On the Importance of Critical Period in Multi-stage Reinforcement Learning

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Abstract

The initial years of an infant’s life are known as the critical period, during which the overall development of learning performance is significantly impacted due to neural plasticity. In recent studies, an AI agent, with a deep neural network mimicking mechanisms of actual neurons, exhibited a learning period similar to human’s critical period. Especially during this initial period, the appropriate stimuli play a vital role in developing learning ability. However, transforming human cognitive bias into an appropriate shaping reward is quite challenging, and prior works on critical period do not focus on finding the appropriate stimulus. To take a step further, we propose multi-stage reinforcement learning to emphasize finding “appropriate stimulus” around the critical period. Inspired by humans’ early cognitive-developmental stage, we use multi-stage guidance near the critical period, and demonstrate the appropriate shaping reward (stage-2 guidance) in terms of the AI agent’s performance, efficiency, and stability.

1. Introduction

The Critical Period is a core maturational stage of an intelligent organism’s cognitive development (Smart, 1991; Rice & Barone, 2000). To learn a cognitive skill, appropriate guidance must be provided in this stage; otherwise, the organism struggles or even fails to attain the skill (Nickerson, 2021). In detail, neurological studies suggest that synaptic connectivity is noticeably facilitated in this stage (Takesian & Hensch, 2013). This leads to enhanced neural plasticity and sensitivity to external stimuli, and thus an organism can learn more with the same observation (Nickerson, 2021). For this reason, early interaction and feedback for a human baby is vital in its future development (Nickerson, 2021; White et al., 2013).

Recent works (Achille et al., 2017; Park et al., 2021; Kleijn et al., 2022) investigate whether the critical period only holds for biological agents and not for artificial intelligence. These works were conducted under the intuition that, since deep neural networks are related to biological nervous systems, similar biological characteristics such as critical periods might emerge. One study (Achille et al., 2017) discovered the critical period phenomenon in CNNs: neural plasticity peaks at a particular stage of training. Other works (Park et al., 2021; Kleijn et al., 2022) found the critical period for reinforcement learning (RL) agents, and linked human guidance and interaction with critical period.

Unfortunately, prior works lack a deeper investigation of what the appropriate stimulus is for the critical period.
They focused on the time duration of early experiences, and naively applied reward or penalty scaling as guidance. To address this, we propose the multi-stage human guidance approach inspired by human’s early cognitive developmental stages. Our key insight follows from the fact that human infants are not given task-specific goals from the start. Rather, newborn babies first explore the surroundings in an unsupervised manner, and gradually move towards supervised objectives: guidance, games, and jobs (Gibson, 1988; Piaget & Cook, 1952). Specifically, our multi-stage guidance consists of 3 stages, as shown in Fig 1. In the first Free Exploration stage, the agent is not guided. In the second stage, Guided-Play stage, which starts from the critical period, a moderate guidance signal is given. In the final Gamification stage, a much richer guidance is provided.

We empirically demonstrate the appropriate stimulus through multi-stage guidance richer in terms of the critical period. We first illustrate the critical period for an RL agent in ViZDoom environments (Kempka et al., 2016). Next, we demonstrate that our multi-stage guidance notably enhances the performance compared to naïve reward scaling guidance at the critical period. Our study corroborates that it is crucial to design the appropriate guidance for the RL agent’s critical period.

2. Related Work

Critical Period in ML. Critical period is a stage in an organism’s early cognitive development during which external stimuli play a critical role in its future development (Smart, 1991; Rice & Barone, 2000). For instance, a child who grew up abroad during his or her critical period of language acquisition will have more trouble learning the native language than a child who did not (Snow & Hoefnagel-Höhle, 1978). The critical period is a decisive stage for general cognitive development of language acquisition, vision and auditory learning, social relationships, and others (Nickerson, 2021). So a natural question is whether such phenomenon also occurs for machine learning algorithms. While a few studies discovered analogical observations in machine learning, e.g. for vision (Achille et al., 2017) and RL (Park et al., 2021; Kleijn et al., 2022) tasks, these prior works did not investigate how to leverage such critical period for better learning performance and training speed. We introduce a multi-stage training strategy to utilize the critical period and demonstrate the most appropriate stimulus around the critical period among sequential hand-crafted N-stage guidance.

