

Parameterized Fuzzy Negation for Complex Query Answering over Knowledge Graphs

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Abstract

Answering complex queries on incomplete knowledge graphs remains a challenging yet crucial task. Prior research has demonstrated that neural link predictors, primarily trained on single-hop queries, can effectively answer complex queries requiring multi-hop reasoning, including those involving both disjunctive and conjunctive logical operations. Apart from these two logical operators, negation also appears often in the queries. While there exist works focusing on performing multi-hop reasoning on complex queries, only a few of them consider the negation operation in queries. In this work, we bridge this gap by introducing novel, parameterized negation operations to answer queries that involve negations. To handle these complex queries, we propose two parameterized fuzzy logic norms, specifically, Sugeno and Yager. Our experiments on four datasets with five link predictors show that using Sugeno and Yager consistently improves the performance across models and datasets.

Keywords

Knowledge graphs, Multi-hop question answering, Fuzzy operators

1. Introduction

Knowledge graphs (KGs) are widely used as structured representations of factual knowledge in applications such as web search, question answering, recommendation, and social media analytics. Despite their widespread use, a common and persistent limitation of KGs is incompleteness, i.e., many valid links between entities are missing from the graph. To address this problem, neural link predictors have been widely applied for KG completion. These models learn continuous representations of entities and relations and use them to assign plausibility scores to candidate triples, thereby enabling the prediction of missing links [1]. While link predictors have achieved strong performance on standard link prediction benchmarks, many real-world information needs go beyond predicting a single missing triple. In particular, web search and question-answering systems often require answering *complex queries* that involve multiple relations, intermediate variables, and logical operators such as conjunction, disjunction, and negation. Such queries require models that can reason over several hops in the graph and combine the scores of multiple subqueries in a logically meaningful way.

Several approaches have therefore been proposed for complex query answering over KGs using neural link predictors [2, 3, 4, 5]. Among these, methods based on fuzzy logic have received considerable attention, since they provide differentiable operators for modeling logical conjunctions, disjunctions, and negations over continuous link prediction scores [2, 3]. A prominent example is continuous query decomposition (CQD) proposed by Arakelyan et al. [4]. However, despite its effectiveness, the original formulation of CQD has important limitations and struggles with queries that contain negation. Recently, Arakelyan et al. [6] proposed adaptive CQD (CQD^A) [6], which improves the handling of negated queries by adapting fuzzy operators to query answering. Nevertheless, CQD^A introduces additional computational overhead by calibrating link prediction scores on a query dataset, and it still relies on the so-called standard negation norm for modeling negated subqueries.

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In this work, we extend the CQD framework for complex query answering with negation by incorporating parameterized nonlinear fuzzy negation operators. We focus on two representative operators, namely Sugeno and Yager negation norms, and use them as alternatives to standard negation within the CQD framework. Unlike CQD^A, our approach does not require learning an additional calibration layer or training on complex queries. Instead, each parameterized negation operator introduces only a single scalar hyperparameter for Sugeno and for Yager—which is selected through grid search on held-out validation data for each model, dataset, and query type. This keeps the method lightweight while allowing the negation behavior to adapt to the underlying link predictor. We evaluate the proposed approach with five neural link predictors across different multi-hop query types involving negation. Our results show that parameterized fuzzy negation can improve the handling of negated queries and provide strong performance without sacrificing the training-free nature of CQD.

