IOP Conference Series: Materials Science and Engineering

PAPER • **OPEN ACCESS**

A Survey of Knowledge Reasoning based on KG

To cite this article: Rui Lu *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **569** 052058

View the article online for updates and enhancements.

This content was downloaded from IP address 120.25.253.117 on 14/10/2019 at 22:54

IOP Conf. Series: Materials Science and Engineering **569** (2019) 052058 doi:10.1088/1757-899X/569/5/052058

A Survey of Knowledge Reasoning based on KG

Rui Lu[1], Zhiping Cai[2*], Shan Zhao[2]

[1] Unit 73089, Xuzhou, Jiangsu, 221007, China

[2] College of Computer, National University of Defense Technology,Changsha,Hunan,41008,China

[*]Corresponding author's e-mail: zpcai@nudt.edu.cn

Abstract. Knowledge Reasoning(KR) has become the core issue in the field of Artificial Intelligence(AI) and even Natural Language Processing(NLP). KR based on Knowledge Graph(KG) is based on existing KG's facts. It uses some inference models and algorithms to infer new unknown knowledge and targets at improving the completeness and accuracy of KG. This article presents a brief overview of KR based on KG, expounds the connotation and research scope of it, judges the two main research directions(Knowledge Graph Completion(KGC) and Question Answering over Knowledge Graph (QA-KG)) of current KR and summarizes the four main technical methods. A series of latest results of current research on KR are also listed in this paper . Finally, we look forward to the future improvement of KR.

1. Introduction

With the continuous development of the Internet, the all-round penetration of the Internet of Things, the continuous breakthrough of computing power, the increasingly sophisticated intelligent algorithms, the leapfrogging of computer software and hardware technologies, and the rise of research in cloud computing, big data, blockchain, etc. The Artificial Intelligence(AI) research has strong material and technical support, which triggers the fourth technological revolution centered on artificial intelligence[1][2].

Faced with massive data resources, how to effectively manage data and knowledge, extract useful information from big data through data mining and knowledge management, provide intelligent decision-making and intellectual support for all aspects of human society, has become hotspots and difficulties in AI research. In this era, the Knowledge Graph(KG) came into being.

The KG was first proposed by Google in 2012[3], which was used by Internet companies to provide a large database for intelligent search services. Formally, it is a knowledge carrier represented by graph data structure, where nodes represent entities in the objective world and edges represent relationships between entities. In the specific implementation, the KG uses the Resource Description Framework (RDF) in the Semantic Web to uniformly represent the content of the knowledge system and the instance data to form a complete knowledge system[9]. KG provides an effective solution for organizing, managing and understanding the vast amount of information in the Internet, which makes the network more intelligent and closer to human cognitive thinking, hoping to provide users with intelligent services, such as understanding the semantics of search and providing more accurate search answers. As shown in Figure 1, using the Baidu to search for Yun Ma. Since its introduction, it has received widespread attention from the government, industry and academia. At present, KG has been applied in Intelligent Search, Question Answering, Personalized Recommendation, social network and some vertical industries[4][5][6] ,which shows good development prospects.

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.
Published under licence by IOP Publishing Ltd



Fig 1. An example of BAIDU KG

The core of AI is actually a process of learning and reasoning[8]. At present, Knowledge Reasoning(KR) has become the core issue in the field of AI and even NLP. Based on the KG, this paper focuses on the research directions, technical methods and research progress of KR, it also looks forward to the future of KR technology.

2. Summary of KR Based on KG

Reasoning is an important concept in the disciplines of logic, philosophy, psychology, artificial intelligence, etc. KR based on KG is based on existing KG's facts, using some inference models and algorithms to infer new unknown knowledge and improve the completeness and accuracy of KG. KR plays a very important role in the entire technical system of KG. As shown in Figure 2, a typical KG technology system consists of six parts: data source, knowledge extraction, data storage and management, distributed computing, KR and KG application. Among them, data source, knowledge extraction and data storage constitute the technical basis of KG. KR is the only way to connect the underlying foundation and application, and it is also the key to the effective function of KG. At the same time, KR can form a good interaction with the knowledge base and promote each other. To some extent, KR fully reflects the "intelligent" connotation of KG technology.