Curriculum Learning. Curriculum learning (CL) is a strategy to train an ML model using tasks gradually increasing in difficulty, similar to how humans learn throughout their lifetime (Wang et al., 2021). Human education is organized as a curriculum; humans start with easy examples but gradually advance to more complex concepts. A natural idea is to apply such curricula to ML, not only for the resulting final performance but also for training speed (Hacohen & Weinshall, 2019) and safety (Turchetta et al., 2020). Theoretically, CL acts like unsupervised pretraining (Bengio et al., 2009). It facilitates generalization and boost the convergence (Weinshall & Cohen, 2018).

Starting from its original concept of easy-to-hard progression, CL generalizes to a sequence of arbitrary training criteria (Wang et al., 2021). In this view, our work reverses the curricula from hard to easy in terms of the sparsity of the reward, and thus can be understood as anti-curriculum learning. Our strategy depicts the early cognitive development of a human being; unsupervised exploration dominates in the early stage, proceeding then to task-specific supervised learning (Zosh et al., 2017).

Recent approaches in curriculum RL design a set of intermediate tasks (MDPs) and sequence them to increase the performance or efficiency of the RL agent in the final MDP. However, no prior work investigated the role of the critical period for the RL agent within the curriculum design, nor did they analyze the effects of the critical period on the curriculum. In contrast, our work is the first to formalize and exploit the critical period into the domain of CL.

3. Multi-stage RL and the Critical Period

In this section, we formalize the critical period and the multi-stage RL within the framework of the curriculum learning.

3.1. Preliminaries

RL is a field of machine learning where the agent learns through trial and error, similar to how human actually acquires skills. It is applied to various tasks that involve sequential decision making. Markov Decision Process (MDP) is defined as 〈S, A, P, R, γ〉, where S is a set of environment states, A is a set of possible actions, P : S × A → Δ(S) is a transition model, R : S × A → R is a reward function, and γ is a discount factor. The agent in the current state s ∈ S performs the action a ∈ A according to the policy π(a|s), and receives the next state s’ and reward R(s, a) through the transition function P(s′|s, a). RL aims to obtain an optimal policy π∗ ∈ Π∗ that maximizes the expected cumulative rewards Еs∼P, a∼π ∑∞r=0 γrR(s, a) with γ applied, where Π∗ is the set of the optimal policies.

3.2. Curriculum Learning for RL

It is well-known that the current RL algorithms (Haarnoja et al., 2018; Schulman et al., 2017; Mnih et al., 2013) struggle in the sparse-reward environments (Aubret et al., 2019). Our approach to resolve this issue is to provide a sequential guidance as a feedback, where the guidance represents the dense reward shaping. To begin with, we first formulate the
the stage transition work with sequential guidance and where only a small portion of the state space is included in the sequential guidance. We now define an anti-curriculum, a sequence of MDPs where the reward function becomes progressively denser.

Definition 3.1 (Anti-curriculum). Let \( \{M_i\}_{i=1}^N \) be a set of MDPs where \( M_i = \langle S_i, A_i, P_i, R_i, \gamma \rangle \) for each \( i \). We denote the sequence of MDPs \( \{M_1, M_2, \ldots, M_N\} \) as anti-curriculum if \( \text{supp}(R_1) \subseteq \text{supp}(R_2) \subseteq \cdots \subseteq \text{supp}(R_N) \) and \( \Pi_0^{*} \supseteq \Pi_1^{*} \supseteq \cdots \supseteq \Pi_N^{*} \) hold. Here, we denote each \( R_i \) as a guidance.

