Name: Bharghav Srikhakollu

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Topic:

Low-Dimensional Knowledge Graph Embeddings via Hyperbolic Rotations

https://grlearning.github.io/papers/101.pdf

What is the problem discussed in the paper?

In Knowledge Graphs, for encoding the entities and relationships in the graphs, the common approach followed is embeddings into vector spaces which yields very good results but with little use of memory, it is difficult to preserve the complex relationships.

By increasing the dimensionality, the expressiveness of embeddings is improved which in turn helped in expanding the memory that is useful to store the knowledge graphs. In place of Euclidean space, hyperbolic space is used where the hyperbolic geometry resembles the continuous version of trees. Yet, the approach is limited to simpler graphs like weighted trees but cannot be extended to work on complex and diverse relationships in knowledge graphs.

Why is it important?

In Current approaches, the two main problems are as below.

1. Preserving all relational patterns in the embedding space is challenging.
2. Euclidean embeddings require large dimensions i.e., high memory.

So, it is very important to bring a new approach which takes the important properties in the existing approaches and build on top it.

What are the main ideas of the proposed solution for the problem?

In the proposed approach, it takes the best aspects of the existing approaches. It can seek the representations presented by hyperbolic space along with transformations that are needed to infer logical patterns in knowledge graphs. To make this possible, they have parametrized rotations and translations of hyperbolic space which enabled them to learn relationship specific hyperbolic transformations. For optimizing the hyperbolic models, they applied techniques like trainable curvature and tangent space optimization. The basic model is the embeddings in the hyperbolic space with trainable curvatures which involves the attention based relational operators. During the hyperbolic rotations and reflections, they concluded that rotations could encode logical properties which is antisymmetric whereas reflections can encode symmetry. Hyperbolic rotations and reflections around the origin are isometries.

In the final output of the experiment, they observed that the new approach outperforms existing methods in low dimensions, and it works in both low and high dimensional regimes. Also, the approach has flexible representations to capture logical patterns.

Reference citation: https://www.youtube.com/watch?v=Yf03-CBYKe4