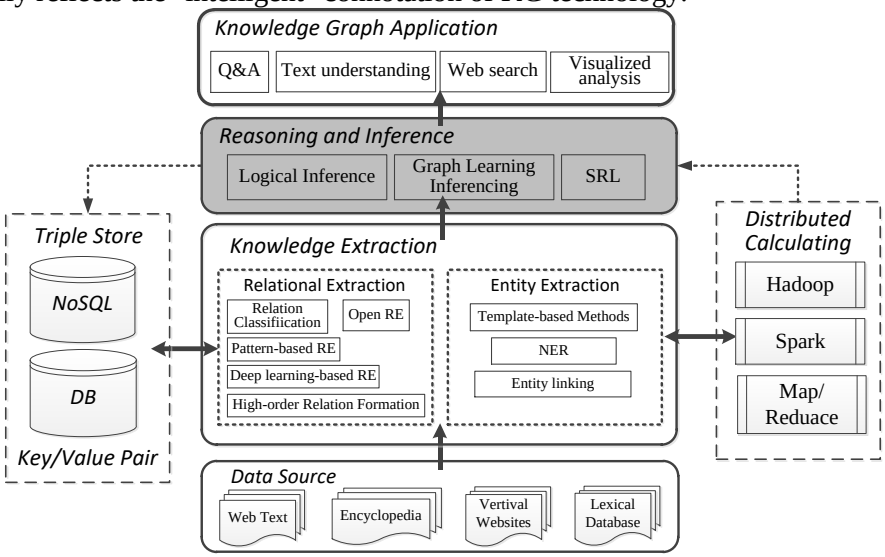


Fig 2. The Technology Framework of KG

Traditional KR methods (including ontology reasoning methods) are developed on the basis of a large number of practices, with strong theoretical foundation and guiding significance, and can be used for KR oriented to KG. Due to the characteristics of the times and the application background of KG, KR based on KG also has new features and requirements which are mainly reflected in the following three aspects: Firstly, traditional KR is mainly deductive reasoning, while KR based on KG is mainly based on inductive reasoning, which is mainly determined by the material composition basis of KG. Secondly, there are a large number of instances within the KG, which cover a wide range of contents

(for example, DBpedia has more than 28 million entities in 127 languages and hundreds of millions of RDF triples). Traditional reasoning methods have certain limitations when applied to KG, which are mainly reflected in the fact that the rules and ontology constraints with effective and wide coverage are difficult to obtain, and it is difficult to deal with the scarcity of samples, so the KR based on KG needs more efficient and scientific approaches. Thirdly, with the development and continuous breakthrough of distributed representation, neural network and other technologies, it provides many new ideas for knowledge representation, such as distributed representation based reasoning, neural network based reasoning and hybrid reasoning, etc. Good results have been achieved in practical applications.

3. The main research directions of KR

The current research directions of KR can be mainly divided into Knowledge Graph Completion(KGC) and Question Answering over Knowledge Graph (QA-KG). The KGC focuses on the improvement and refinement of the KG, while the QA-KG focuses on the application of the KG.

3.1. Knowledge Graph Completion(KGC)

In order to make better use of the KG, the industry and academia have proposed a variety of construction methods[10].Whichever approach is taken for constructing a knowledge graph, the result will never be perfect[11]. Consequently, coverage and accuracy have become bottlenecks in the application of KG.

The purpose of KGC is to use existing information to predict the lost entities, types and the relationships between entities, thereby improving the coverage and accuracy of the KG. According to the specific objects of the triples to be completed, the KGC can be divided into two sub-tasks: entity prediction and relationship prediction. In order to make the KG have good usability, fault diagnosis[12] is also needed in the process of KGC to ensure the triplet has good accuracy.

3.2. Question Answering over Knowledge Graph (QA-KG)

Question Answering over Knowledge Graph (QA-KG)[14]aims to use facts in the KG to answer natural language questions. It helps end users more efficiently and more easily access the substantial and valuable knowledge in the KG, without knowing its data structures. The inference engine has evolved from the original stand-alone inference engine to the current distributed semantic inference engine based on Hadoop MapReduce or Spark. Currently, KR also plays an increasingly important role in the field of Chatbot[15], vertical field question answering systems[16], Knowledge Recommendation[17], Commonsense Reasoning[18], not listed here one by one.

In short, the methods and technology of KR used for KRC and QA-KG are essentially the same, that is, inferring the missing parts of the triples through certain methods. The main technology and methods of KR will be discussed in detail in Chapter 4.

4. The main technology and methods of KR

4.1. Path Ranking Algorithms(PRA) based Reasoning

PRA was first proposed by Lao and Cohen[19]in 2010. PRA is a random walk inference technique and it's key idea is to explicitly use paths that connect two entities as features to predict potential relations between them. Recently, Gardner et al.[20], Shi et al.[21] and X. Wang et al[17] have respectively explored various novel extensions which mainly focused on single-task version of PRA. Wang Q et al.[22], Liu Q et al.[23]proposed a novel multi-task learning framework for PRA, referred to as coupled PRA (CPRA), CPRA takes relation association into account and enables implicit data sharing among them. Zhang Y et al.[24] propose an end-to-end learning framework for question answering with knowledge graph named variational reasoning network(VRN), As shown in Figure 3. In order to solve the problem of the association of large KG entities, Chen W et al.[25]combine the path search and path reasoning from the perspective of latent variable graph model, and introduce the variational

inference framework DIVA in KG reasoning, which improve the stability of the KG inference model. Xiong W et al.[26] proposed a reinforcement learning (RL) framework for learning multi-hop relational paths, offering better control and more flexibility in the pathfinding process. In the field of data mining, KIM J et al.[13]predict relationships between entities by mining entity relationships in the KG. At present, there are still three problems in PRA that need further research. Firstly, the graph algorithm used in the logic rule model has higher computational complexity and poor scalability. It is necessary to study computational efficiency and universality. Secondly, the nodes in the KGs tend to obey the long tail distribution, the sparsity problem has a greater impact on the logical reasoning algorithm. Thirdly, the existing logic rule model can't solve the problem of long path reasoning, usually the path length is limited to 3 steps, so the long path reasoning problem needs to be solved.

