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A Tutorial on Meta-Reinforcement Learning

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Editorial Scope

Foundations and Trends® welcomes monographs that touch on fundamental problems in machine learning from theoretical, methodological, and/or computational perspectives. We are particularly interested in monographs that seek to bridge such problems and perspectives with those from related fields, including (but not limited to) statistics, economics, and optimization.

Information for Librarians

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Contents

A Tutorial on Meta-Reinforcement Learning

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ABSTRACT

While deep reinforcement learning (RL) has fueled multiple high-profile successes in machine learning, it is held back from more widespread adoption by its often poor data efficiency and the limited generality of the policies it produces. A promising approach for alleviating these limitations is to cast the development of better RL algorithms as a machine learning problem itself in a process called meta-RL. Meta-RL is most commonly studied in a problem setting where, given a distribution of tasks, the goal is to learn a policy that is capable of adapting to any new task from the task distribution with as little data as possible. In this survey, we describe the meta-RL problem setting in detail as well as its major variations. We discuss how, at a high level, meta-RL

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research can be clustered based on the presence of a task distribution and the learning budget available for each individual task. Using these clusters, we then survey meta-RL algorithms and applications. We conclude by presenting the open problems on the path to making meta-RL part of the standard toolbox for a deep RL practitioner.

1

Introduction

Meta-reinforcement learning (meta-RL) considers a family of machine learning (ML) methods that *learn to reinforcement learn*. That is, meta-RL methods use sample-inefficient ML to learn sample-efficient RL algorithms, or components thereof. As such, meta-RL is a special case of meta-learning (Vanschoren, 2018; Hospedales *et al.*, 2020; Huisman *et al.*, 2021), with the property that the learned algorithm is an RL algorithm. Meta-RL has been investigated as a machine learning problem for a significant period of time (Schmidhuber, 1987; Schmidhuber *et al.*, 1997; Thrun and Pratt, 1998; Schmidhuber, 2007). Intriguingly, research has also shown an analogue of meta-RL in the brain (Wang *et al.*, 2018).

Meta-RL has the potential to overcome some limitations of existing human-designed RL algorithms. While there has been significant progress in deep RL over the last several years, with success stories such as mastering the game of Go (Silver *et al.*, 2016), stratospheric balloon navigation (Bellemare *et al.*, 2020), or robot locomotion in challenging terrain (Miki *et al.*, 2022). RL remains highly sample inefficient, which limits its real-world applications. Meta-RL can produce (components of) RL algorithms that are much more sample efficient than existing RL methods, or even provide solutions to previously intractable problems.

At the same time, the promise of improved sample efficiency comes with two costs. First, meta-learning requires significantly more data than standard learning, as it trains an entire learning algorithm (often across multiple tasks). Second, meta-learning fits a learning algorithm to meta-training data, which may reduce its ability to generalize to other data. The trade-off that meta-learning offers is thus improved sample efficiency at test time, at the expense of sample efficiency during training and generality at test time.

Example application Consider, as a conceptual example, the task of automated cooking with a robot chef. When such a robot is deployed in somebody's kitchen, it must learn a kitchen-specific policy, since each kitchen has a different layout and appliances. This challenge is compounded by the fact that not all items needed for cooking are in plain sight; pots might be tucked away in cabinets, spices could be stored on high shelves, and utensils might be hidden in drawers. Therefore, the robot needs not only to understand the general layout but also remember where specific items are once discovered. Training the robot directly in a new kitchen from scratch is too time consuming and potentially dangerous due to random behavior early in training. One alternative is to pre-train the robot in a *single* training kitchen and then fine-tune it in the new kitchen. However, this approach does not take into account the subsequent fine-tuning procedure. In contrast, meta-RL would train the robot on a *distribution* of training kitchens such that it can adapt to any new kitchen in that distribution. This may entail learning some parameters to enable better fine-tuning, or learning the entire RL algorithm that will be deployed in the new kitchen. A robot trained this way can both make better use of the data collected and also collect better data, e.g., by focusing on the unusual or challenging features of the new kitchen. This meta-learning procedure requires more samples than the simple fine-tuning approach, but it only needs to occur once, and the resulting adaptation procedure can be significantly more sample efficient when deployed in the new test kitchen.

