Curriculum goal masking for continuous deep reinforcement learning*

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Abstract—Deep reinforcement learning has recently gained a focus on problems where policy or value functions are independent of goals. Evidence exists that the sampling of goals has a strong effect on the learning performance, but there is a lack of general mechanisms that focus on optimizing the goal sampling process. In this work, we present a simple and general goal masking method that also allows us to estimate a goal’s difficulty level and thus realize a curriculum learning approach for deep RL. Our results indicate that focusing on goals with a medium difficulty level is appropriate for deep deterministic policy gradient (DDPG) methods, while an “aim for the stars and reach the moon-strategy”, where hard goals are sampled much more often than simple goals, leads to the best learning performance in cases where DDPG is combined with for hindsight experience replay (HER). We demonstrate that the approach significantly outperforms standard goal sampling for different robotic object manipulation problems.

I. INTRODUCTION

How can we improve reinforcement learning algorithms for real robots such that they converge faster and lower the physical wear and tear on expensive hardware during training? One approach to avoid hundreds of hours of physical robot training is to pre-train agents in simulation, and to transfer the learned models to physical robots. Andrychowicz et al. [2] show that using domain randomization and adding noise to actions and observations makes it possible to train models in simulation and to apply them to a real robot directly, or with only a few training rollouts for fine-tuning the learned parameters.

However, despite these advances, some tasks remain particularly hard to solve by contemporary reinforcement learning agents, especially when learning goal-independent policies and value functions in a continuous space. This pertains specifically to situations where achieving the goal involves the implicit learning of causal dependencies. For example, Andrychowicz et al. [2] have recently introduced the hindsight experience replay (HER) sampling method and demonstrated a significant increase in learning performance for off-policy actor-critic DQN [4] and DDPG algorithms [5]. However, difficult tasks like the pick-and-place task depicted in Figure 1 (c,d), where a robot must pick up a single object and position it at a coordinate in 3d space, converges very slowly with the algorithm. The difficulty of this benchmark task stems from high-level causal relations that the agent needs to implicitly learn, namely that grasping is a causal requirement for lifting the object to the target location.

Andrychowicz et al. [2] show that HER can overcome this problem if simpler goals are added, e.g. goals where the goal position is on the table, so that the robot only needs to push the object without lifting it up. This way, the robot can acquire positive training examples for the simpler cases, which allows it to extrapolate its policy to more difficult goals (i.e. transfer learning). This observation supports the idea of curriculum learning (CL) approaches [6], where agents start to learn to solve simple tasks first and gradually increase the task difficulty, thus following a curriculum as may be given by a teacher.

The underlying idea of CL is that, as an agent learns to master simple tasks, it will, at some point, not learn from such cases anymore and must try to accomplish more challenging goals. Ideally, the agent will train under “Goldilocks” conditions, where goals are neither too hard nor too easy, to achieve optimal learning performance. This principle, that is also observed in the context of the cognitive development of human infants [7], leads to our following central research question:

What is the optimal difficulty level for reinforcement learning goals to maximize the learning performance?

A major problem is, that it is hard to estimate the difficulty of a goal during the training process because goals are generally continuous, and the difficulty of a previously unseen goal often cannot be simply interpolated from the difficulty level of similar goals that have been tackled before. Furthermore, the goal difficulty is dynamic in the sense that goals will become easier to achieve as the agent learns. Therefore, we must also ask the following:

How can we dynamically and precisely estimate the difficulty level of continuous reinforcement learning goals, and how can we efficiently sample goals with a certain desired difficulty level?

