
Environments for Lifelong Reinforcement Learning

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Abstract

To achieve general artificial intelligence, reinforcement learning (RL) agents should learn not only to optimize returns for one specific task but also to constantly build more complex skills and scaffold their knowledge about the world, without forgetting what has already been learned. In this paper, we discuss the desired characteristics of environments that can support the training and evaluation of lifelong reinforcement learning agents, review existing environments from this perspective, and propose recommendations for devising suitable environments in the future.

1 Introduction

Humans acquire skills and build on them to solve increasingly complex tasks. For instance, consider a child learning to play basketball. This involves learning to hold the ball properly, to throw and catch, then learning to pass and dribble. These skills are then combined to learn more complex skills. For example, a lay-up is a composition of dribbling while running and a throw, while ensuring that the sequence of steps is not too long and that the throw lands the ball in the hoop. The entire task of playing a game relies on various subtasks and requires developing skills of increasing complexity. More importantly, skills need to work in different games and against different opponents.

In contrast, reinforcement learning (RL) agents, while able to achieve human-level performance in complex games like Go, usually focus on becoming really proficient at one task, and train from scratch in each new problem they face.

Lifelong learning agents can learn from a stream of experience spanning many tasks (possibly of different nature) over its lifetime Silver et al. [2013], Ring [1997], Thrun [1996]. The early work of Ring [1997] describes a continual learning agent as an autonomous agent trained on a sequence of tasks with no final task. This process bears different names in the literature - incremental and continual learning Solomonoff [1989], never-ending learning Carlson et al. [2010], etc.

In this work, we focus on lifelong learning performed in the context of reinforcement learning. In addition to optimizing returns, a lifelong RL agent should be able to:

- Learn behaviors, skills, and predictions about the environment while solving given tasks.
- Learn incrementally throughout its lifetime
- Combine previously learned skills and build on top of them to solve increasingly complex tasks
- Plan for short-term and long-term goals

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We argue that virtual-embodiment is perhaps the most natural setup for training and evaluating lifelong reinforcement learning agents. We review existing environments to understand if they are appropriate for training and evaluating a lifelong learning agent. Based on this comparative analysis, we propose recommendations for RL environments suitable for lifelong learning.

2 Background and Motivation

Recent breakthroughs in RL research Silver et al. [2016], Mnih et al. [2015] have been powered in part by advances in deep learning and the availability of diverse simulation environments to train RL agents. The Arcade Learning Environment (ALE) Bellemare et al. [2013], originally proposed in 2013, is a suite of Atari 2600 games which provides dozens of problems in which to train and evaluate RL agents. More recently, OpenAI’s Gym Brockman et al. [2016] was developed and offers a broader variety of environments ranging from toy text and grid world problems to continuous control tasks and Atari-based games.

One of the shortcomings of the originally proposed ALE platform is the deterministic nature of the environments, which can result in memorization of state-action sequences as opposed to generalization. A more recent version of ALE Machado et al. [2018] supports multiple game modes and provides a form of stochasticity.

Moving towards a more realistic setting, frameworks such as DeepMind Lab Beattie et al. [2016] and VizDoom Kempka et al. [2016] offer 3D first-person-view environments. Both VizDoom and DeepMind Lab support stylized labyrinths catered to navigation tasks. However, they lack naturalistic appeal in terms of their layout, appearance and objects. Another platform that the RL community has explored in recent years is Minecraft Duncan [2011], which offers a highly complex environment with characteristics that could be potentially leveraged for lifelong learning Tessler et al. [2017].

Simulators such as Gazebo Koenig and Howard [2004] have been intensively used in robotics research and are tailored towards learning agents which train in simulation but are then evaluated on physical robots. Aligned with recent efforts toward reproducible research, Mahmood et al. [2018] introduced benchmark tasks for physical robots which allow experiments to be reproduced in different locations and under diverse conditions. While these tasks are quite challenging and push RL agents’ limits, for lifelong learning they may be too difficult at the moment, given that robotics platforms have limitations in terms of their ability to support many different tasks. However, they do have a feature which we find very useful for continual learning: embodiment. We will discuss next what we mean by embodiment and why it is useful for lifelong learning.