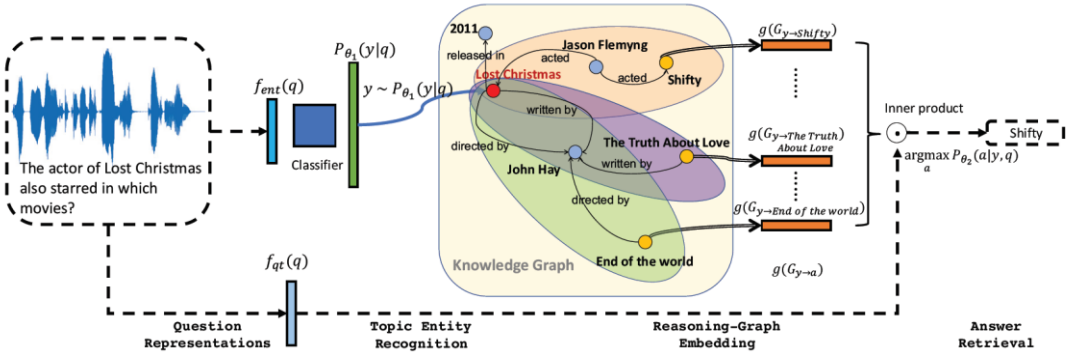


Fig 3. End-to-end architecture of the variational reasoning network (VRN) for question-answering with knowledge graph.

4.2. Representation Learning based Reasoning

The basic idea of the Representation Learning based KR is to represent the semantic information contained in the target object (word or morpheme) as a low-dimensional vector, and then perform linguistic correlation calculation based on the semantic vector. Since the Representation Learning model is convenient for the computer to simulate the whole inference process by vector calculation, it has the advantages of high inference accuracy and good algorithm scalability, and has been a hot topic in the field of KR in recent years.

KR based on tensor/matrix decomposition treats the triples as element tensors/matrices in tensors/matrices, and performs representation learning by tensor/matrix decomposition methods. In 2011, Nickel et al.[27]proposed the RESCAL. The core idea of the RESCAL is to encode the entire KG into a three-dimensional tensor. After RESCAL was proposed, many researchers(such as Tay et al.[28], Seyed Mehran Kazemi et al.[29], Koki Kishimoto et al.[30]) consecutively proposed extensions of RESCAL which greatly improved the effect of KGC.

In 2013,Bordes et al.[31] proposed the first translation-based representation model TransE, which set off a research boom in the Trans series. Wang Z et al.[32], Lin Y et al.[33], Ji G et al.[34], Jia Y et al.[35], Xiao H et al.[36], Fan M et al.[37] proposed extended models of TransE respectively. The models have been discussed in detail in article[35][37][38] and will not be described here.

In addition to the typical translation model and PRA, experts and scholars have put forward many other effective methods based on them. The results since 2017 mainly include: Tim Dettmers et al.[39]introduce ConvE, a multi-layer convolutional network model for link prediction; Baoxu Shi et al.[40] introduce an open-world KGC model called ConMask; Shi B et al.[41] present a shared variable neural network model called ProjE to fills-in missing information in a KGs; Lin Y et al.[42] distinguish existing KG relations into attributes and relations, and propose a new KR model with entities, attributes and relations(KR-EAR); Agustinus Kristiadi et al.[43]proposed LiteralE, which is an extension that can be plugged into existing latent feature methods; Guo S et al.[44] proposed Rule-Guided Embedding (RUGE), a novel paradigm of KG embedding with iterative guidance from soft rules; Ding B et al. [45]investigated the potential of using very simple constraints to improve KG

by examining non-negativity constraints on entity representations and approximate entailment constraints on relation representations.

Recently, Takuma Ebisu et al.[46]proposes a novel embedding model, TorusE, which can solve the regularization problem of prior embedding models through embedding objects on other than a real or complex vector space. Xiao Huang et al.[47]proposed an effective Knowledge Embedding based Question Answering (KEQA) framework, which targets at jointly recovering the question's head entity, predicate, and tail entity representations in the KG embedding spaces, As shown in Figure 4.

