A differentiable first-order rule learner for inductive logic programming (Abstract Reprint)

Kun Gao [1,2] , **Katsumi Inouet**[3] , **Yongzhi Cao**[1] and **Hanpin Wang**[4,1]
[1] Key Laboratory of High Confidence Software Technologies (MOE)
[2] Key Laboratory of High Confidence Software Technologies (MOE), School of Computer Science, Peking University
[3] National Institute of Informatics, Tokyo 101-8430, Japan
[4] School of Computer Science and Cyber Engineering, Guangzhou University, China
kungao@pku.edu.cn, inoue@nii.ac.jp, caoyz@pku.edu.cn, whpxhy@pku.edu.cn

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Abstract

Learning first-order logic programs from relational facts yields intuitive insights into the data. Inductive logic programming (ILP) models are effective in learning first-order logic programs from observed relational data. Symbolic ILP models support rule learning in a data-efficient manner. However, symbolic ILP models are not robust to learn from noisy data. Neuro-symbolic ILP models utilize neural networks to learn logic programs in a differentiable manner which improves the robustness of ILP models. However, most neuro-symbolic methods need a strong language bias to learn logic programs, which reduces the usability and flexibility of ILP models and limits the logic program formats. In addition, most neuro-symbolic ILP methods cannot learn logic programs effectively from both small-size datasets and large-size datasets such as knowledge graphs. In the paper, we introduce a novel differentiable ILP model called differentiable first-order rule learner (DFORL), which is scalable to learn rules from both smaller and larger datasets. Besides, DFORL only needs the number of variables in the learned logic programs as input. Hence, DFORL is easy to use and does not need a strong language bias. We demonstrate that DFORL can perform well on several standard ILP datasets, knowledge graphs, and probabilistic relation facts and outperform several well-known differentiable ILP models. Experimental results indicate that DFORL is a precise, robust, scalable, and computationally cheap differentiable ILP model.

References

[Gao *et al.*, 2024] Kun Gao, Katsumi Inoue, Yongzhi Cao, and Hanpin Wang. A differentiable first-order rule learner for inductive logic programming. *Artificial Intelligence*, 331:104108, 2024.