In the above definition, the first condition
\[
\text{supp}(R_1) \subseteq \text{supp}(R_2) \subseteq \cdots \subseteq \text{supp}(R_N)
\] (2)
denotes that the reward function becomes more dense, i.e., the guidance becomes more explicit. The second condition,
\[
\Pi_0^{*} \supseteq \Pi_1^{*} \supseteq \cdots \supseteq \Pi_N^{*},
\] (3)
constrains the optimality to be preserved during the transition of the MDPs, i.e., the optimal policies of \( M_1 \) are also optimal in \( M_{i+1} \). At a high level, the sequence of MDPs in the above definition is anti-curriculum in the sense that the reward functions are arranged in the order of the sparsity, i.e., “sparse-to-dense”, in contrast to the conventional curriculum learning which boost the training by arranging the tasks as “easy-to-hard”.

The sequential guidance \( \{R_1, R_2, \ldots, R_N\} \), which we call the \( N \)-stage guidance, can be designed with the inductive biases such as the domain-specific prior knowledge. Importantly, we hypothesize that the specific timings of the transition of the guidances highly influence the agent’s performance under the given sequential guidance. We now introduce multi-stage RL, the anti-curriculum learning framework with sequential guidance and the stage transition.

Definition 3.2 (Multi-stage RL). Let \( \{R_1, R_2, \ldots, R_N\} \) be a sequential guidance such that \( \{M_1, M_2, \ldots, M_N\} \) is the anti-curriculum where \( M_i = \langle S_i, A_i, P_i, R_i, \gamma \rangle \) for each \( i \) with the initial sparse-reward MDP \( M_1 \). Multi-stage RL aims to obtain an optimal policy under the MDP \( M = \langle S, A, P, R, \gamma \rangle \) where
\[
\bar{R}(s_t, a_t) = R_i(s_t, a_t) \quad \text{if} \quad t \in [t_{i-1}, t_i]
\] (4)
for each \( i \), where \( t_0 = 0 \). We denote \( \{t_1, t_2, \ldots, t_N\} \) as the stage transitions.

In this work, we consider a sparse-reward environment where only a small portion of the state space is included in \( \text{supp}(\mathcal{R}) \), e.g., \( |\text{supp}(\mathcal{R})| \ll |S| \). We now define an anti-curriculum, a sequence of MDPs where the reward function becomes progressively denser.

Definition 3.3 (Critical Period). Let \( r_n(\phi|s) \) be the policy parametrized with \( \phi \). Suppose that \( \phi^t \) is updated according to an arbitrary RL algorithm \( G \) for each time step \( i \), under the multi-stage RL framework \( M = (S, A, P, R, \gamma) \) with the \( N \)-stage guidance \( \{R_1, R_2, \ldots, R_N\} \) and the stage transition \( t = \{t_1, t_2, \ldots, t_N\} \). Here, the \( \epsilon \)-convergence step is defined as:
\[
L(\bar{R}, t; G, \epsilon) = \min\{i \mid \forall s, |V^\pi^t(s) - V^\pi(s)| < \epsilon \}. \tag{5}
\]

The critical period \( t^* \) is defined as follows:
\[
t^* = \arg\min_{\epsilon} L(\bar{R}, t; G, \epsilon). \tag{6}
\]

Intuitively, critical period is the stage transition which obtains the optimal policies with the fastest convergence of the based RL algorithm. In Section 4, we empirically demonstrate critical period which shows distinguished performance among the stage transitions.

4. Experiments

4.1. ViZDoom 3D-Navigation Environments

We developed 3D navigation environments using ViZDoom (Kempka et al., 2016). Four objects are generated in the map, one of which is the randomly specified goal object that the agent must navigate to. Each object may spawn as one of two variants of colors or appearances. The map size
is 700 × 700 (unit distance), and the agent starts at the center of the map every episode. As shown in Fig 2, there are three ViZ-level environments with increasing complexity. The objects are prevented from being generated too closely to the agent, so that we can maintain a certain level of difficulty. Arrival at a goal and non-goal object respectively grants a reward of 10.0 or -1.0 to the agent and terminates the episode. Failing to reach any object within episode time limit (25 time steps for level 1 and 2, or 37 time steps for level 3) results in a reward of -0.1. A reward of -0.01 is given every time step to induce active exploration.

