Abstract

In the 1960s, a prototype of the knowledge graph was proposed to enable formal reasoning and code representations of knowledge. Decades of development followed, with particularly significant progress in the past ten years. The release of large-scale knowledge graphs and the springing up of powerful embedding models have sparked the enthusiasm of researchers. Today, knowledge graphs are being applied in many fields, including natural language processing, autonomous driving, biology, and finance.

Knowledge graph representation learning, also known as knowledge graph embedding, aims to represent a knowledge graph using a set of vectors and matrices in a low-dimensional vector space. This is essential for utilizing knowledge graphs in deep learning models. Currently, most available knowledge graph embedding models only embed entities and relations using the triples provided by the knowledge graphs. This approach does not make full use of available resources. However, some knowledge graph representation models have been proposed to learn knowledge graph embeddings using not only the facts in the knowledge graph but also additional useful information, such as entity type, entity description, and logic rules.

In many scenarios, the interactions between entities are inherently associated with different uncertainties, frequencies, or intensities. For example, the interaction possibility between two proteins and the importance of friends in a social network can vary greatly. Weighted knowledge graphs extend deterministic knowledge graphs by associating a weight with the triples to formalize the weighted interactions between entities. Many weighted knowledge graphs have been published, which has led to an increased focus on the weighted knowledge graph and its embeddings.

Our research focuses on two main areas: learning better representations from weighted knowledge graphs, and utilizing these representations in downstream tasks. To improve representations from weighted knowledge graphs, we explore *weight-aware knowledge graph embedding* and *weighted knowledge graph embedding*. Weight-aware knowledge graph embedding involves learning embeddings for a deterministic knowledge graph with the aid of weight information from triples. However, the learned embedding cannot deduce the weight of the triple. On the other hand, weighted knowledge graph embedding is used to embed the weighted knowledge graph, with the ability to deduce not only the triples but also their weights.

To extend the existing embedding models for deterministic knowledge graphs to learn weight-aware embeddings and weighted embeddings from weighted knowledge graphs, we propose two general frameworks, *WaExt* and *WeExt*, respectively. To evaluate the learned embeddings from weighted knowledge graphs, we introduce two evaluation tasks, *weight-aware link prediction* and *weight-aware triple classification* for weight-aware knowledge graph embedding, and *weighted link prediction* for weighted knowledge graph embedding. For utilizing the representations in downstream tasks, we propose a framework *KGWE* to fine-tune word embeddings using knowledge graph embeddings.

The three proposed frameworks outperform the baselines on the target tasks, indicating their effectiveness in improving the performance of knowledge graph embeddings. Furthermore, the evaluation tasks introduced in this study provide a more comprehensive evaluation of these embeddings.

Keywords: Artificial Intelligence, Weighted Knowledge Graph, Knowledge Graph Embedding, Evaluation Tasks, Word Embedding.