2. Background & Related Work

Knowledge Graphs & Embeddings. A KG is a structured representation of information within a specific domain, consisting of a set of assertions that connect entities through relationships. These assertions are typically represented as *triples* in the form $\langle h, r, t \rangle \in \mathcal{E} \times \mathcal{R} \times \mathcal{E}$, where $\mathcal{E}$ denotes a discrete set of entities and $\mathcal{R}$ denotes a discrete set of relations. Despite their utility, KGs are difficult to process directly due to their discrete nature. To address this, knowledge graph embedding (KGE) algorithms have been developed. These algorithms transform the knowledge contained within a KG into a continuous, low-dimensional vector space, enabling more efficient computation. Let $\mathbb{V}$ represent a normed-division algebra, such as $\mathbb{R}$, $\mathbb{C}$, $\mathbb{H}$, or $\mathbb{O}$ [7, 8, 9, 10, 11]. In a KGE model, the embeddings for entities and relations are given by $\mathbf{E} \in \mathbb{V}^{|\mathcal{E}| \times d_e}$ and $\mathbf{R} \in \mathbb{V}^{|\mathcal{R}| \times d_r}$, where d_e and d_r denote the dimensionality of the entity and relation embeddings, respectively. For simplicity, we use d to represent the embedding size across all vectors. KGEs models are also termed as *neural link predictors* and play a pivotal role in addressing data sparsity in incomplete KGs by assigning plausibility scores to candidate triples. This task is typically formulated through a scoring function $\phi_\Theta : \mathcal{E} \times \mathcal{R} \times \mathcal{E} \rightarrow \mathbb{R}$, where Θ represents the model parameters, which often include the entity embeddings $\mathbf{E}$, the relation embeddings $\mathbf{R}$, and additional parameters such as affine transformations, batch normalizations, and convolutions. For a given relation r , we write ϕ_Θ^r for the relation-specific scoring function that assigns a score to the triple $\langle h, r, t \rangle \in \mathcal{E} \times \mathcal{R} \times \mathcal{E}$, indicating whether the relation r exists between h and t . More formally, $\hat{y} = \phi_\Theta(\langle h, r, t \rangle) = \phi_\Theta^r(h, t)$, where $\hat{y}$ denotes the predicted score. Typically, the value of $\hat{y}$ lies in $[0, 1]$.

Complex Multi-hop Query Answering. Multi-hop query answering over KGs is a complex task, extending beyond KG completion to encompass queries with logical operators including conjunctions and disjunctions. Recent studies have introduced innovative approaches using neural-symbolic processors, which combine the pattern recognition of neural networks with the structured reasoning of symbolic logic. These processors can be categorized into geometric, probabilistic, and fuzzy logic based on their method of modelling logical operations [5]. Examples include Query2Box [12] using geometric computations, BetaE [13] employing probabilistic embeddings, and LogicE [3] applying fuzzy logic for logical operations. These models primarily embed the complex queries and learn the embeddings which can be resource intensive. Addressing this challenge, Continuous Query Decomposition (CQD) [4] was introduced. This approach answers Extended Positive First-Order (EPFO) queries by breaking them down into simpler single-hop subqueries, evaluating each subqueries using a pre-trained link predictor such as ComplEx-N3, and combining the resulting scores using fuzzy-logic operators. Specifically, CQD uses t-norms and t-conorms to model conjunction and disjunction, respectively. In subsequent work, CQD was extended to support queries involving numeric literal values [14] and CQD’s answers were explained in terms of Shapley values [15].

3. Query Answering with Conjunction, Disjunction, and Negation

Queries with Negations. An existential first-order logical query Q on a KG involving conjunction, disjunction, and *negations* can be written in disjunctive normal form as

$$Q = E_? . \exists E_1, \dots, E_m : (a_1^1 \wedge \dots \wedge \neg a_{n_1}^1) \vee \dots \vee (a_1^d \wedge \dots \wedge \neg a_{n_d}^d), \quad (1)$$

where

- $a_i^j = p(e, E)$, with $E \in \{E_?, E_1, \dots, E_m\}$, $p \in \mathcal{R}$, $e \in \mathcal{E}$ or
- $a_i^j = p(E, E')$, with $E, E' \in \{E_?, E_1, \dots, E_m\}$, $E \neq E'$, $p \in \mathcal{R}$ or
- $\neg a_i^j = \neg p(e, E)$, with $E \in \{E_?, E_1, \dots, E_m\}$, $p \in \mathcal{R}$, $e \in \mathcal{E}$ or
- $\neg a_i^j = \neg p(E, E')$, with $E, E' \in \{E_?, E_1, \dots, E_m\}$, $E \neq E'$, $p \in \mathcal{R}$