3 Learning in Embodied Agents

Theories of *embodied cognition* Kiefer and Truppp [2012] suggest that cognition is grounded in perception and action. Embodied learning allows agents to actively interact with the environment and utilize a rich, multi-modal sensori-motor stream of data. However, training physically embodied agents can be slow, expensive and sometimes impractical. Therefore, virtual embodiment can be seen as an alternative approach. More importantly, virtual embodiment is closer to how humans learn through interaction with their environment via multiple sensors and effectors of different types. Interaction modalities include (3D) vision, audio signals, natural language, experiencing and exerting physical forces etc. Environments that support a multitude of these modalities are generally more difficult to solve, but they provide diversity and richness that can be very useful in order to build good generalizations.

Virtual embodiment has several other advantages such as i) **curriculum learning** - virtual environments are easy to modify in terms of complexity thereby making it easier to train agents in progressive fashion, ii) **short-term and long-term goals** - these are equivalent respectively with skills and composition of skills, iii) **mimic agents in real-world scenarios** - embodied learning tries to encapsulate the real world dynamics in a simulated environment as faithfully as possible, which creates more realistic domains and iv) **cause-and-effect learning** - rich, multi-modal data streams can help agents to understand the causality relationships of various events and opportunities associated with each object, through actions that are afforded by these objects.

So far, virtual embodiment environments have been used for tasks like navigation Wu et al. [2018], Anderson et al. [2018], visual question answering Das et al. [2018], teaching to execute instructions or programs Puig et al. [2018]. We will now summarize the characteristics of these environments, which we believe would provide good testbeds for training and evaluating lifelong learning algorithms.

4 Virtual Embodiment Environments: A Short Review

4.1 House 3D

House3D Wu et al. [2018] is a realistic and extensible environment built on top of the SUNCG dataset Song et al. [2017] (a large dataset of over 45,000 human designed 3D house layouts). The environment supports rendering photo-realistic 3D visuals with support for diverse 3D objects and layouts. Each scene is annotated with 3D coordinates and other meta-data like room and object type. The paper introduced the room navigation task where a set of episodic environments $E = E_1, \dots, E_n$ and a set of semantic concepts $I = I_1, \dots, I_m$ are pre-defined. During each episode, the agent interacts with one of the environments $e \in E$ and is given a concept $i \in I$. The agent starts at a random position in e and at each time-step, receives a visual signal x_t corresponding to the first person view. The agent needs to navigate to reach a target destination.

While the environment can be customized for defining new tasks and can be used to load other 3D scene datasets (like Chang et al. [2017], Armeni et al. [2017] etc), the environment itself does not allow defining varying difficulty tasks. In particular, once a layout is selected, we can not make the layout “harder” or “easier” for the agent. For instance, one can not “add” obstacles that the agent needs to overcome before the task is considered complete.

4.2 HoME: Household Multimodal Environment

HoME Brodeur et al. [2017] is similar to House3D as it is also built on top of the SUNCG dataset. Along with 3D visual rendering and semantic image segmentation, HoME also provides natural language descriptions of objects and audio rendering. It further supports rigid body dynamics (through a physics engine) and external forces like gravity. This environment supports many more modalities compared to the other virtual embodiment environments and also supports “adding” or “removing” objects. This makes it a suitable candidate for training and evaluating lifelong learning agents in RL.

4.3 MINOS: Multimodal Indoor Simulator for Navigation in Complex Environments

MINOS Savva et al. [2017] is a simulation framework specifically designed for multi-sensory navigation models. It can use layouts from both SUNCG and Matterplot3D. While it is not as rich as some other environments (like HoME or House3D), it allows for easy customization. In particular, MINOS supports material variation (for texture and colors), object clutter variation (where a set of specified categories of objects can be removed), navigation goal specification (where goals can be at arbitrary points in space or can be arbitrary instances of a category), task specification (where the task can be specified through an arbitrary Python function which returns reward signals and episode success or failure at each state).

