HousE: Knowledge Graph Embedding with Householder Parameterization

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Abstract

The effectiveness of knowledge graph embedding (KGE) largely depends on the ability to model intrinsic relation patterns and mapping properties. However, existing approaches can only capture some of them with insufficient modeling capacity. In this work, we propose a more powerful KGE framework named HousE, which involves a novel parameterization based on two kinds of Householder transformations: (1) *Householder rotations* to achieve superior capacity of modeling relation patterns; (2) *Householder projections* to handle sophisticated relation mapping properties. Theoretically, HousE is capable of modeling crucial relation patterns and mapping properties simultaneously. Besides, HousE is a generalization of existing rotation-based models while extending the rotations to high-dimensional spaces. Empirically, HousE achieves new state-of-the-art performance on five benchmark datasets. Our code is available at `https://github.com/anrep/HousE`.

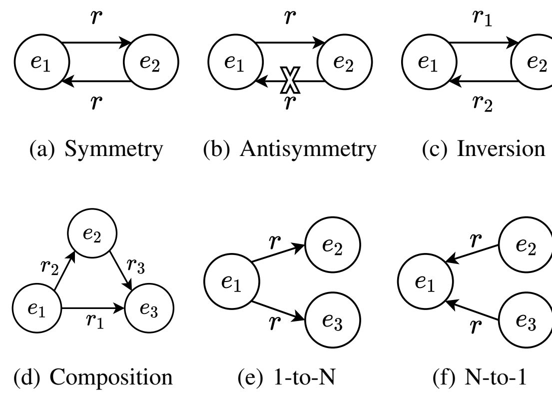

Figure 1. Illustrations of four relation patterns (a-d) (Sun et al., 2019) and two challenging RMPs (e-f) (Bordes et al., 2013).

1. Introduction

Knowledge graphs (KGs) store massive human knowledge as a collection of factual triples, where each triple (h, r, t) represents a relation r between head entity h and tail entity t. With a wealth of human knowledge, KGs have demonstrated their effectiveness in a myriad of downstream applications (Xiong et al., 2017). However, real-world KGs such as Freebase (Bollacker et al., 2008) and Yago (Suchanek et al., 2007)) usually suffer from incompleteness. Knowledge Graph Embedding (KGE), which learns low-dimensional representations for entities and relations, excels as an effective tool for predicting missing links.

A crucial challenge of KGE lies in how to model relation patterns (e.g., symmetry, antisymmetry, inversion and composition) and relation mapping properties (RMPs, i.e., 1-to-1, 1-to-N, N-to-1 and N-to-N) (Bordes et al., 2013; Sun et al., 2019) as shown in Figure 1. Most works design specific vector spaces and operations to capture such patterns and RMPs. For example, TransE (Bordes et al., 2013) represents relations as translations, which fails in modeling symmetry and RMPs. Recently, RotatE (Sun et al., 2019) represents relations as rotations in the complex plane to model the four relation patterns, but it is incapable of handling RMPs due to the distance-preserving property of rotations. Rotate3D (Gao et al., 2020) and QuatE (Zhang et al., 2019) introduce quaternions to extend rotations to 3-dimensional and 4-dimensional spaces, and achieve better performance with larger model capacity.

However, as far as we know, none of the existing methods is capable of modeling all the relation patterns and RMPs as shown in Table 1, leading to the sub-optimal performance. Furthermore, some advanced approaches, such as (Sun et al., 2019; Gao et al., 2020; Zhang et al., 2019), are specifically designed on 2,3,4 dimensional spaces, which may be inadequate to capture the sophisticated structures of KGs (Zhang et al., 2019). Therefore, this brings us a question: *is there*

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