Research on Inductive Logic Programming with Neuro-Symbolic Methods

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ABSTRACT

Logic program is a knowledge representation framework composed of logic rules that can reason based on known facts to discover new ones. Inductive logic programming (ILP) is an effective method for knowledge discovery that takes relational facts as input and outputs first-order logic rules. In the ILP approach, the accuracy of symbolic ILP methods decreases with increasing noise in the data, while Neuro-Symbolic ILP (NSILP) methods are more robust to handle noisy data with neural networks.

However, most NSILP methods rely on strong language bias and lack of scalability. Regarding language bias, some NSILP models require users to introduce many assumptions and constraints to limit the model search space. The models that heavily rely on language biases not only require users to have domain knowledge, but the strong language bias limits the syntactic formats of logic rules, which may require users to try different assumptions multiple times to generate logic rules with high accuracy. Regarding scalability, NSILP methods are unable to generate complete logic programs in some small-scale data due to generalization problems. Additionally, in some large-scale data, NSILP methods require a large amount of computing resources, making it difficult to generate logic programs on local CPU devices within the required time. To address these two issues while ensuring robustness, this thesis proposes a differentiable logic programming method and two scalable NSILP methods, one of which does not rely on strong language bias. Specifically, the main contributions of the thesis are as follows:

1. **A differentiable logic programming method and neural networks with reasoning capabilities are proposed.** General neural networks have strong learning abilities and nonlinear mapping capabilities, but lack the reasoning ability of logic programming. In the thesis, a differentiable logic programming method is proposed, which transforms logic programs into matrices and realizes an algebraic logic program reasoning process. Next, the

logic program matrix is converted into neural network parameters. Based on the operations in the differentiable logic programming method, a neural network with reasoning capabilities is proposed. Under appropriate hyperparameters, experiments show that the proposed neural networks can fully simulate the reasoning process of logic programs.

2. **An NSILP method based on bottom clause propositionalization is proposed.** The conventional NSILP methods are hard to train with a few training parameters, and it is hard to learn from different sizes of data with CPU devices. The thesis uses the bottom clause propositionalization to transform the relational data into first-order feature vectors. Based on the proposed neural networks with small parameters and inference capability, the thesis design a semantic loss function to ensure that the fitted parameters in the neural networks correspond to a first-order logic program matrix. Based on the transformation between logic programs and their matrices, the first-order logic programs can be extracted from the neural network. Compared with three advanced ILP models, experiments show that the proposed model generates logic programs with higher accuracy under multiple experimental conditions, demonstrating robustness and scalability.

3. **A data sampling method, a propositionalization method, and a fully differentiable NSILP model are proposed.** Conventional NSILP methods depend on strong language biases as assumptions to reduce the search space, which increases the usage threshold of NSILP models. The thesis proposes an NSILP model with the number of variables in first-order rules as the input languages bias and generates first-order rules with multiple syntactic formats. The data sampling method in the model reduces the number of facts without losing accuracy but improves efficiency. The propositionalization method converts relational data into feature vectors for training the neural network. Based on the neural networks with reasoning capability, the thesis designs syntactic loss functions to make the parameters in neural networks correspond to multiple syntactic format rules. In 20 small-scale ILP datasets, the model can accurately generate target logic programs. Compared with five state-of-the-art link prediction models, the proposed model increases the average reciprocal ranking values on the knowledge graph datasets WN18 and FB15KSelected by more than 4.84% and 7.56%, respectively, indicating that the model is scalable. In addition, the model can generate accurate logic programs in incomplete and fuzzy datasets, indicating that the model is robust.

KEYWORDS: Machine learning, Neuro-symbolic methods, Inductive logic programming, Knowledge representation and reasoning, Interpretability