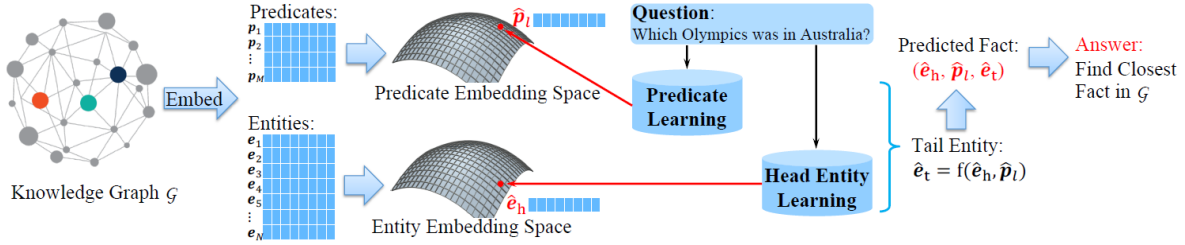


Fig 4. The KEQA framework

4.3. Neural Network based Reasoning

Currently, KR methods based on neural network models can be divided into Single Layer Model (SLM) and The Neural Tensor Network (NTN). SLM uses the standard single-layer neural network nonlinear standard to implicitly connect the entity vector triples to solve the problem that SE (Structured Embedding) cannot coordinate and accurately describe the semantic relationship between entities and relationships.

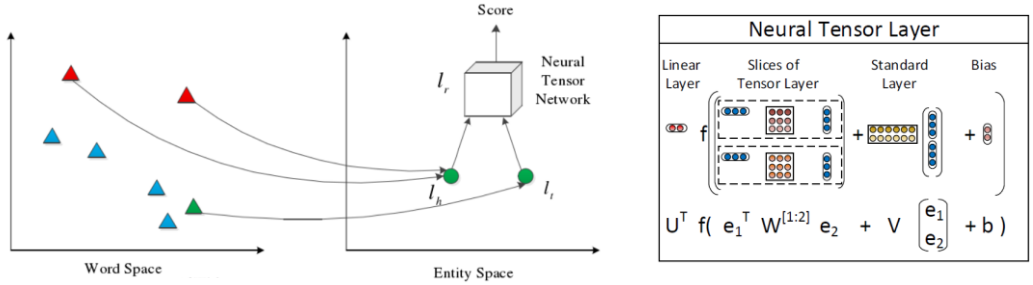


Fig 5. The Neural Tensor Network (NTN) model

Socher et al.[48]proposed the NTN. The main idea is to replace the standard linear neural network layer with a bilinear tensor layer, and to associate the head and tail entities across different dimensions to characterize the complex semantic connections between entities. The basic principle of NTN is shown in Figure 5.It is worth noting that although NTN can accurately describe the complex semantic connections between entities and relationships and alleviate the sparseness problem of entity representation learning, the computational complexity is very high, and a large number of triplet samples are needed to fully learn. Experiments show that NTN has a poor effect on large-scale sparse KGs.

Based on the research of SLM and NTN, Neelakantan et al. [49] use RNNs to compose the distributed semantics of multi-hop paths in KBs; however for multiple reasons, the approach lacks accuracy and practicality. Rajarshi Das et al.[50] using a neural attention model to introduce multiple paths of association for reasoning and show significant performance gains via multitasking. To preserve more original information, Qu Y et al. [51]proposed an attentive recurrent neural network with similarity matrix based convolutional neural network (AR-SMCNN) model, which is able to capture comprehensive hierarchical information utilizing the advantages of both RNN and CNN. Through research and comparison, CNN is good at extracting position in variant features and dealing with spatially related data, and RNN is good at modeling units in sequence and dealing with temporal signals.

4.4. Hybrid reasoning

Hybrid reasoning is based on the nature and characteristics of inference tasks, making full use of the advantages of different inference methods (such as high accuracy of PRA based reasoning, strong computing ability of representation learning based Reasoning and strong learning ability and generalization ability of neural network based reasoning), reasoning by mixing two or more inference methods.

The main recent research is as follows: Han et al.[52]proposed a graph-based representation method-a predictive graph model, to exploit semantic relevance by using predictive feature correlation statistics and semantic dependencies between abstract tuples. Wang et al.[53]aimed at the problem of not using logic rules and low accuracy in the embedded reasoning model, seamlessly embedding logic rules and physical rules in the representation model, formalizing the reasoning into an overall linear programming problem (ILP) . Guo et al.[54]coded the domain knowledge into simple rules, and proposed a rule-enhanced relational learning method for KBC. The core idea is to use the rules of domain knowledge to further refine the reasoning results provided by TransE and PRA. Lu K et al.[55] integrated logical-probabilistic KRR with model-based RL, enabling agents to simultaneously reason with declarative knowledge and learn from interaction experiences. Toutanova et al.[56] proposed a method for reasoning using a convolutional neural network to learn textual relationships. Xie R et al.[57]proposed the DKRL(description-embodied knowledge representation learning) which can use entity descriptions to improve inference. Wang H [58]proposed the Rule-embedded Neural Network (ReNN) to overcome the lack of interpretability and prerequisite needs of big dataset. Monireh Ebrahimi et al.[59] reviewed the history of reasoning combined with deep learning and logical rules, combined the transferability of classical deductive symbolic reasoning and robustness of neural-subsymbolic reasoning, and presented the construction of memory networks for emulating the symbolic deductive reasoning.