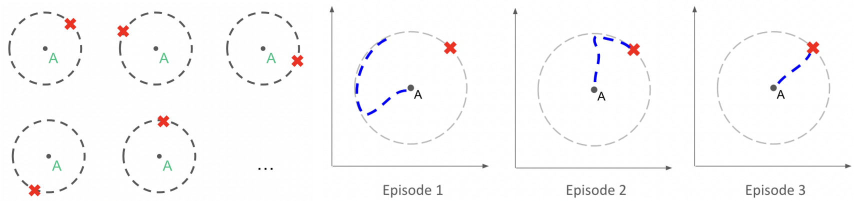
This example illustrates how, in general, meta-RL may be particularly useful when the need for efficient adaptation is frequent, so the cost of meta-training is relatively small. This includes, but is not limited to, safety-critical RL domains, where efficient data collection is necessary and exploration of novel behaviors is prohibitively costly or dangerous. In many cases, a large investment of sample-inefficient learning upfront (either with oversight, in a laboratory, or in simulation) is worthwhile to enable subsequent improved adaptation behavior. This example represents an aspirational application for meta-RL. In practice, meta-RL is applied to more limited robotics tasks such as robotic manipulation (Akkaya *et al.*, 2019; Zhao *et al.*, 2022b) and locomotion (Song *et al.*, 2020b).

Survey scope This is a survey of the meta-RL topic in machine learning and leaves out research on meta-RL in other fields such as neuroscience. Research on closely related machine learning topics is discussed in Section 2.6. To capture the breadth and depth of machine learning research on meta-RL, we surveyed the proceedings of several major machine learning conferences, as well as specialized workshops from the time period between 2017 and 2022. We found that a major portion of the meta-RL literature emerged post-2016, with the lion's share of contributions being concentrated in three conferences: NeurIPS, ICML, and ICLR. For a full list of conferences and workshops covered, see Appendix A. While our survey primarily emphasizes these conferences and the specified timeframe, we also discuss a selection of relevant papers from outside this scope. From the proceedings of these conferences and workshops, we searched for papers that explicitly mention meta-RL as well those that do not make an explicit reference but that we judged to nevertheless fit the topic. Finally, we do not claim exhaustive coverage of meta-RL research included in our survey scope but rather a holistic overview of the most salient ideas and general directions.

Survey overview The aim of this survey is to provide an entry point to meta-RL, as well as reflect on the current state of the field and open areas of research. In Section 2, we define meta-RL and the different problem settings it can be applied to, together with two example algorithms.

In Section 3, we consider the most prevalent problem setting in meta-RL: few-shot meta-RL. Here, the goal is to learn an RL algorithm capable of *fast adaptation*, i.e., learning a task within just a handful of episodes.

These algorithms are often trained on a given task distribution, and meta-learn how to efficiently adapt to any task from that distribution. A toy example to illustrate this setting is shown in Figure 1.1. Here, an agent is meta trained to learn how to navigate to different (initially unknown) goal positions on a 2D plane. At meta-test time, this agent can adapt efficiently to new tasks with unknown goal positions.



(a) Meta-Training Tasks **(b)** Rollout at Meta-Test Time

Figure 1.1: Example of the *fast adaptation* meta-RL problem setting discussed in Section 3. The agent (A) is meta-trained on a distribution of meta-training tasks to *learn* to go to goal position (X) located on a unit circle around its starting position **(a)**. At meta-test time, the agent can adapt quickly (within a handful of episodes) to new tasks with initially unknown goal positions **(b)**. In contrast, a standard RL algorithm may need hundreds of thousands of environment interactions when trained from scratch on one such task.

In Section 4, we consider many-shot settings. The goal here is to learn general-purpose RL algorithms not specific to a narrow task distribution, similar to those currently used in practice. There are two flavors of this: training on a distribution of tasks as above, or training on a single task but meta-learning alongside standard RL training.

Next, Section 5 presents some applications of meta-RL such as robotics. To conclude the survey, we discuss open problems in Section 6. These include generalization to broader task distributions for few-shot meta-RL, optimization challenges in many-shot meta-RL, and reduction of meta-training costs.

To provide high-level summaries of meta-RL research cited in this survey, we collect representative papers discussed in each section in a summary table presented within the section.

Appendix

A

List of Venues Surveyed

This survey is primarily based on the meta-RL research presented in the following conferences and workshops for the years from 2017 to 2022:

- International Conference on Learning Representations (ICLR)
- Conference on Neural Information Processing Systems (NeurIPS)
- International Conference on Machine Learning (ICML)
- Autonomous Agents and Multiagent Systems (AAMAS)
- Annual AAAI Conference on Artificial Intelligence (AAAI)
- Conference on Robot Learning (CoRL)
- Robotics: Science and Systems (RSS)
- International Conference on Intelligent Robots and Systems (IROS)
- NeurIPS Workshop on Meta-Learning
- ICLR Workshop on Meta-Learning

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