To answer our research questions, we propose a general and efficient curriculum goal masking (CGM) method to automatically create goals of appropriate difficulty. The masking also allows for estimating the difficulty of a previously unseen masked goal as the recent success rate of the learner for goals on which the same mask has been applied. Our approach builds on this success rate estimate to sample masked goals of the optimal Goldilocks difficulty level to maximize the learning performance.
II. RELATED WORK

A. Curriculum learning for deep reinforcement learning

The term Curriculum learning (CL) for neural networks was coined by Bengio et al. [6], describing the idea that solving easier problems first has advantages to learn more complex goals later and thus that learning can be optimized by presenting the problems in an optimal order, a curriculum. The problem of automatically finding this optimal order has been addressed by several researchers, e.g. Pentina et al. [8], who proposed to use a generalization bound criterion to order multiple tasks that have to be learned, Matiisen et al. [9], who introduced a teacher-learner method where the teacher selects goals depending on the slope of the learning curve for those subtasks, or Graves et al. [10], who introduced intrinsically motivated curriculum learning, using prediction gain as well as complexity gain measures to select subtasks. Generally, approaches using such a CL method showed performance gains in the learning process when tasks are presented to the neural network in a favorable sequence, instead of learning all tasks in parallel. For example, Bengio et al. [11] also show that using a curriculum from true targets to generated targets, shows significant improvements. A limiting factor is that most of the existing approaches assume a given set of predefined subtasks, relying on previous knowledge, and often the proposed ordering process is computationally expensive, adding to the already costly learning process.

Recently, CL has also been used for reinforcement learning scenarios. For example, Narvekar et al. have presented a method to automatically define subtasks for a given target task [13], as well as learning the optimal sequence by incorporating a parallel reinforcement loop [13]. The generation of sub goals includes, besides others, a method to simplify the problem, but the authors assume it to be predefined for a given problem domain. Our masking method can be seen as an automated, domain-independent, and general solution of such a simplification approach.

A similar approach has recently been proposed by Florensa et al. [14]. The authors introduce a Generative Adversarial Network (GAN) that is trained to produce goals of the dynamic optimal difficulty given the current learning progress. For measuring the difficulty, the authors also use the training success rate of the previous time steps for the same goal. In their experiments, Florensa et al. combine their goal sampling method with trust region policy optimization (TRPO) algorithm [13], which they also use as a baseline for their evaluation. In contrast to our work, the authors have not yet combined their algorithm with hindsight experience replay (HER) [2], but propose to do so in future work. Another difference to our work is that training a GAN to generate goals is computationally more expensive than goal masking process.

A multi-agent implementation of automated curriculum generation is the work by Sukhbaatar et al. [16] who propose to use two agents using intrinsically motivated self-play that generate goals for each other. Their results are comparable to those by Florensa et al. [14], but the authors do not evaluate their work in a robotic domain.

Curriculum learning is also related to self-paced learning (SPL) [17], where samples are selected in each step that are getting increasingly less easy to solve. It thus is similar to CL in that it produces a kind of curriculum, but the sequence is not relying on a predefined set of goals. The complexity of samples is estimated by monitoring the training error and thus on the current performance of the learner. This approach has also be combined with CL [18], but despite the learner-centric influence of SPL, the approach still relies on a predefined set of goals “predetermined by an oracle” [18]. One of our main aims is to mimic the learner-centric approach of SPL by selecting goals for RL depending on the current performance, combined with the sequential nature of CL, but with a complexity measurement that can also deal with sparse rewards.

Fournier et al. [19] also present an approach to simplify goals. However, instead of masking the goals, they simplify tasks by reducing the required precision for successful completion. Although the accuracy measurement is similar and the task simplification is of comparable complexity to our goal masking method, our results show a much better performance gain and are also evaluated on a more complex pick-and-place tasks. Kerzel et al. [20] perform a similar approach as Fournier et al., in the sense that they also simplify targets by increasing the target thresholds. However, in addition they partition the learning process into stories,
where for each story a new goal is chosen. This effectively results in an adaptive goal reachability estimate that doubles the learning performance. The authors evaluate their work on a reach-for-target task that does not involve grasping, using a real two dof robotic arm.

