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Editorial

Neuro-symbolic AI and the semantic web

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1. Motivation for this special issue

Neural (*aka* subsymbolic) AI methods, in particular, those based on deep learning, recently achieved great successes in various application domains, e.g., [10,19]. However, they are often criticized for poor generalization, lack of interpretability, need for large amounts of training data, and inability of accounting for background knowledge, which is invaluable for advancing machine intelligence. At the same time, symbolic AI methods focus on knowledge representation and reasoning and allow for definition of such domain/commonsense knowledge and reasoning at high levels of abstraction. However, symbolic AI methods when applied in isolation often suffer from the issues of scalability and limited performance in uncertain scenarios.

Neuro-symbolic AI has emerged as a promising paradigm that combines subsymbolic and symbolic AI methods for their mutual benefit. While neuro-symbolic AI has a long history, this area of research has become especially active only recently [2–6,9,13,15,17,18], and it is now believed to play a major role in the future of AI for the development of more flexible and intelligent AI systems [4,18]. Neuro-symbolic AI approaches have been studied from various perspectives [2] and developed in different communities, e.g., statistical relational learning [13] or graph neural networks [12]. Since foundations of Semantic Web research have been traditionally mainly based on symbolic AI [8], neuro-symbolic AI is certainly very relevant for this community as well (see [9] for further details).

This special issue is broadly related to neuro-symbolic AI in the context of Semantic Web.

2. Contributions

The special issue attracted 6 submissions covering relevant areas of research. In total, 5 papers were accepted for publication after two review rounds by 2–3 experts. The accepted papers presented methods that leverage combinations of neural and symbolic techniques for getting insights from knowledge graphs and link prediction, as well

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as discussed applications of neuro-symbolic AI methods in natural language processing and computer vision. In the following, we provide a broad overview of all the accepted papers.

- *Bram Steenwinckel, Filip De Turck and Femke Ongenae. INK: Knowledge Graph Representation for Efficient and Performant Rule Mining* [16] presents a novel method named INK for extracting relational association rules from knowledge graphs, which can be used for both task specific and task agnostic rule mining. INK represents KG node neighbourhood as a binary matrix and exploits Bayesian rule mining techniques. Evaluation analysis has revealed that INK produces rules of higher confidence than those mined by alternative top-down methods, and manages to extract new rules though often at higher computational and memory cost.
- *Ariam Rivas, Diego Collarana, Maria Torrente and Maria-Esther Vidal. Neuro-Symbolic System over knowledge graphs for Link Prediction* [14] describes a method for link prediction in KGs which combines deductive reasoning with knowledge graph embeddings, and evaluates its effectiveness on a knowledge graph for lung cancer treatments. In this application symbolic system deductively infers drug-drug interactions in lung cancer treatments, while the sub-symbolic system exploits knowledge graph embedding models for predicting the effectiveness of a lung cancer treatment. The experimental results demonstrate that the symbolic reasoning improves the performance of KG embedding models on the considered KG.
- *Dariusz Max Adamski, Jedrzej Potoniec. Reason-able Embeddings: Learning Concept Embeddings with a Transferable Neural Reasoner* [1] presents a novel method for learning data-driven concept embeddings in $\mathcal{ALC}$ ontologies, which relies on an entailment classifier based on neural networks. The proposed method can be effectively used for fast approximate reasoning. The significant part of the approximate reasoner is transferable across ontologies which allows to save time avoiding retraining the reasoner from scratch.
- *Kyle Hamilton, Aparna Nayak, Bojan Bozic and Luca Longo. Is Neuro-Symbolic AI Meeting its Promises in Natural Language Processing? A Structured Review* [7] surveys various existing neuro-symbolic AI approaches in the area of natural language processing, and aims at estimating to which degree these approaches address the challenges that pure deep learning methods struggle with, namely out-of-distribution generalization, interpretability, reduced size of training data, transferability and reasoning. For that the authors carefully selected 59 high-quality journal and conference papers specific to Neuro-symbolic AI, and performed exploratory data analysis to categorize them based on the methods they present and goals that they aim at achieving. An attempt has been made to evaluate the progress in the field by studying in details the computational costs and performance of neuro-symbolic AI methods and their neural baselines on the NLP benchmarks. The authors concluded that to make definite conclusions unified challenging benchmarks reflecting real-world scenarios and standard evaluation protocols are desired.
- *M. Jaleed Khan, John G. Breslin and Edward Curry. NeuSyRE: Neuro-Symbolic Visual Understanding and Reasoning Framework Based on Scene Graph Enrichment* [11] proposes a new loosely-coupled Neuro-Symbolic framework for scene graph generation. In particular, scene graphs generated with state-of-the-art (neural) methods are enriched with semantic (symbolic) information taken from Semantic Web resources in the form of embeddings. Such enrichments involve new nodes and edges with respect to the original scene graphs. The semantically enriched scene graphs are of a better quality and improve the performance of the caption generation task on the COCO dataset.

The papers in this special issue witness the development of neuro-symbolic AI approaches not only in the context of learning over knowledge graphs but also beyond.

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