Accuracy-based Curriculum Learning in Deep Reinforcement Learning

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Abstract
In this paper, we investigate a new form of automated curriculum learning based on adaptive selection of accuracy requirements, called accuracy-based curriculum learning. Using a reinforcement learning agent based on the Deep Deterministic Policy Gradient algorithm and addressing the Reacher environment, we first show that an agent trained with various accuracy requirements sampled randomly learns more efficiently than when asked to be very accurate at all times. Then we show that adaptive selection of accuracy requirements, based on a local measure of competence progress, automatically generates a curriculum where difficulty progressively increases, resulting in a better learning efficiency than sampling randomly.

1. Introduction
When an agent has to learn to achieve a set of tasks, the curriculum learning problem can be defined as the problem of finding the most efficient sequence of learning situations in these various tasks so as to maximize its learning speed, either over the whole set of tasks or with respect to one of these tasks.

A rule of thumb in curriculum learning is that one should address easy tasks first and switch to more difficult tasks once the easy ones are correctly mastered, because competences obtained on learning from the easy ones may facilitate learning on the more difficult ones, through transfer learning. However, as machine learning algorithms have complex biases, it is often difficult to design by hand an efficient learning curriculum. Also, various task sets, as well as various learners, may differ in terms of which are the best learning curriculum. An important scientific challenge is thus how to design algorithms that can incrementally and online generate a curriculum that is efficient for a specific set of tasks and a specific learner.

An idea that has been explored in various strands of the literature (Schmidhuber, 1991; Oudeyer et al., 2007) has been to generate a learning curriculum by dynamically selecting learning situations which provide maximal learning progress at a given point in time. This idea has been used to automate the generation of learning curriculum for training robots (Baranes and Oudeyer, 2013), deep neural networks (Graves et al., 2017), as well as human learners in educational settings (Clement et al., 2013). It entails several challenges, including how to efficiently estimate expected learning progress, and how to optimize exploration and exploitation to maximize learning progress with bandit-like algorithms.

Another important challenge entailed by this approach is how to parameterize learning situations, i.e. to design the parameters over which learning progress is estimated and compared. In the case of an agent learning to reach various goals in the environment, the general notion of learning progress which might for instance denote progress in predicting some signal is replaced by a narrower notion of competence progress, which is more specific to learning to act. In the case of reaching, a natural parameterization consists in defining learning situations as particular regions of goal states (e.g. (Baranes and Oudeyer, 2013)), or particular regions of starting states (e.g. (Florensa et al., 2017)), or particular combinations of starting and end states. As some target or starting states might be easier to learn than others, thus producing higher competence progress in the beginning, a strategy based on competence progress will first focus on them and then move towards more complicated ones. If this parameterization is continuous, architectures like SAGG-RIAC (Baranes and Oudeyer, 2013) can be used to dynamically and incrementally learn these regions, and concurrently use them to select and order learning situations.

In this paper, we focus on another way to parameterize learning situations based on the notion of accuracy requirement of the tasks/goals. Many robotics tasks can be made more or less difficult by requiring different degrees of accuracy from the robot: learning to bring its end-effector within 10cm of a point may be easier than within 10mm. A task which was easy with loose accuracy requirements can become difficult if the accuracy constraint becomes tighter. The impact of accuracy requirement on learning efficiency in the context of curriculum learning can be particularly powerful, since in reinforcement learning (RL) progress is made by finding

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rewarding experiences, and it is harder to find a source of reward when the accuracy requirement is stronger.

To capture this idea, we consider the required accuracy $\epsilon$ as a parameter of learning situations, and we define accuracy-based curriculum learning as a specific form of curriculum learning which acts on the value of $\epsilon$ to improve learning efficiency. Then we study the impact of accuracy-based curriculum learning on the learning efficiency of a multi-goal deep RL agent trying to learn various reaching tasks.

Our contributions are the following. First, we show that being trained with various accuracy requirements is beneficial to learning efficiency even when the required accuracies are sampled in a random order. Then we show that using accuracy-based curriculum learning based on the competence progress as defined in (Baranes and Oudeyer, 2013) enables to automate the sampling of accuracy constraints in order of increasing difficulty, and that such ordering results in a better learning efficiency than random sampling.

The paper is organized as follows. In Section 2, we present some works that are related to our main concerns. In Section 3, we quickly describe the Reacher environment used as experimental setup, the deep RL algorithm, Deep Deterministic Policy Gradient (DDPG) (Lillicrap et al., 2015) and its Universal Value Function Approximation (UVFA) extension, as well as the accuracy-based curriculum learning algorithm we are using. We describe our results in Section 4. Finally, we discuss these results, conclude and describe potential avenues for future work in Section 5.

2. Related work

Our work contributes to the domain of curriculum learning, leveraging contributions made in different fields.

One line of research in machine learning (Schmidhuber, 1991) has proposed that measures of improvement of prediction errors could be used as intrinsic rewards to be maximized, generating a learning curriculum in an intrinsically motivated RL framework (Chentanez et al., 2005). It was later extended on to drive the selection of problems in the Powerplay framework (Schmidhuber, 2013).