B. Continuous goal-independent reinforcement learning with sparse rewards

Most reinforcement learning approaches build on manually defined reward functions based on a metric that is specific to a single goal, such as the body height, posture and forward speed of a robot that learns to walk [15]. Goal independent reinforcement learning settings do not require such reward-shaping (c.f. [21]), as they allow one to parameterize learned policies and value functions with goals. At each step \( t \), the agent executes an action \( a_t \in \mathbb{R}^m \) given an observation \( o_t \in \mathbb{R}^n \) and a goal \( g \subseteq \mathbb{R}^m \), according to a policy \( \pi \) that maps from the current observation and goal to a probability distribution over actions.

An action generates a reward \( r_t \) if the goal is achieved at time \( t \). To decide whether a goal has been achieved, a function \( f(o_t) \) is defined that maps the observation space to the goal space, and the goal is considered to be achieved if \( |f(o_t) - g| < \epsilon \) for a small threshold \( \epsilon \). This sharp distinction of whether or not a goal has been achieved based on a distance threshold causes the reward to be sparse and renders shaping the reward with a hand-coded reward function unnecessary.

The DDPG algorithm [5] is an off-policy actor-critic deep reinforcement learning method. For the goal-independent case, a rollout worker process performs a fixed number \( n_p \) of \( n_p \) parallel rollout episodes during each epoch and records a state transition \( s = (o_t, g, a_t, o_{t+1}) \) for each action step. After each set of parallel rollouts, the neural network models for the actor and the critic are trained off-policy. At the end of each epoch, DDPG performs evaluation rollouts to record the convergence process and to allow for early stopping mechanisms.

Hindsight experience replay (HER) [2] has been presented as an extension to all continuous goal-independent RL algorithms, including DDPG. In brief, HER considers unsuccessful rollouts as positive learning examples by pretending in hindsight that for a current step \( t \), an observation \( o_{t+l} \), that has been achieved at some random future step \( t + l \), was actually the goal state. Formally, state transitions \( (o_t, g, a_t, o_{t+1}) \) in the replay buffer are modified after each rollout cycle, such that \( g \) is replaced by \( f(o_{t+l}) \), where \( l \in (0, T - t) \) is randomly chosen, with \( T \) being the maximal number of steps of the respective rollout. Andrychowicz et al. [2] demonstrate that the best learning performance is achieved if 80% to 90% of all state transition samples are modified this way.

HER is orthogonal to CL, in the sense that instead of selecting goals of an appropriate difficulty level in the first place, goals of an appropriate difficulty level are claimed to be achieved in hindsight. One may argue that this renders the idea of applying CL to deep RL obsolete, but our experiments described in Sec. [IV] demonstrate that a significant gain in performance can be achieved when combining CL with HER.

III. CURRICULUM GOAL MASKING (CGM)

In the introduction (Sec. [I]), we identify the major challenge for realizing CL-based RL methods as the problem of estimating the difficulty of a goal and to sample goals according to their dynamic difficulty level. As a solution, we propose to mask combinations of subgoals, and to associate a difficulty level with each mask. We consider a training rollout to be successful if those subgoals are achieved that are not masked. For example, if the z-axis of the goal of the pick-and-place task is masked, as in Figure 1(d), the goal is considered to be achieved if only the x- and y coordinates are reached. Assuming that all goals created with the same mask share approximately the same difficulty allows for estimating the difficulty level of a simplified goal as the difficulty level assigned to the corresponding goal mask.

Formally, given a goal vector \( g \in \mathbb{R}^n \), we define the space of goal masks as \( M = \{1, 0\}^n \), and we apply a goal mask \( m \in M \) as follows: Let \( o_t \) be the current observation at a rollout or training step \( t \). For that step, we mask the original goal \( g \) to obtain the masked goal \( g^m \) by keeping those elements where the mask is 1 and by setting all other elements to the corresponding values of the observation vector \( o_t \).

\[
g^m = g \odot m + o_t \odot (-m + 1) \tag{1}
\]

This effectively renders those elements of the goal vector that are masked to be achieved at the current step, which causes the reward to be provided if all non-masked goal elements are achieved.

