Title of the proposed topic:

Learn to Explain - Explain to Learn (L2EE2L)

Supervisors (name, affiliation, email)

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The laboratory and/or research group

Laboratory I3S - Inria Sophia Antipolis (Maasai Team, https://team.inria.fr/maasai/) and University of Siena (SAILAB Team, http://sailab.diism.unisi.it/)

Deadline to apply

19/05/2020

Summary of the project

In the last few years, the explosion of interest in deep learning has led to improve dramatically the performance of intelligent systems in a remarkable number of different fields. However, recent critical analyses provide evidence of their limitations. In machine learning, one is typically concerned with communication protocols, the purpose of which is to explain the task to be learned. However, the interest is growing on high human-like interactions capable of supporting a sort of *Leaning to explain and explain to learn* (L2EE2L) protocol.

In this PhD project the student is expected to explore a constrained-based modeling of the environment that makes it possible to unify learning and inference within the same mathematical framework. The unification is based on the abstract notion of constraint, which provides a representation of knowledge granules gained from the interaction with the environment. The agents are based on deep neural network architectures, whose learning and inferential processes are driven by different schemes for enforcing the environmental constraints.

In this PhD we plan to address this core question for AI field by including logic constraints into machine learning models from both directions:

- Top-Down: Logic constraints from relational knowledge graph will be translated into real-valued functions arising from the adoption of opportune *t-norms* as in [1]. Computational models like Graph Neural Networks (GNN) will be incorporated in the proposed framework thanks to the expression of structured domains by constraints [2]. Based on such neural architectures, as Deep Logic Models, we should be able to strengthen and enrich the existing knowledge (for instance by predicting links between concepts in knowledge graphs) [3, 4].

- Bottom-Up: The architecture of a deep network trained on a given dataset can be related to the underlying knowledge between the concepts represented in this dataset [6, 7, 8]. Thus, both the knowledge graph between considered concepts and the deep neural network can strengthen and improve each other though reasoning and semantic relational consistency preservation.

The project is build up on massive research activity carried out at SAILAB in the last few years http://sailab.diism.unisi.it/learning-from-constraints/ and it is also supposed to evolve the studies in the growing community of GNN. Not surprisingly this intense research activity at SAILAB echoes with innovative and prominent researches conducted in the 3IA Institute. The new techniques investigated in the 3IA to bridge the gap between not explainable decisions made by deep networks with fully explainable knowledge-based reasoning, are very complementary with SAILAB activities. This context of cross-fertilization will benefit to the PhD project to reinforce the existing links between the 3AI and SAILAB.

This PhD project is expected to provide solid foundations on explanation by learning new (logic) constraints paired with those given from the environment. The theoretical results are expected to be validated mostly on a truly on-line virtual environment based on visual and linguistic interaction, that is currently under development at SAILAB.

Conditions

Remuneration: around 2650€ gross

Teaching obligation: the 3IA PhD students are subject to a teaching obligation of 64 hours per year.

References

1. Claudio Saccà, Michelangelo Diligenti, Marco Gori, Marco Maggini, “ *Integrating Logic Knowledge into Graph Regularization: an application to image tagging* ”, In Proceedings of the 9th Workshop on Mining and Learning with Graphs (MLG 2011), San Diego, CA (USA), August 20-21, 2011

2. Luís C. Lamb, Artur d'Avila Garcez, Marco Gori, Marcelo Prates, Pedro Avelar, Moshe Y. Vardi (2020) Graph Neural Networks Meet Neural-Symbolic Computing: A Survey and Perspective. IJCAI 2020 - 29th International Joint Conference on Artificial Intelligence, July 2020

3. M. Diligenti, S. Roychowdhury and M. Gori, "Integrating Prior Knowledge into Deep Learning," 2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA), Cancun, 2017, pp. 920-923.

4. Quan Liu, Hui Jiang, Zhen-Hua Ling, Si Wei, and Yu Hu, "Probabilistic Reasoning via Deep Learning: Neural Association Models", in IJCAI-16 Workshop (DLAI) Deep Learning for Artificial Intelligence, 10 July 2016, New York (USA), http://home.earthlink.net/~dwaha/research/meetings/ijcai16-dlai-ws

5. Léon Bottou. 2014. "From machine learning to machine reasoning". Mach. Learn. 94, 2 (February 2014), 133–149. DOI:https://doi.org/10.1007/s10994-013-5335-x

6. Hexiang Hu, Guang-Tong Zhou, Zhiwei Deng, Zicheng Liao and Greg Mori, "Learning Structured Inference Neural Networks with Label Relations", in IEEE Computer Vision and Pattern Recognition (CVPR), 2016.

7. Z. Kuang, Z. Li, T. Zhao and J. Fan, "Deep Multi-task Learning for Large-Scale Image Classification," 2017 IEEE Third International Conference on Multimedia Big Data (BigMM), Laguna Hills, CA, 2017, pp. 310-317.

8. Zhenzhong Kuang, Jun Yu, Zongmin Li, Baopeng Zhang, and Jianping Fan. 2018. "Integrating multi-level deep learning and concept ontology for large-scale visual recognition". Pattern Recogn. 78, C (June 2018), 198–214. DOI:https://doi.org/10.1016/j.patcog.2018.01.027