As shown in Table 1, this paper lists the current important embedding models.

5. Conclusions and further discussion

This article presented a brief overview of KR based on KG. Firstly, the thesis expounds the connotation and research scope of KR based on KG, and discusses the important role of KR in the whole KG framework system; Secondly, it judges the two research directions of current KR: KBC and QA-KG, and introduces the research results in these two directions; Thirdly, it summarizes the main technical methods of current KR technology; Finally, it summarize the KR based on KG and make some further discussion.

At present, the development level of KR is still in its infancy, and it is moving from simple low-level KR to complex high-level KR. This paper argues that the following difficulties and challenges are faced in the future development:

1. KR based on multi-source heterogeneous big data. The current KR mainly relies on structured and semi-structured text materials (or triples).In fact, the meaning of knowledge contains not only text, but also pictures, audio, video, etc., how to effectively fuse multi-source heterogeneous information and use it for KR will be the difficulty and direction of future research.

2. KR that mixes multiple inference methods. PRA based reasoning, representation learning based reasoning and neural network based reasoning all have their own advantages, how to effectively use their advantages, achieve deep integration, and improve the efficiency of reasoning will be a hot topic in the future.

3. KR Based on Dynamic KG. The facts and triples in the KGs change over time, so there are different inference results in different time coordinates. The good news is that many scholars are currently involved in it and have achieved remarkable results. Such as R Trivedi et al.[60], which present Know-Evolve, a novel deep evolutionary knowledge network that can effectively predicts occurrence or recurrence time of a fact.

4.Reasoning based on Event Evolutionary Graph(EEG). The EEG which consists of a static entity graph and a dynamic event logic graph is a new generation of dynamic KG with "event" as the core.

KGs have been intensively cultivated in various fields, gradually revealing value, but the form of knowledge representation needs to be broken, and the reasoning ability needs to be improved. Deep integration of KG and EEG will become a hot topic in future research.

Table 1. The current important embedding models(incomplete).

Model	Score function: $F_r(h, t)$	Which problem to solve
TransE[31]	$\|h+r-t\|_{1/2}^2, h,r,t \in \mathbb{R}^n$	Complexity
TransH[32]	$\left\|\left(h-w_r^T h w_r\right)+r-\left(t-w_r^T t w_r\right)\right\|_2^2, h,r,t,W_r \in \mathbb{R}^n$	N-1,1-N
TransR[33]	$\|W_r h+r-W_r t\|_2^2, h,t \in \mathbb{R}^n, r \in \mathbb{R}^k, W_r \in \mathbb{R}^{k\times n}$	Multidimensional space
CTransR[33]	$\|h_{r,c}+r_c-t_{r,c}\|_2^2+\alpha\|r_c-r\|_2^2, h,t \in \mathbb{R}^n, r \in \mathbb{R}^k, W_r \in \mathbb{R}^{k\times n}$	Multi-type
TransD[34]	$\left\|\left(I+w_r^T w_h\right)h+r-\left(I+w_r^T w_t\right)t\right\|_2^2, w_h, r \in \mathbb{R}^n, w_r, w_t \in \mathbb{R}^k$	Multi-type
TransA[[35]	$\left(h+r-t\right)^T W_r \left(h+r-t\right), h,r,t \in \mathbb{R}^d$	Loss function is too simple Dimensional weight
TransG[[36]	$\sum_{m=1}^{M_r} \pi_{r,m} e^{\frac{\|u_h+u_{r,m}-u_t\|_2^2}{\sigma_h^2+\sigma_t^2}}$, $\pi_{r,m}$: mixing factor	Multi-type
TransM[37]	$w_r \|h+r-t\|; r \in \mathbb{R}^d, w_r \in \mathbb{R}$	leverage the structure of knowledge graph
Transparse[38]	$\left\|W_r^h\left(\theta_r^h\right)v_h+v_r-W_r^t\left(\theta_r^t\right)v_t\right\|; W_r^h, W_r^t \in \mathbb{R}^{n\times k}$; $\theta_r^h, \theta_r^t \in \mathbb{R}; v_r \in \mathbb{R}^n$	Heterogeneity and imbalance
DKRL[57]	$E=E_s+E_D, E_s=\|h+r-t\|, E_D=E_{DD}+E_{DS}+E_{SD}$; $E_{DD}=\|h_d+r-t_d\|, E_{DS}=\|h_d+r-t_s\|, E_{SD}=\|h_s+r-t_d\|$	taking advantages of entity descriptions.
ConvE[40]	$v_t^{\mathrm{T}} g\left(vec\left(g\left(concat\left(\bar{v}_h, \bar{v}_r\right)*\Omega\right)\right)W\right)$	learn less expressive features
ConMask[40]	$W_{\phi(e)} \circ f_\omega\left(W_{\phi(e)}, W_{\psi(r)}\right), W_{\phi(e)} \in \mathbb{R}^{\|\phi(e)\|\times k}, W_{\psi(r)} \in \mathbb{R}^{\|\psi(r)\|\times k}$	open-world KGC task
ProjE[41]	$g\left(W^c f\left(e \oplus r\right)+b_p\right), W^c \in \mathbb{R}^{s\times k}$	complex feature space
RUGE[44]	$\mathrm{Re}\left(\sum_m [e_i]_m [r_k]_m \left[\bar{e}_j\right]_m\right), e_i, e_j, r_k \in \mathbb{C}^d$	Combine embedding learning with soft rules
TorusE[46]	$\min_{(x,y)\in([h]+[r])\times[t]} \|x-y\|_i, [h],[r],[t] \in T^n$	TransE's regularization
SimplE[29]	$\frac{1}{2}\left(\left\langle h_{ei}, v_r, t_{ej}\right\rangle+\left\langle h_{ej}, v_r-1, t_{ei}\right\rangle\right), h_e, t_e, v_r \in \mathbb{R}^d$	the independence of embedding vectors
Binarized CP Decomposition[30]	$\sum_{d\in[D]} a_{id}^{(b)} b_{jd}^{(b)} c_{kd}^{(b)}, a_{id}^{(b)}=Q\Delta\left(a_{id}\right), b_{jd}^{(b)}=Q\Delta\left(b_{jd}\right)$, $c_{kd}^{(b)}=Q\Delta\left(c_{kd}\right) \in \left(-\Delta, \Delta\right)$	Reduce the memory requirement