This masking approach allows us to address our second research question, by estimating a success chance for each subgoal combination as the average over the successes of the last \( h \) evaluation rollouts for goals created by this mask.

However, a problem is that the number of subgoal combinations grows exponentially with the number of goal dimensions, which renders a naive version of the masking approach feasible only for low-dimensional goals. To overcome this issue, we assume that the success of achieving each individual subgoal is conditionally independent of the success of achieving other subgoals. With this assumption, we only need to record the successes of each individual subgoal during the evaluation phase of each epoch, and we approximate the success chance \( c_m \) of a goal mask \( m \) as the product of the success chances of the individual subgoals that are not masked.

This allows us to address our central research question, because we can now investigate whether there exists an optimal estimated success chance \( c_g \), such that the convergence speed is maximal if we simplify goals by applying goal masks that have a success rate \( c_m \) close to \( c_g \). Formally, we implement

1In preliminary experiments, we also tried to implement the masking by setting masked subgoals and their corresponding elements of the observation vector to zero, as in recent neural attention models (e.g. [22]), but this resulted in inferior performance.
IV. EXPERIMENTS AND RESULTS

We evaluate our approach by running two goal-based RL algorithms on two different benchmarking problems for various parameterizations. We use DDPG with and without HER in a robotic simulation of a fetch robot depicted in Figure 1, performing different object manipulation tasks. We trained the agents with a Gaussian action noise with $\sigma = 0.2$ and exploration rate of $\epsilon = 0.3$. For the HER agent, we used the future strategy [2] with a hindsight rate of $k = 6$, i.e., for six HER-modified state transitions in the replay buffer one was not modified. During each epoch, 4 parallel rollouts and 64 rollout cycles were performed. To estimate the success chance of the individual subgoals, we compute the average over the last $h = 10$ evaluation rollouts.

A. Experiments

Push the object to a position on the table.
The robot arm has to push an object to a random location on the table’s surface. Since lifting the object is not required, the robot does not have to use its gripper.

Pick up and place an object at a position above table.
The robot has to pick up the object and move it to a goal position above the table’s surface. The task can be expressed as a sequence of three individual causally related subtasks that the robot has to learn implicitly, namely, moving the gripper to the object, grasping the object, and moving the object to the target location. The necessity for a RL agent to implicitly learn the causal relation between these subtasks makes the pick-and-place task a challenging benchmark problem.

B. Results

What is the optimal “Goldilocks” difficulty level?

Figure 2 illustrates the results for the pick-and-place and the pushing experiment with a single object. For both experiments, we ran several tests for different target success rates $c_g \in \{0, 10, 20, 40, 60, 80\}$ and values for $\kappa \in \{1, 4, 32\}$, where $c_g = 1$ causes a relatively homogeneous sampling of goal masks compared to $\kappa = 32$, which causes the sampling to follow a very sharp sampling distribution.

The graphs show at which epoch an evaluation success rate of 50% is achieved for different values for $c_g$ and $\kappa$. For the HER-based algorithm, the learning performance decreases significantly for success chances above 60%. It is roughly constant for values below 40%, with a minimum at $c_g = 10, \kappa = 32$ for the pick-and-place task and $c_g = 40, \kappa = 4$ for the pushing task. For DDPG without HER, the minima are at $c_g = 40, \kappa = 32$ for the pushing task and $c_g = 40, \kappa = 4$ for the pick-and-place task.

To find these parameters, we executed more than 5,000,000 training and evaluation rollouts in total. The number of used CPUs has an effect on the interleaving of rollout execution and neural network training because each CPU independently performs parallel rollouts which are merged during the experience replay to perform the training. Since

the goal mask sampling by selecting a mask $m \in M$ with a probability $p_g \propto |r_m - c_g|^\kappa$. The exponent $\kappa$ controls the sharpness of the probability distribution.
we used 16 CPUs for the pick-and-place task and 4 CPUs for the pushing task, the results between both experiments are not comparable. For example, DDPG requires less epochs for the pick-and-place task with 16 CPUs than for the pushing task with 4 CPUs.