Another independent line of research, in the domain of developmental robotics, has focused on modeling children’s curiosity-driven exploration as a mechanism that enables them to learn world models through the adaptive selection of learning situations that maximize learning progress (Oudeyer et al., 2007). This line of research has developed algorithms enabling learning progress to be efficiently estimated in large continuous high-dimensional spaces (Baranes and Oudeyer, 2009), enabling robots to self-organize a learning curriculum and learn incrementally and online complex skills such as locomotion (Baranes and Oudeyer, 2013).

In this context, our work follows closely the multi-goal architecture from the Hindsight Experience Replay (HER) algorithm (Andrychowicz et al., 2017). The key innovation in HER consists in letting the agent learn again from previous experience by replaying real transitions of an episode with different goals reached during that episode. The algorithm is built on a combination of Universal Value Function Approximators (UVFA) (Schaal et al., 2015) and the DDPG (Lillicrap et al., 2015) deep RL algorithm. It is shown to provide the agent with a form of implicit curriculum learning based on target goal positions. The present work is also built on UVFAs and DDPG but unlike HER, it relies on a principled idea of competence progress to provide an explicit curriculum for the agent. To our knowledge, our work is the first to combine UVFAs, DDPG and an explicit measure of competence progress.

3. Methods

The idea of building a curriculum of tasks on the base of various accuracy requirements can be applied to many environments and learning algorithms, provided that the latter can incorporate such requirements. In this paper we apply it to solve the simple Reacher environment from OpenAI Gym (Brockman et al., 2016) with the DDPG algorithm.
3.1. Reacher

The reacher environment is a two degree of freedom arm that must reach a target in its plane. In this environment, the agent state contains the arm angles and angular velocities, its end-effector position \( p_{\text{finger}} \) and the target position \( p_{\text{target}} \). We use a sparse reward function that happens to naturally incorporate a notion of accuracy:

\[
r = \begin{cases} 0, & \text{if } |p_{\text{finger}} - p_{\text{target}}| \leq \epsilon \\ -1, & \text{otherwise} \end{cases}
\]

(1)

with the parameter \( \epsilon \) determining the accuracy required from the agent for being successful.

Importantly, a new target position \( p_{\text{target}} \) is randomly sampled after each trial, providing a natural form of exploration.

3.2. DDPG

DDPG is implemented as a form of Universal Value Function Approximator (UVFA) (Schaul et al., 2015).

However, we use a slightly more complex representation than just this state. Indeed, in the standard setting for RL with sparse rewards, the \( \epsilon \) parameter is set at the beginning of training to a user-defined value and left untouched afterwards, whereas here \( \epsilon \) changes from one training episode to the next. But changing \( \epsilon \) during the reward/termination calculation without adding its value to the state would remove the MDP structure of the problem: a given state could be either terminal or not depending on \( \epsilon \), leading to incoherent updates for DDPG. Thus we extend the UVFA framework to contain both states and accuracies using a \( V(s, \epsilon, \theta) \) representation. The MDP structure of the environment is not changed by this addition: \( \epsilon \) simply keeps constant whatever the transition, and is only used to compute the termination condition.

3.4. Epsilon-based curriculum

Two training strategies are studied in this work. The first, called \textsc{random-}\( \epsilon \), consists in sampling a training accuracy \( \epsilon \) uniformly from \( E = \{0.02, 0.03, 0.04, 0.05\} \) at the beginning of each episode, and adding it to the input state of the UVFA for all the duration of the episode.

The second, called \textsc{active-}\( \epsilon \), consists in measuring the agent competence progress for each \( \epsilon \in E \) all along training, and sampling an accuracy at the beginning of each episode proportionally to its current competence progress measurement. Specifically, if \( cp_i \) is the competence progress for \( \epsilon_i \), then we define the probability of sampling \( \epsilon_i \) as

\[
P(\epsilon_i) = \frac{cp_i^\beta}{\sum_k cp_k^\beta}.
\]

(2)

The exponent \( \beta \) determines how much prioritization is used, with \( \beta = 0 \) corresponding to the uniform sampling case (\textsc{random-}\( \epsilon \)), and \( \beta = \infty \) to only sampling the accuracy value \( \epsilon \) resulting in the maximum competence progress. In the experiments below, we determined by sampling \( \beta \) in the range \([0, 8]\) that using a value of \( \beta = 4 \) was providing the best results.

Both strategies are compared to a baseline that corresponds to the DDPG algorithm being trained to reach target positions with rewards obtained from the hard accuracy \( \epsilon = 0.02 \). Thus the baseline is always trained with accuracy constraints that correspond to that used for evaluation. By contrast, both \textsc{active-}\( \epsilon \) and \textsc{random-}\( \epsilon \) are designed to sometimes train on easier requirements, and thus train less with the evaluation accuracy constraint.