References

[1] Li ,Y et al. (2017) Intelligent Revolution - Meeting the Social, Economic and Cultural Changes in the Age of Artificial Intelligence. CITIC Publishing House, Beijing
[2] Spyros, M. (2017)The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. Futures, 90: 46–60.
[3] AMIT S: (2012) Introducing the knowledge graph. http://googleblog.blogspot.co.uk/2012/05/ introducing-knowledgegraph-things-not.html.
[4] Tennakoon C, Zaki N, Arnaout H, Elbassuoni S, Wassim E.H. (2019) Biological Knowledge Graph Construction, Search, and Navigation. Leveraging Biomedical and Healthcare Data. https://doi.org/10.1016/B978-0-12-809556-0.00007-1.

[5] Liu, J., Lu, Z., Du, W. (2019)Combining Enterprise Knowledge Graph and News Sentiment Analysis for Stock Price Volatility Prediction. In: Proceedings of the 52nd Hawaii International Conference on System Sciences. Hawaii. pp. 1247-1255.
[6] Li, Z., Ding, X., Liu, T. (2018)Constructing Narrative Event Evolutionary Graph for Script Event Prediction. In: Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence. Hong Kong. pp. 4201-4207.
[7] Rashkin, H., Bell, Eric., Choi, Y., Volkova, S. (2017) Multilingual Connotation Frames: A Case Study on Social Media for Targeted Sentiment Analysis and Forecast. In: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Short Papers).Vancouver .PP:459–464.
[8] Zeng, L., Li, Z., Wu, T. et al. (2017)Mapping Knowledge Domain Research in Big Data: From 2006 to 2016. Data Mining and Big Data, 2017:234-246.
[9] Zhao, J., Liu, Kang., He, S., Chen, Y. (2018) Knowledge Mapping. Higher Education Press, Beijing.
[10] Xie, G. (2018) Review of knowledge graph refinement. Application of Electronic Techniqu-e,44(9):29-33,38.
[11] Bordes, A., Gabrilovich, E. (2014)Constructing and Mining Web-scale Knowledge Graphs. In: Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. New York. pp. 1967–1967.
[12] K. Verbert, R. Babuška, B. De Schutter. (2017) Bayesian and Dempster-Shafer reasoning for knowledge-based fault diagnosis-A comparative study. Engineering Applications of Artificial Intelligence,vol.60:pp.136–150.
[13] KIM, J.,KIM, E K.,WON, Y., et al. (2018)The association rule mining system for acquiring knowledge of DBpedia from Wikipedia categories. http://semanticweb.kaist.ac.kr.
[14] Hao, Y., Zhang, Y., Liu, K.et al.(2017) An End-to-End Model for Question Answering over Knowledge Base with Cross-Attention Combining Global Knowledge. In: Annual Meeting of the Association for Computional Linguistics(ACL). Vancouver .pp. 221–231.
[15] Qiu, M., Li, F., Wang, S. et al.(2017)AliMe Chat: A Sequence to Sequence and Rerank based Chatbot Engine. In: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Short Papers). Vancouver .pp.498–503.
[16] Neves, M., Folkerts, H., Jankrift, M. et al. (2017) Olelo: A Question Answering Application for Biomedicine. In:Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics-System Demonstrations. Vancouver .pp. 61–66.
[17] Wang, X. et al. (2018) Mashup-Oriented API Recommendation via Random Walk on Knowledge Graph. Digital Object Identifier 10.1109/ACCESS.2018.2890156.VOLUME 7:7651-7662.
[18] Wolff, J. (2018) Commonsense Reasoning, Commonsense Knowledge, and The SP Theory of Intelligence. arXiv:1609.07772v2 [cs.AI] 4 Aug 2018.
[19] Lao, N. and William, W. (2010) Relational retrieval using a combination of path-constrained random walks. Machine Learning, 81(1):53–67.
[20] Gardner, M and Mitchell, Tom. (2015) Efficient and expressive knowledge base completion using subgraph feature extraction. In: Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing. Lisbon. pp. 1488–1498.
[21] Shi, B and Weninger, T. (2015)Fact checking in large knowledge graphs: A discriminative predict path mining approach. In arXiv:1510.05911.
[22] Wang, Q. et al (2016) Knowledge Base Completion via Coupled Path Ranking. In: Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics. Berlin. pp. 1308–1318.

