knowledge triples would curtail the range of reasoning. Numerous research endeavors aim to investigate an expanded range of reasoning by utilizing Recurrent Neural Networks (RNNs) to scrutinize the knowledge trajectory, which is periodically comprised of entities and relations. The integration of diverse knowledge path representations could potentially yield significant results in this study. Additionally, Recurrent Neural Networks (RNNs) have the potential to be utilized for the purpose of examining textual descriptions of entities. The KGDL approach, which is a commonly used technique, employs long short-term memory (LSTM) networks to generate embeddings for knowledge graphs that incorporate entity descriptions. Specifically, the method encodes relevant textual descriptions using LSTM, and subsequently encodes entity descriptions using triples, ultimately enabling the prediction of missing knowledge.

In recent years, there has been extensive exploration of Graph Neural Networks (GNN) [16] for knowledge reasoning, as KGs are based on the structure of the graph. The utilization of GNN broadens the scope of learning beyond a solitary CNNs triple or knowledge pathways in RNNs, to incorporate the knowledge subgraph. The SACN model, as an example, employs a weighted graph convolutional network (GCN) in its encoder and a Conv-TransE convolutional network in its decoder. Consequently, the SACN model achieves the capability to adaptively learn semantic information within the surrounding neighborhood structure of a given node. Despite its strong subgraph learning capability, GCN exhibits a limitation in its modeling approach by representing a unidirectional relationship as bidirectional, resulting in a modeling error pertaining to the directionality of the relationship. The Graph Attention Network (GAT) [17] apparently dissociates the edge bidirectionality. ReInceptionE is a novel approach that integrates KBGAT and ConvE to enhance the comprehension of structural data in knowledge graphs.

Regarding interactive modeling concepts, Deep Reinforcement Learning (DRL) [18] offers a novel approach to knowledge inference. The Deeppath model, which is widely used, considers the entities of knowledge as the state spaces and navigates between them by selecting relations. Upon successfully identifying the appropriate solution entity, The Deeppath will be granted a significant reward. This methodology essentially institutes a logical approach that relies on exploring paths of relationships. Consequently, the utilization of Deep Reinforcement Learning (DRL) techniques has the potential to substantially enhance the efficacy and variety of knowledge inference.

III. CONCLUSION AND FUTURE PROSPECTS

The present study centers on the methods of reasoning, given the crucial significance of knowledge reasoning in the pragmatic implementation of knowledge graphs, which is grounded on logical rules, representation learning, and neural networks. The aforementioned has advantageous implications for subsequent tasks, specifically in regards to link prediction. This paper presents TLKH as a proposed solution for enhancing the efficacy and efficiency of knowledge reasoning and updating in KG. TLKH is capable of representing spatio-temporal relations, thereby facilitating faster knowledge reasoning and updating. The implementation of KG represents a departure from conventional KS and usage methodologies, as it furnishes a robust knowledge base that can be leveraged to facilitate the advancement of AI systems that are predicated on knowledge acquisition. In forthcoming times, it is plausible that KG may exert an impact on cognitive intelligence, and the application and expansion of knowledge reasoning could conceivably encompass additional domains.

The subsequent stage in the domain of machine learning entails the training of a machine learning model. This process involves furnishing an ML algorithm with training data and salient features, thereby enabling it to learn a function that facilitates making predictions. Machine learning models that lack context necessitate comprehensive training, rigidly prescriptive regulations, and are limited to particular use cases. The incorporation of knowledge graphs provides contextual information that leads to improved predictive caapabilities, utilizing pre-existing data. Knowledge graphs facilitate graph feature engineering through the utilization of basic graph queries and/or advanced graph algorithms. It is widely acknowledged that relationships exhibit a high degree of predictability with respect to behavior. Therefore, the incorporation of these interrelated contextual features serves to optimize the predictive capacity of models, while simultaneously enhancing the scope of their applicability. Upon the development of a machine learning framework, it is imperative to ascertain its utility and accuracy in making predictions. Incorporating relationship information into knowledge graphs facilitates graph investigations and counterfactual analysis by domain experts. Professionals may verify conjectures through the examination of analogous communities within the knowledge graph or troubleshoot anomalous outcomes by delving into hierarchies and interdependencies.

The utilization of graph technologies in constructing knowledge graphs presents notable benefits, as graphs inherently possess the capability to store, process, and evaluate interconnections and associations within data. Furthermore, graph algorithms are designed to utilize the topology of data via connections in order to identify communities, reveal influential components, and deduce patterns and structure. The integration of predictive contextual features derived from a knowledge graph into machine learning algorithms not only enhances precision but also mitigates the occurrence of erroneous positive identifications. The concept of graph-native learning pertains to the execution of machine learning tasks within a graph framework, thereby elevating the application of knowledge graph augmented machine learning to a higher level. The feature extraction process is facilitated by the graph itself, enabling the acquisition of generalized and predictive features without prior knowledge of the most predictive data structures. The aforementioned holds great significance as organizations often lack knowledge regarding the prioritization of features and the appropriate representation of connected data for utilization in machine learning techniques.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Ethics Approval and Consent to Participate

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