PhD Position: Neuro-Symbolic Learning of Planning Domains Applied to Programming by Demonstration for Collaborative Robotics

University: Univ. Grenoble Alpes (France)
Laboratory: Laboratoire d'informatique de Grenoble
Team: Marvin
Supervisor: Damien Pellier Damien.Pellier@imag.fr
Recruitment Starting: From 01/09/2026

Scientific Context and Problem Statement

Within the framework of Industry 4.0, reprogramming robots for complex assembly tasks remains a major hurdle. The HUBOT chair, funded by the MIAI institute in Grenoble, proposes to overcome this bottleneck through Programming by Demonstration (PbD) [1, 4]. However, for a robot to collaborate effectively, it must not simply reproduce or generalize a physical movement; it must understand the conceptual and semantic logic of the task: What are the operator's intentions? What are the logical preconditions and the effects of each action on the environment?

To address this challenge, this thesis is fully aligned with Neuro-Symbolic Artificial Intelligence approaches. This hybrid paradigm is indispensable here:

- The neural component (Deep Learning) is used for the grounding of perceptions: it segments and translates raw data streams from observations into discrete events and abstract concepts [2].
- The symbolic component (Formal Logic / PDDL) builds upon these concepts to induce, structure, and validate the global logical model of the task, making the robot's behavior planformable, auditable, and explainable for the human operator [3].

Objectives of the Thesis

The central objective is to design a neuro-symbolic architecture capable of automatically learning a complete PDDL domain from semantic demonstrations:

- **Neuro-Symbolic Grounding (State & Action Grounding):** Train neural models to detect and extract abstract concepts, environment states (e.g., part_aligned, component_grasped), and action transitions from discretized execution traces.
- **Induction of PDDL Domains (Domain Learning):** Develop symbolic learning algorithms by induction (such as Inductive Logic Programming or grammar completion approaches) capable of automatically generating PDDL operators (predicates, logical preconditions, effects, and resource constraints) [3].
- **Explainability and Model Editing (No-code):** Leverage the readable nature of the symbolic layer to allow production operators who are non-AI experts to review, audit, and manually modify the learned PDDL domain, ensuring a trustworthy and transparent approach.

Scientific Bottlenecks to Overcome

- **Learning with Limited Data (Few-shot learning):** How can a neuro-symbolic model induce strict and valid logical rules in PDDL from fewer than 10 human demonstrations?
- **Robustness Against Noise:** Human demonstrations contain errors, variations, or superfluous steps. The hybrid approach must be capable of abstracting this semantic noise to capture only the logical invariants of the task.

Profile Sought (Research Master)

- **Education:** Master 2 Research (or equivalent from a Grande École) in Fundamental Computer Science, Artificial Intelligence, or Semantic Computer Science.
- **Key Skills:**
  - **Symbolic AI & Planning:** Solid knowledge of formal logic, knowledge representation, and proficiency in the PDDL (or HDDL) language.
  - **Machine Learning:** Mastery of neural network concepts (PyTorch / TensorFlow) applied to state abstraction or sequence processing.
  - **Programming:** Excellent skills in Python and the use of classic automated solvers/planners (e.g., Fast Downward).
- **Qualities:** Capacity for mathematical abstraction, autonomy, and scientific rigor.

Environment and Impact within the HUBOT Chair

The subject is based at LIG (Laboratoire d'Informatique de Grenoble - Marvin Team), under the direction of the chair holders. The automatically learned PDDL domain will serve as the foundation for the planning module to generate autonomous action sequences. These models will be tested in simulation and then validated on the chair's dual-arm robots (ABB YuMi at LIG and Stäubli at the Institut Pascal) within the context of industrial assembly tasks for clip-on components.

Thesis Conditions and Funding

- **Funding:** CHAIR MIAI Hubot secured for a duration of 36 months.
- **Location:** Laboratoire d'Informatique de Grenoble (LIG), Marvin Team, Université Grenoble Alpes.

Application Procedures

Interested candidates must send an application package including a CV, a cover letter, Master's transcripts (M1/M2), and contact details for at least one academic reference to Damien Pellier (Damien.Pellier@imag.fr). Applications will be reviewed on a rolling basis. After an initial contact, the candidate will be asked to complete a small software development task to validate their understanding of the topic using the library http://pddl4j.imag.fr/.

- **Application Deadline:** July 1, 2026.

References

[1] Ravichandar, H., Polydoros, A. S., Chernova, S., & Billard, A. (2020). Recent Advances in Robot Learning from Demonstration. *Annual Review of Control, Robotics, and Autonomous Systems*, 3, 297-330.

[2] d'Avila Garcez, A. S., Gori, M., Lamb, L. C., Serafini, L., Spranger, M., & Tran, S. N. (2019). Neural-symbolic computing: An effective methodology for principled integration of machine learning and reasoning. *arXiv preprint arXiv:1905.06088*.

[3] Ghallab, M., Nau, D., & Traverso, P. (2004). *Automated planning: theory and practice*. Morgan Kaufmann.

[3] Arora, A., Fiorino, H., Pellier, D., Pesty, S., & Belouaer, L. (2018). A review of learning planning domain models. *Knowledge Engineering Review*, 63, 831-875.

[4] Liang, Y. S., Pellier, D., Fiorino, H., & Pesty, S. (2022). iRoPro: An Interactive Robot Programming Framework. *International Journal of Social Robotics*, 14(1), 177-191.