[23] Liu, Q., Jiang, L., Han, M., Liu, Y., Qin, Z. (2016)Hierarchical random walk inference in knowledge graphs. In: Proc. of the 39th Int'l ACM SIGIR Conf. on Research and Development in Information Retrieval. New York. pp. 445.
[24] Zhang, Y., Dai, H., Kozareva, Z. et al.(2017) Variational Reasoning for Question Answering with Knowledge Graph. In: The Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18). Lousiana.pp.6069-6076.
[25] Chen, W., Xiong, W., Yan X.et al. (2018) Variational Knowledge Graph Reasoning. arXiv:1803.06581v3 [cs.AI] 23 Oct 2018.
[26] Xiong, W., Hoang, T. , Wang, Y. (2017)DeepPath: A Reinforcement Learning Method for Knowledge Graph Reasoning. In: Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing. Denmark .pp. 564–573.
[27] Nickel, M., Tresp, V., Kriegel, HP. (2011) A three-way model for collective learning on multi-relational data. In: Proc. of the 28th Int'l Conf. on Machine Learning. New York. pp. 809-816.
[28] Tay, Y., Luu, AT., Hui, SC., Brauer, F.(2017) Random semantic tensor ensemble for scalable knowledge graph link prediction. In: Proc. of the10th ACM Int'l Conf. on Web Search and Data Mining. New York. pp. 751-760.
[29] Seyed, MK., David, P. (2018) SimplE Embedding for Link Prediction in Knowledge Graphs. In:32nd Conference on Neural Information Processing Systems (NeurIPS 2018), Montréal. pp.1-12.
[30] Koki, K. et al. (2019)Binarized Knowledge Graph Embeddings. arXiv:1902.02970v1 [cs.LG] 8 Feb 2019.
[31] Bordes, A. et al. (2013) Translating embeddings for modeling multi-relational data. In: Proc. of the Advances in Neural Information Processing Systems. Red Hook .pp. 2787-2795.
[32] Wang, Z., Zhang, J., Feng, J., Chen, Z. (2014) Knowledge graph embedding by translating on hyperplanes. In: Proc. of the 28th AAAI Conf. on Artificial Intelligence. Menlo Park. pp. 1112-1119.
[33] Lin, Y., Liu, Z., Sun, M., Liu, Y., Zhu, X. (2015) Learning entity and relation embeddings for knowledge graph completion. In: Proc. of the 29th AAAI Conf. on Artificial Intelligence. Menlo Park. pp. 2181-2187.
[34] Ji, G., He, S., Xu, L., Liu ,K., Zhao, J. (2015) Knowledge graph embedding via dynamic mapping matrix. In: Proc. of the 53rd Annual Meeting of the Association for Computational Linguistics. Stroudsburg. pp. 687-696.
[35] Jia, Y., Wang, Y., Lin, H., Jin, X., Cheng, X.(2016)Locally adaptive translation for knowledge graph embedding. In: Proc. of the 30th AAAI Conf. on Artificial Intelligence. Menlo Park. pp. 992-998.
[36] Xiao, H., Huang, M., Hao, Y., Zhu, X. (2015)TransG: A generative mixture model for knowledge graph embedding. arXiv Preprint arXiv:150905488, 2015.
[37] Fan, M., Zhou, Q., Chang, E., Zheng, TF. (2014)Transition-Based knowledge graph embedding with relational mapping properties. In: Proc. Of the 28th Pacific Asia Conf. on Language, Information and Computation. Stroudsburg. pp. 328-337.
[38] Nguyen, DQ.(2017) An overview of embedding models of entities and relationships for knowledge base completion. arXiv preprint arXiv:1703.08098, 2017.
[39] Dettmers, T., Minervini, P., Stenetorp, P., and Riedel, S. (2017) Convolutional 2d knowledge graph embeddings.arXiv preprint arXiv:1707.01476.
[40] Shi, B. , Weninger, T. (2017) Open-world knowledge graph completion. arXiv:1711. 03438v1 [cs.AI] 9 Nov 2017.
[41] Shi, B., Weninger, T.(2017)ProjE: Embedding projection for knowledge graph completion. In: Proc. of the 31st AAAI Conf. on Artificial Intelligence. Menlo Park. pp. 1236-1242.