Further, $p : \mathcal{E} \times \mathcal{E} \mapsto \{1, 0\}$ indicates whether a relation exists between two entities whereas $\neg p$ denotes its negation. The query's target variable $E_?$ and existentially quantified variables $E_1, \dots, E_m$ are bound to subsets of entities of the given KG. We follow the combinatorial optimisation technique [4, 14] to answer the query in Equation 1 by translating it into a greedy optimization problem as

$$\arg \max_{E_?, E_1, \dots, E_m} (a_1^1 \top \dots \top \neg a_{n_1}^1) \perp \dots \perp (a_1^d \top \dots \top \neg a_{n_d}^d) \quad (2)$$

where

- $a_i^j = \phi_{\Theta}^{r_i}(e, E)$, with $E \in \{E_?, E_1, \dots, E_m\}$, $p \in \mathcal{R}$, $e \in \mathcal{E}$ or
- $a_i^j = \phi_{\Theta}^{r_i}(E, E')$, with $E, E' \in \{E_?, E_1, \dots, E_m\}$, $E \neq E'$, $p \in \mathcal{R}$ or
- $\neg a_i^j = \neg(\phi_{\Theta}^{r_i}(e, E))$, with $E \in \{E_?, E_1, \dots, E_m\}$, $p \in \mathcal{R}$, $e \in \mathcal{E}$ or
- $\neg a_i^j = \neg(\phi_{\Theta}^{r_i}(E, E'))$, with $E, E' \in \{E_?, E_1, \dots, E_m\}$, $E \neq E'$, $p \in \mathcal{R}$.

Here, $\top$ denotes a triangular norm (t-norm), i.e., a function $\top : [0, 1] \times [0, 1] \mapsto [0, 1]$ that provides a continuous generalization of the logical conjunction [16, 17]. We utilize t-norms to combine the link prediction scores from multiple atoms within a conjunctive clause.

Parameterized Fuzzy Negation Norms. A fuzzy negation norm is a function $\neg : [0, 1] \mapsto [0, 1]$ [18] that maps a score to the score of its negation. For queries involving negation, in this paper, we explore a range of negation norms. Specifically, we investigate the parameterized Sugeno and Yager norm in addition to the non-parameterized standard negation [18]. The standard negation is defined as $N(x) = 1 - x$, where $x \in \mathbb{R}$. The Sugeno and Yager negation norms are defined as

$$N_{\lambda}(x) = \frac{1 - x}{1 + \lambda x}, \quad \lambda > -1 \quad (3)$$

$$N_w(x) = (1 - x^w)^{1/w}, \quad (4)$$

where $\lambda, w \in \mathbb{R}$ denote parameters of the Sugeno and Yager negation norms, respectively.

4. Experiments

Experimental Setup. We consider several benchmark knowledge graphs in our evaluation. Among the smaller knowledge graphs, the UMLS [19] includes 135 medical entities connected by 46 distinct relations, capturing various medical concepts and their relationships. KINSHIP [20] focuses on the kinship dynamics of the Alyawarra tribe, consisting of 25 unique relationship types that model familial connections. The larger NELL-995 [21] and FB15k-237 [22] are subsets of the Never-Ending Language Learning dataset and Freebase [23], respectively. For query generation, we leverage the query sampler

from SNAP [13]. We experiment with the knowledge graph embedding models DistMult, ComplEx, QMult, Keci, and MuRE. We evaluate the five negated query structures 2in, 3in, pin, pni, and inp. We use beam sizes $k \in \{2, 4, 8, 16, 32\}$, except for the projection-containing query structures pin, pni, and inp on the larger NELL-995 and FB15k-237 datasets, for which we restrict the beam size to $k \in \{2, 4, 8\}$ due to the substantially higher computational cost. We also utilize two different t-norms namely: Gödel (min) and product (prod). For conjunction, we consider the Gödel (minimum) and product t-norms. We treat the choice of t-norm as a hyperparameter and select the best-performing operator on the validation set for each query type, i.e., the selected operator is subsequently used for evaluation on the corresponding test queries. In case of queries with negation, an array of parameters are used for both Sugeno and Yager norm, wherein $\lambda = 10^i \in \{1, 2, 3, 4\}$ and $-(10^i)$ for $i \in \{-1, -2, -3, -4\}$ and $w \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8\}$, respectively. We perform grid search regarding the parameters of Sugeno and Yager and report the best results corresponding to the parameter from the wide range of values. In our code, we employ both MRR scores and Hits@k for evaluation. However, for brevity, we report only the MRR scores here.