3.5. Competence progress measurement

The way we measure learning progress is directly taken from the SAGG-RIAC algorithm (Baranes and Oudeyer, 2013).
For each possible value of $\epsilon \in E$, the agent is tested every 1000 steps on its ability to reach 10 randomly sampled target positions with this accuracy, providing a competence score between 0 and 1. From the ordered list of scores obtained this way during training, we extract a measure of competence progress following (Baranes and Oudeyer, 2013): if $c_j^i$ is the score measured for $\epsilon_i$ at measurement time $t_k$, then the competence progress $cp_i$ at time $T$ is the discrete absolute derivative of competence scores for $\epsilon_i$ over a sliding window of the $2N$ more recent evaluations:

$$cp_i = \left| \left( \sum_{j=T-N}^{T} c_j^i \right) - \left( \sum_{j=T-2N}^{T-N} c_j^i \right) \right| / 2N.$$  

(3)

The use of an absolute value guarantees that if competence starts dropping for a given $\epsilon$, then its associated progress will be negative with high absolute value and thus will be sampled in priority over other slowly progressing accuracies. This avoids catastrophic forgetting. For all experiments, $N = 3$ is used to compute progress on sliding windows containing 3000 steps.

4. Results

In this Section we validate the hypotheses that: (1) sampling $\epsilon$ randomly from $E$ is more efficient for learning high accuracy behaviors than always using the strongest accuracy requirement ($\epsilon = 0.02$), and this despite seeing less experience with such a high accuracy; (2) sampling $\epsilon$ using competence progress on each accuracy level results in ordering accuracy requirements from the easiest to the most difficult; (3) the resulting curriculum improves learning efficiency over random selection.

Figure 1 shows the benefits from training with multiple accuracies as well as that of prioritizing values of $\epsilon$ depending on the level of competence progress of the agent. Every 1000 steps, the evaluation consists in running the agent for ten 50-step episodes on randomly sampled target positions, and recording the proportion of successful episodes for $\epsilon = 0.02$.

The RANDOM-$\epsilon$ strategy already provides a clear gain over the baseline: one can observe a significant increase in accuracy as well as a reduction of the variance across different runs. The active-$\epsilon$ strategy is shown with $\beta = 4$. The resulting curriculum provides even better learning performance than RANDOM-$\epsilon$: progress is faster at the beginning of the learning curve, the agent is more accurate in the end and shows less variability.

Figures 2 and 3 focus on the curriculum obtained with $\beta = 4$ and parallels the evolution of competence progresses for each value of $\epsilon$ with their sampling frequencies. We observe on Fig. 2 that lower precisions lead to quicker progress at the beginning of learning compared to the most demanding task with $\epsilon = 0.02$. After about 150K steps, the opposite trend is observed: the agent competence on low precisions starts to reach a plateau as it masters the reaching task with these accuracies, leading to a decrease in progress; instead high accuracy remains challenging and the associated competence progress stays higher until later during training.

In parallel, Fig. 3 shows the proportions of all $\epsilon$ sampled represented by each specific value of $\epsilon$, and reflects how their sampling frequency changes with training. During the first 150K steps priority is given to low accuracy objectives with high competence progresses, and the situation is reverted afterwards, with the agent almost only sampling the strongest accuracy requirement in the end, for which it is still making progress.

5. Discussion and conclusion

We have shown that simply training on multiple accuracies and thus seeing less experience with $\epsilon = 0.02$ in favor of larger $\epsilon$ values provides a substantial gain over the baseline. This suggests that the agent is able to take advantage of rewarding experience acquired with large $\epsilon$ values and then properly generalize the policy learned from these values to smaller ones. This idea is independent of the Reacher environment and could be leveraged to many simulated
environments such as the Fetch environment from OpenAI (Brockman et al., 2016) or even to real robots. However, this result may depend from a specific feature of accuracy-based difficulty, which is that a trajectory fulfilling some accuracy requirement also fulfills any easier accuracy requirement. Difficulties in terms of final points do not share a similar structure, for instance.

Also we demonstrated that competence progress is an effective metric to build a curriculum in the context of deep reinforcement learning, and could be used with groups of tasks that differ by other aspects than their accuracy requirements as it is the case here. Specifically, one could apply this methodology to extract a curriculum from tasks corresponding to reaching distinct regions for a robotic arm, or from tasks distinct in nature and difficulty inside a more complex environment.

The idea of incorporating the final accuracy of the arm movement in the reward scheme of the agent reminds of dense reward functions used in standard versions of Reacher-like environments. In these cases, the shaped reward is proportional to the Euclidean distance between the extremity of the arm and the target position. Yet, we have no guarantee that two target positions close in the Euclidean space can be reached with close policies for complex robotic agents, and thus such shaping could be misleading. On the contrary, in our case, there is no assumption that the image of the control space in the goal space is Euclidean as the generalization from one accuracy to another is learned by the agent through the addition of $\epsilon$ to the input state of UVFAs.

In the future, it would be useful to compare the efficiency of the curriculum obtained from our method with that of a method where a fixed increasing difficulty curriculum is used (see e.g. (Clement et al., 2013; Forestier et al., 2017)). Besides, we intend to compare the explicit form of curriculum based on competence progress used here and the implicit form of curriculum resulting from the HER mechanism.

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