4.2. Results on ViZDoom Environments

We demonstrate the impact of the multi-stage learning ranging from Free Exploration (stage-1 guidance) to Gamification (stage-3 guidance), and examine the critical periods. For this, we measure the agent’s performance across three different stage transitions: \(t_1, t_1 + 2M, t_1 + 4M\) such that \(t_1 \in \{1M, 2M, 3M\}\). We denote these three curricula as \(\tilde{M}_1, \tilde{M}_2, \tilde{M}_3\) respectively. Through these experiments, we also show how an appropriate stimulus affects the learning performance according to the critical period. Also, we compare multi and uni-stage learning (denoted as \(\tilde{M}_4\)), in which the richest guidance (stage-3) is given during the whole run. A3C (Mnih et al., 2016) was used as the RL algorithm, and the means and standard deviations were recorded across three trials.

**Results on ViZ-level1 Environments.** In Fig 3-(a), the agent reaches a perfect success rate (100%) in the order of \((\tilde{M}_1)\) and \((\tilde{M}_2)\). \((\tilde{M}_3)\) shows the lowest success rate (92%). The uni-stage model \((\tilde{M}_4)\) cannot even reach the lowest success rate of the multi-stage models (90.7%).

**Results on ViZ-level2 Environments.** In the results of Fig 3-(b), \((\tilde{M}_2)\) shows a superior success rate (78%). The \((\tilde{M}_1)\) also shows a moderate performance (57%). In contrast, in \((\tilde{M}_3)\) and \((\tilde{M}_4)\), the agent cannot solve the task properly at all (0%).

**Results on ViZ-level3 Environments.** For the most complex environment, all models show a larger improvement according to stage-2,3 guidance. As shown in Fig 3-(c), \((\tilde{M}_1)\) (90%), \((\tilde{M}_2)\) (83%) and \((\tilde{M}_3)\) (78%) exhibit best to worst performances in order.

**Overall Analysis.** We observe vast performance improvements during stage-2 guidance (and during stage-3 guidance to a smaller extent) in all environments, particularly with the best performing models of ViZ-level2 \((\tilde{M}_2)\) and level3 \((\tilde{M}_1)\). As a result, the appropriate stimulus, which leads to the steepest performance improvement for all ViZ-levels environments, is the stage-2 guidance. Thus, we can speculate that the periods where the best performing models are given stage-2 guidance are the critical periods (level1-(\(\tilde{M}_1\)): 1~3M/level2-(\(\tilde{M}_2\)): 2~4M/ level3-(\(\tilde{M}_1\)): 1~3M).

We also observe that standard deviations are high when stage-2 guidance is given outside the critical period. Therefore, we believe that a proper amount of free exploration stage (stage-1) is essential to stable learning so that the agent fully learns an optimal trajectory. For uni-stage \((\tilde{M}_4)\), even if it is the richest reward, the agent fails completely in level 2 and 3. However, we found that stage-3 guidance transforms into a beneficial guidance through stage transition \((t_2)\) in multi-stage approach.

5. Conclusion

Appropriate reward shaping is a crucial performance factor for successful learning in MDP. However, it is imperfect due to human cognitive bias. Therefore, to find a beneficial reward shaping more clearly, we introduce multi-stage RL and demonstrate the appropriate stimulus. Our work is the first to formalize and exploit critical period within the framework of curriculum RL. Our empirical experiments demonstrate the effectiveness of multi-stage learning near the critical period in terms of the performance, efficiency, and stability of the training for the RL agent. While feedback types within anti-curriculum learning have been rather underex-
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