Experimental Results. Table 1 presents the average MRR performances of various models on negated queries across the benchmark datasets UMLS, KINSHIP, NELL, and FB15k-237, respectively. Across datasets, the application of Sugeno (S) and Yager (Y) norms boosts the performance of KGEs models compared to the standard negation norm. For instance, in the UMLS dataset, the application of Sugeno and Yager norms consistently enhances model performance, particularly for the MuRE model. Using the Yager norm with $w = 0.4$, MuRE achieves the best average MRR score of 0.604, outperforming its performance with the standard negation norm (MRR = 0.488). ComplEx and QMult also benefit significantly from these norms, with Sugeno and Yager norms leading to improvements of 0.07–0.08 in average MRR compared to the standard norm on UMLS. Similar trends are also observed in the KINSHIP dataset. The application of Sugeno and Yager norms boosts the performance of ComplEx, QMult, and Keci. For instance, ComplEx achieves its highest average MRR score of 0.522 using the Yager norm with $w = 0.4$, compared to 0.462 with the standard negation norm. Additionally, Keci improves its performance from 0.433 to 0.508 when using the Yager norm. We observe a similar trend in the larger NELL-995 and FB15k-237 datasets. Although less pronounced, the impact of the Sugeno and Yager norms remains noticeable. The smaller improvements on NELL-995 and FB15k-237 may be attributable to the greater difficulty of the underlying link-prediction task on bigger, more heterogeneous knowledge graphs with more diverse and complex relationships. In particular, the improvements from the Sugeno and Yager norms are most pronounced for 2in and 3in. For query structures involving projection, the results are less consistent: pin and pni generally show smaller gains, whereas inp exhibits gains comparable to those of 2in on NELL-995 but little or no improvement on FB15k-237. This suggests that the interaction between negation and query structure may influence the effectiveness of parameterized negation norms and should be investigated further in future work. Note that Keci and DistMult yield identical results on NELL-995. This is expected: under the hyperparameter configuration selected for Keci on this dataset, Keci reduces to DistMult. The datasets, model, and necessary code to replicate the results reported in this paper are made publicly available ¹.

5. Conclusion & Future Work

In this work, we propose to incorporate fuzzy logic norms to answer queries involving negations in multi-hop QA tasks. Our results show that applying parameterized fuzzy logic norms, such as Yager or Sugeno, improve the performance of neural link prediction models across various datasets. Future work can extend this direction along several dimensions. A deeper theoretical analysis of how different fuzzy negation norms interact with embedding geometries could provide principled guidance for norm selection rather than relying solely on empirical tuning. Additionally, adaptive or learnable negation norms, where parameters are optimized jointly with model embeddings, may allow models to better capture dataset-specific logical patterns and uncertainty.

¹<https://github.com/skapoe03/parametrized-multi-hop>

Table 1

MRR scores for KGE models using different negation norms on queries with negation. Bold numbers represent the best score for each model and query type, while underlined values show the best score overall per query type within a dataset.