[42] Lin, Y., Liu, Z., Sun, M.(2017) Knowledge Representation Learning with Entities, Attributes and Relations. In: Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence (IJCAI-16). New York.pp.2866-2872.
[43] Kristiadi, A., Khan, MA., Lukovnikov, D., Lehmann, J. (2018) Incorporating Literals into Knowledge Graph Embeddings. arXiv:1802.00934v2 [cs.AI] 25 May 2018.
[44] Guo, S., Wang, Q., Wang, L. et al.(2018) Knowledge graph embedding with iterative guidance from soft rules. In: Proceedings of the 32nd AAAI Conference on Artificial Intelligence. Louisian. pp. 4816–4823.
[45] Ding, B., Wang, Q., Wang, B. et al. (2018) Improving Knowledge Graph Embedding Using Simple Constraints. arXiv:1805.02408v2 [cs.AI] 8 May 2018.
[46] Ebisu, T., Ichise, R. (2018)TorusE: Knowledge Graph Embedding on a Lie Group. arXiv: 1711.05435vl[cs.AI] 15 Nov 2017.
[47] Huang, X., Zhang, J., Li D. et al.(2019)Knowledge Graph Embedding Based Question Answering. In: The Twelfth ACM International Conference on Web Search and Data Mining (WSDM '19) . Melbourne. pp. 11-15.
[48] SOCHER, R.,CHEN, D.,MANNING, C D.et al. (2013)Reasoning with neural tensor networks for knowledge base completion. https://www.cnblogs.com/wuseguang/p/4168963.html.
[49] Neelakantan, A., Roth, B., McCallum, A. (2015)Compositional Vector Space Models for Knowledge Base Inference. In: 2015 AAAI Spring Symposium. California.pp.31-34.
[50] Das, R., Neelakantan, A., Belanger, D., McCallum, Andrew. (2017)Chains of Reasoning over Entities, Relations, and Text using Recurrent Neural Networks. arXiv:1607.01426v3 [cs.CL] 1 May 2017.
[51] Qu, Y., Liu, J., Kang, L. et al.(2018) Question Answering over Freebase via Attentive RNN with Similarity Matrix based CNN. arXiv preprint arXiv:1804.03317, 2018.
[52] Han, X., Le, S. (2016) Context-Sensitive inference rule discovery: A graph-based method. In: Proc. of the 26-th Int'l Conf. on Computational Linguistics. Stroudsburg. pp. 2902-2911.
[53] Wang, Q., Wang, B., Guo, L. (2015) Knowledge base completion using embeddings and rules. In: Proc. of the 24th Int'l Joint Conf. on Artificial Intelligence. San Francisco. pp. 1859-1866.
[54] Guo, S., Ding, B., Wang, Q., Wang, L., Wang, B. (2016) Knowledge Base Completion via Rule-Enhanced Relational Learning. Springer-Verlag, CCIS 650: 219–227.
[55] Lu, K., Zhang, S., Peter, S., Chen, X.(2018) Robot Representation and Reasoning with Knowledge from Reinforcement Learning. arXiv:1809.11074v3 [cs.AI] 22 Nov 2018.
[56] Toutanova, K., Chen, D., Pantel, P., Poon, H., Choudhury, P., Gamon, M. (2015) Representing text for joint embedding of text and knowledge bases. In: Proc. of the Conf. on Empirical Methods in Natural Language Processing. Stroudsburg. pp. 1499-1509.
[57] Xie, R., Liu, Z., Jia, J., Luan, H., Sun, M. (2016)Representation learning of knowledge graphs with entity descriptions. In: Proc. of the 30th AAAI Conf. on Artificial Intelligence. Menlo Park. pp. 2659-2665.
[58] Wang, H. (2018) ReNN: Rule-embedded Neural Networks.https://m.doc88.com/p-786355482 1684.html.
[59] Monireh, E., Sarker, MK., Bianchi, F. et al (2018) REASONING OVER RDF KNOWLEDGE BASES USING DEEP LEARNING. arXiv:1811.04132v1 [cs.LG] 9 Nov 2018.
[60] Rakshit, T. et al. (2017)Know-Evolve: Deep Temporal Reasoning for Dynamic Knowledge Graphs. arXiv:1705.05742v3 [cs.AI] 21 Jun 2017.