These characteristics make MINOS a good candidate for lifelong learning. It can be easily used to design tasks with different levels of complexity or to design tasks that require the use of just one skill or composition of skills. These benefits also set it apart from other environments like AI2-THOR Zhu et al. [2017] which supports only 32 single-room environments or CHALET Yan et al. [2018] in which only a small set of discrete actions are supported.

4.4 VirtualHome: Simulating Household Activities via Programs

VirtualHome Puig et al. [2018] crowdsourced a dataset of “programs” for performing different activities in a house. Most common and atomic (inter)actions were identified and implemented in the Unity3D game engine. The programs and the simulated environment can be used to train an agent to perform household tasks based on language instructions. If we think of each atomic action as a skill, then each program, which is a sequence of atomic actions, can be seen as a composition of skills. This is a major advantage of using VirtualHome - the ready availability of the program dataset

(which can be seen as a composition of skills). A disadvantage of this environment, however, is that it does not allow for creating variations of a scene, which is important for designing tasks of varying complexity.

Before wrapping up this section, we also consider some of the prominent RGB-D datasets which are useful building blocks for developing environments for virtual embodied agents. The environments discussed earlier use one or more of these datasets.

4.5 Matterport3D: Learning from RGB-D Data in Indoor Environments

Matterport3D Chang et al. [2017] introduced a large RGB-D dataset of indoors scenes (10,800 panoramic views from 194,400 RGB-D images of 90 building-scale scenes). It includes annotations for surface reconstruction, camera poses and 2D and 3D semantics segmentation. Even though an embodied learning agent is not introduced as part of the task setup, many follow-up works like Anderson et al. [2017] and Savva et al. [2017] used this work as the starting point for defining a plethora of tasks related to computer vision.

4.6 SUNCG: A Large 3D Model Repository for Indoor Scenes

SUNCG Song et al. [2017] is a large scale dataset of richly annotated scenes. The dataset contains over 45,000 manually created room and object layouts along with semantic annotations. The dataset was created to learn semantic scene completion, where given a single-view depth map observation, a complete 3D representation, along with semantic labels is generated. Follow-up works like Das et al. [2018] and Wu et al. [2018] used it for training embodied agents.

In the following section, we discuss what is missing in these frameworks in order to perform lifelong learning.

5 Recommendations for a lifelong learning testbed

To conclude, we discuss features that, in our view, would be important to support by any framework for training and evaluation of lifelong learning agents.

1: The proposed testbed should support a multitude of tasks of different difficulty. The lowest level tasks should require only one skill to solve, while tasks more complex tasks should require a composition of skills learned in the previous levels. Tasks could for example be structured in a hierarchy, such that task complexity would increase as the learning agent moves up. Solving a task in the $i + 1^{th}$ level should require the agent to solve the task at level i and also learn to compose previously acquired skills. The environment should be able to present the agent with tasks that test its ability to make compositions.

2: A lifelong learning framework would ideally provide easy addition or removal of objects from a scene or a variety of scenes. Such a framework would facilitate the incremental expansion of the data that the agent sees over time. This could be achieved by providing the flexibility to scale up the size of the environment, the quantity of objects with which the agent can interact, etc.

3: Tasks should be generated in the environment in a way that requires the agent to do both short-term and long-term planning. Dealing with many goals that span different time scales would test an agent's capacity to learn different types of knowledge and to generalize across time scales.

4: As the learning agent moves to more complex tasks, the environment should continue to challenge it with previously seen tasks, in order to assess whether the agent can resist catastrophic forgetting.

As discussed above, some of the already existing environments align well with these desiderata. However, more work can be done to expand the set of environments used in lifelong learning. More importantly, assessing the performance of lifelong learning agents and defining the objective that they should optimize is still a problem that has not been tackled much, and is critical for progress in our field. We hope that this paper is at least useful in outlining some of the intuitive desiderata for lifelong learning, and that as a community we can all work to make these more formal and precise.

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