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Guest Editorial

Knowledge graph representation and reasoning

1. Introduction

Recent years have witnessed the release of many open-source and enterprise-driven knowledge graphs with a dramatic increase of applications of knowledge representation and reasoning in fields such as natural language processing, computer vision, and bioinformatics. With those large-scale knowledge graphs, recent research tends to incorporate human knowledge and imitate human's ability of relational reasoning [1]. Factual knowledge stored in knowledge bases or knowledge graphs can be utilized as a source for logical reasoning and, hence, be integrated to improve real-world applications [2–6].

Emerging embedding-based methods for knowledge graph representation have shown their ability to capture relational facts and model different scenarios with heterogenous information [7]. By combining symbolic reasoning methods or Bayesian models, deep representation learning techniques on knowledge graphs attempt to handle complex reasoning with relational path and symbolic logic and capture the uncertainty with probabilistic inference [8,9]. Furthermore, efficient representation learning and reasoning can be one of the paths towards the emulation of high-level cognition and human-level intelligence. Knowledge graphs can also be seen as a means to tackle the problem of explainability in AI. These trends naturally facilitate relevant downstream applications which inject structural knowledge into wide-applied neural architectures such as attention-based transformers and graph neural networks [10,11].

2. Contents of the special issue

This special issue focused on emerging techniques and trendy applications of knowledge graph representation learning and reasoning in fields such as natural language processing, computer vision, bioinformatics, and more. We received 31 valid paper submissions for this special issue. After several rounds of rigorous reviews and revisions, we decided to publish 11 of them.

The first article is entitled "Topic Analysis and Development in Knowledge Graph Research: A Bibliometric Review on Three Decades" [12] and opens the special issue with an overview of knowledge graph research from 1991 to 2020 based on 386 research articles. Authors conducted the analysis in terms of (1) visualization of the trends of annual article and citation counts, (2) recognition of major institutions, countries/regions, and publication sources, (3) visualization of scientific collaborations of major institutions and countries/regions, and (4) detection of major research themes and their developmental tendencies.

Next, "Learning Graph Attention-Aware Knowledge Graph Embedding" [13] proposes a graph-attention-based model to encode entities, which formulates a knowledge graph as an irregular graph and explores a number of concrete and interpretable knowledge compositions by integrating the graph-structured information via multiple independent channels. To measure the correlation between entities from different angles (i.e., entity pair, relation, and structure), authors develop three attention metrics.

The article "Trans4E: Link Prediction on Scholarly Knowledge Graphs" [14] presents Trans4E, a novel embedding model that is particularly fit for knowledge graphs which include N to M relations with N≫M. This is typical for knowledge graphs that categorize a large number of entities (e.g., research articles, patents, persons) according to a relatively small set of categories. Trans4E was applied on two large-scale knowledge graphs, the Academia/Industry DynAmics (AIDA) and Microsoft Academic Graph (MAG), for completing the information about Fields of Study (e.g., 'neural networks', 'machine learning', 'artificial intelligence'), and affiliation types (e.g., 'education', 'company', 'government'), improving the scope and accuracy of the resulting data.

In "A Generative Adversarial Network for Single and Multi-Hop Distributional Knowledge Base Completion" [15], the authors propose a novel framework, termed Knowledge Completion GANs (KCGANs), for competitively training generative link prediction models against discriminative belief prediction models. KCGAN invokes a game between generator-network G and discriminator-network D in which G aims to understand underlying knowledge base structure by learning to perform link prediction while D tries to gain knowledge about the knowledge base by learning predicate/triplet classification.

"Distant Supervised Relation Extraction with Position Feature Attention and Selective Bag Attention" [16] proposes a novel rela-

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tion extraction method with position feature attention and selective bag attention. The position feature attention is employed to obtain the weighted sentence representation with different position features by calculating all position combinations of the target entity pair. A bag with large noise and a bag with small noise are selected through the selective bag attention mechanism to form a bag pair, and training is performed at the level of the bag pair, which denoises at the bag level and at the same time balances the noise between different bag pairs.

The work "PILHNB: Popularity, Interests, Location used Hidden Naive Bayesian-based model for Link Prediction in Dynamic Social Networks" [17] proposes a modified Latent Dirichlet Allocation (LDA), and Hidden Naive Bayesian (HNB) based link prediction technique named PILHNB model for link prediction in dynamic social networks by considering behavioral controlling elements like relationship network structure, nodes' attributes, location-based information of nodes, nodes' popularity, users' interests, and learning the evolution pattern of these factors in the networks. Experimental results on six real-world networks demonstrate the proposed models' effectiveness and efficiency compared with existing state-of-the-art link prediction techniques.

In "Target Relational Attention-oriented Knowledge Graph Reasoning" [18], the authors design a target relational attention-oriented reasoning model, which focuses more on the relations that match the target relation. They propose a hierarchical (node-level and relational subgraph-level) attention mechanism to aggregate the information of multi-hop neighbors, and to thereby obtain a better node-embedding representation, (with high- order propagation characteristics). The mechanism also relieves over-smoothing to a certain extent. Node-level information aggregation uses the classical graph-attention mechanism, and the distribution of attention in the subgraph-level information aggregation is determined according to the relation in the reasoning task.

The article "A Subgraph-based Knowledge Reasoning Method for Collective Fraud Detection in E-commerce" [19] proposes a subgraph-based method named SubGNN for collective fraud detection. In SubGNN, first, authors extract the subgraphs around the given edges (user behaviors) to be tested. Then, they remove nodes' global IDs so that SubGNN is entity-independent. Finally, by learning knowledge reasoning rules on extracted heterogeneous subgraphs using the proposed relational graph isomorphism network (R-GIN), SubGNN can achieve precise fraud detection. Experiments are conducted on publicly available Amazon and Yelp datasets and a newly collected Taobao dataset.

Next, "Multi-modal Entity Alignment in Hyperbolic Space" [20] proposes a novel multimodal entity alignment approach, Hyperbolic multi-modal entity alignment (HMEA), which extends the Euclidean representation to hyperboloid manifold. Authors first adopt the Hyperbolic Graph Convolutional Networks (HGCNs) to learn structural representations of entities. Regarding the visual information, they generate image embeddings using the densenet model, which are also projected into the hyperbolic space using HGCNs. Finally, authors combine the structure and visual representations in the hyperbolic space and use the aggregated embeddings to predict potential alignment results.

The work entitled "DSKRL: A Dissimilarity-Support-aware Knowledge Representation Learning Framework on Noisy Knowledge Graph" [21] proposes a dissimilarity-support-aware knowledge representation learning framework, which accomplishes knowledge representation learning and noise detection simultaneously. Specifically, authors introduce triple dissimilarity and triple support to construct the model energy function which is based on translation-based methods. The triple dissimilarity measures the matching extent of entities and relations in triples and the triple support measures the credibility of the matching extent. In order to make triple dissimilarity and triple support estimation effective and comprehensive, authors synthesize structural information and auxiliary information (entity hierarchical type and relation path information) in triple dissimilarity and triple support.

Finally, the work entitled "Identification of Drug-Target Interactions via Multi-view Graph Regularized Link Propagation Model" [22] concludes the special issue with a study on computational approaches to drug-target interaction detection. In order to solve the problem of multiple information fusion, authors propose a multi-view graph regularized link propagation model (Mv-GRLP) to predict new drug-target interactions. Multi-view learning could use the complementary and correlated information between different views (features). Compared with existing models, their method achieves comparable and best results on four benchmark datasets.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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