

**Modular Meta Learning for Robotic Manipulation Tasks**

**Summary:** While current reinforcement learning (RL) systems can achieve super-human performance in various domains, they possess two major interconnected drawbacks for real-world applicability: First, they tend to specialize within the task domain that they are trained in, and perform poorly even in only slightly different tasks, usually requiring a whole training process from scratch within the new task domain. Second, mainstream RL systems require large amounts of experience to learn, to the extent that it becomes practically impossible to train in real-world scenarios. The combination of these two factors means that, an RL system deployed in the real-world will need to perform a long and data-intensive training for each task variation it encounters.

Meta-Learning has been proposed and obtained a lot of attention in the recent years as a promising solution to these two drawbacks. The goal of meta-learning can be summarized as “learning to learn:” instead of learning individual specific tasks like mainstream RL techniques, Meta-Learning systems try to learn a system that can quickly adapt its behavior in any task environment (within a given domain, i.e. with structural similarities) and therefore “learn” new tasks rapidly, with a minimal amount of experience needed. A particular meta-learning technique in the literature (Alet et al. (2018)), applied to supervised learning problems (i.e. learning from labeled data, instead of from experience as RL) aims for combinatorial generalization by learning a set of modules that can be combined when a new task is encountered, in order to learn it rapidly or adapt to it.

This project will experiment with the meta-learning technique mentioned above, and aim to adapt it for RL problems. The problem of focus will be realistic robotic manipulation tasks, from the benchmark Meta-World (Yu et al. 2020). The first steps of the project will be the implementation of the method, BounceGrad, (Alet et al.) and using the Meta-World benchmark. The next steps will be the adaptation of BounceGrad to reinforcement learning. Finally, this adaptation will be evaluated on Meta-World to see the performance, and improvement will be conducted accordingly.

**Who is this project aimed for?**
- Students with interest in machine learning or reinforcement learning techniques; their applications, and their limitations,
- Students with interest in meta-learning and robotic manipulation domains.
- **Proposed as:** Master Project.

**Requirements:**
- Good understanding of basic machine learning concepts
- Familiarity with reinforcement learning framework (literacy about basic concepts)
- Familiarity with Python (the more experience the better, but not obligatory)
- Prior experience / familiarity with robotic manipulation or meta-learning is a plus, but not obligatory.

Note: In case of sufficiently early contact, the student can familiarize himself/herself with the missing required areas before the beginning of the project.
**References with brief explanations:**

*The paper that introduces BounceGrad. The main aim of this project will be adaptation of this method to reinforcement learning.*

*This paper introduces the Meta-World benchmark, however a more concrete explanation of the platform can be found on the website: https://meta-world.github.io/*

*A paper that works on a similar problem and applies a modular meta-learning architecture on the Meta-World benchmark. This project differs in the sense of focusing directly on a specific method to adapt for reinforcement learning.*

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