A neuro-symbolic framework for answering conjunctive queries $^{\rm 1}$

Pablo Barceló a, Tamara Cucumides b, Floris Geerts b, Juan Reutter a, Miguel Romero a

^a Pontificia Universidad Católica de Chile {pbarcelo,jreutter,mgromero}@uc.cl ^b University of Antwerp {tamara.cucumidesfaundez,floris.geerts}@uantwerp.be

The challenge of answering logical queries over incomplete knowledge graphs has attracted recent attention in the machine learning community. Neuro-symbolic models are a promising recent approach both for their notable performance and for allowing interpretability results. Most of these methods are, however, limited to a specific type of queries: tree-like queries, where the leaves are entities (anchors). This query type falls short in capturing important properties in knowledge graphs, such as the existence of multiple edges between entities or the presence of triangles. Our goal is to address this limitation by proposing a versatile framework capable of handling arbitrary conjunctive queries over incomplete knowledge graphs.

Our strategy is to approximate general (possibly cyclic) queries by a family of tree-like queries. This allows us to have a generic framework and leverage the performance of existing methods. Furthermore, our approximations enjoy robust guarantees—they are complete, ensuring no false negatives, and optimal, providing the best approximation achievable through tree-like queries. Our implementation is based on GNN-QE [1], a neuro-symbolic architecture that processes anchored tree-like queries in a bottom-up fashion. Anchored leaf nodes are encoded as one-hot vectors, and edges between entities are processed using NBFNet [2]. In order to further increase the types of queries that the model can deal with, we extended GNN-QE to support unanchored queries by encoding unanchored leaves as all-ones vectors.

The experiments show that (1) our approximation framework achieves competitive results for cyclic queries and (2) neural query processors that encode entities as one-hot vectors can be easily extended to unanchored queries

References

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