Model	Neg Norm	UMLS						KINSHIP					
		2in	3in	pin	pni	inp	avg _n	2in	3in	pin	pni	inp	avg _n
DistMult	Standard	0.389	0.401	0.276	0.268	0.336	0.334	0.429	0.481	0.246	0.340	0.360	0.371
	Sugeno	0.536	0.585	0.290	0.323	0.308	0.408	0.478	0.529	0.290	0.361	0.365	0.405
	Yager	0.529	0.569	0.292	0.318	0.320	0.405	0.470	0.529	0.290	0.371	0.357	0.403
ComplEx	Standard	0.499	0.493	0.407	0.283	0.396	0.415	0.590	0.599	0.276	0.407	0.441	0.462
	Sugeno	0.657	0.665	0.448	0.336	0.367	0.495	0.678	0.678	0.341	0.440	0.448	0.517
	Yager	0.655	0.653	0.454	0.332	0.380	0.495	0.679	0.683	0.345	0.461	0.441	0.522
QMult	Standard	0.456	0.447	0.345	0.292	0.336	0.375	0.546	0.554	0.251	0.405	0.400	0.431
	Sugeno	0.586	0.626	0.342	0.346	0.321	0.444	0.611	0.624	0.297	0.439	0.393	0.473
	Yager	0.587	0.610	0.359	0.356	0.337	0.450	0.608	0.628	0.299	0.459	0.386	0.476
Keci	Standard	0.484	0.482	0.286	0.285	0.382	0.383	0.523	0.539	0.258	0.407	0.438	0.433
	Sugeno	0.625	0.645	0.297	0.323	0.348	0.447	0.639	0.633	0.335	0.449	0.445	0.500
	Yager	0.616	0.634	0.293	0.332	0.352	0.445	0.643	0.644	0.344	0.468	0.439	0.508
MuRE	Standard	0.591	0.544	0.480	0.361	0.462	0.488	0.532	0.546	0.277	0.393	0.441	0.438
	Sugeno	0.740	0.714	0.593	0.441	0.475	0.593	0.576	0.608	0.355	0.439	0.441	0.484
	Yager	0.746	0.727	0.593	0.487	0.468	0.604	0.563	0.604	0.362	0.460	0.434	0.485

Model	Neg Norm	NELL-995						FB15k-237					
		2in	3in	pin	pni	inp	avg _n	2in	3in	pin	pni	inp	avg _n
DistMult	Standard	0.130	0.182	0.075	0.102	0.221	0.142	0.050	0.120	0.143	0.125	0.102	0.108
	Sugeno	0.138	0.197	0.076	0.104	0.234	0.150	0.051	0.122	0.143	0.126	0.101	0.109
	Yager	0.142	0.202	0.076	0.109	0.233	0.152	0.051	0.126	0.145	0.128	0.102	0.110
ComplEx	Standard	0.135	0.172	0.077	0.105	0.281	0.154	0.050	0.119	0.146	0.123	0.101	0.108
	Sugeno	0.144	0.199	0.084	0.114	0.298	0.168	0.052	0.129	0.146	0.124	0.099	0.110
	Yager	0.146	0.206	0.081	0.113	0.301	0.169	0.054	0.137	0.147	0.127	0.102	0.113
QMult	Standard	0.114	0.150	0.068	0.099	0.209	0.128	0.035	0.105	0.075	0.088	0.045	0.070
	Sugeno	0.119	0.157	0.065	0.099	0.206	0.129	0.035	0.105	0.075	0.088	0.045	0.070
	Yager	0.120	0.161	0.062	0.103	0.201	0.129	0.035	0.106	0.075	0.089	0.045	0.070
Keci	Standard	0.130	0.182	0.075	0.102	0.221	0.142	0.047	0.115	0.141	0.122	0.099	0.105
	Sugeno	0.138	0.197	0.076	0.104	0.234	0.150	0.048	0.116	0.140	0.122	0.099	0.105
	Yager	0.142	0.202	0.076	0.109	0.233	0.152	0.049	0.120	0.141	0.124	0.099	0.107
MuRE	Standard	0.133	0.165	0.075	0.114	0.267	0.151	0.059	0.122	0.075	0.088	0.065	0.082
	Sugeno	0.158	0.196	0.078	0.119	0.283	0.167	0.060	0.127	0.076	0.089	0.066	0.084
	Yager	0.157	0.189	0.078	0.121	0.286	0.166	0.059	0.130	0.075	0.092	0.064	0.084

Declaration on Generative AI

Generative AI tools were used to assist with the rephrasing of selected passages. All generated text was subsequently reviewed and revised by the authors, who assume full responsibility for the final content.

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