**Improvement of the learning performance.**

To evaluate whether the CGM approach outperforms state-of-the-art algorithms that do not use goal mask sampling, we select the best values $c_g$ and $c$ for each experiment, as identified from Figure 2, and compare it to the case where no goal mask sampling is applied. Results are depicted in Figure 3.

We observe that goal masking has a significant positive effect for all cases but the pushing task with DDPG+HER, where we observe a slightly inferior performance when using CGM. However, for the pushing task, there is a significant positive effect when using CGM with DDPG only, where convergence is reached after approximately 70 epochs with CGM, compared to approximately 110 epochs for the case without CGM.

The largest performance gain is observed for the pick-and-place task, where DDPG alone has never been able to achieve the goal after 300 epochs. If DDPG is combined with HER, convergence is reached only in the upper quartile (orange area in Figure 3 (b)) of all test runs. In the median, DDPG+HER was never able to reach the pick-and-place target. If DDPG and DDPG+HER are combined with CGM, they are consistently able to reach convergence for the pick-and-place task. The median for DDPG+CGM reaches convergence after approximately 170 epochs, and the median for DDPG+HER+CGM reaches convergence after approximately 20 epochs. Hence, we conclude that, for the pick-and-place task, the effect on the increase of the learning performance of CGM on the DDPG algorithm is larger than the effect of HER on DDPG, and that the combination of HER with CGM synergizes well.

**Generalizability of the approach.**

To investigate whether the increase of the learning performance caused by CGM generalizes also over other reinforcement learning tasks, we investigate whether our core assumption, pertaining to the conditional independence of the probability of achieving individual subgoals, holds. To this end, we compute the estimated success chance for each goal mask for the pick-and-place task and compared it to the training success chance for that goal mask. The results are illustrated in Figure 4.

The training success rate for the difficult goal masks that do not involve the masking of the z-axis is significantly lower than the estimated success rates for those masks. The reason for this difference is that during training we apply random actions using the $\epsilon$-greedy strategy, and also an additional noise on actions, which causes around 90% of all training rollouts not to succeed for masks that do not involve the z-axis. However, Figure 4 also depicts that the relative increase of the training success rates is corresponds to the relative increase of the estimated success rates when comparing the individual goal masks. In both cases, the success chance grows after approximately 40 epochs, passes a local minimum at
approximately 75 epochs, and reaches convergence at around 150 epochs. We have observed a similar correspondence for the case of using DDPG+HER. Hence, we conclude that the conditional independence assumption is appropriate, and from this perspective, our approach is generalizable over all problems where the success chance distribution over individual subgoal combinations is not homogeneous.

V. CONCLUSIONS

We propose curriculum goal masking (CGM) as a general add-in to substitute uniform random goal sampling for any continuous deep RL algorithm that uses goal-independent policies and value functions. In this article, we have investigated the effect of CGM on DDPG with and without HER for two different object manipulation tasks. The results indicate that CGM allows deep reinforcement learning algorithms to learn to solve tasks that they are not able to learn without CGM after a reasonable amount of training rollouts.

Related work by Florensa et al. [14] builds on a generative adversarial network (GAN) to sample goals of intermediate difficulty (GOID) within a range parameterized by $R_{\text{min}} = 0.1, R_{\text{max}} = 0.9$, which is equivalent to a desired estimated training success chance between 10% and 90%. However, our results in Figure 4 indicate that the training success chance is not always a precise absolute estimate of the evaluation success chance, especially for problems like in the pick and place task where one specific subgoal, or a combination of subgoals, is harder to achieve than others. This coincides with Florensa et al.’s observation that the GOID range has only a very low effect on the learning performance. In fact, the authors state that a GOID range of $R_{\text{min}} = 0, R_{\text{max}} = 1$ performs similarly well as a GOID range of $R_{\text{min}} = 0.1, R_{\text{max}} = 0.9$, which renders their approach equivalent to the baseline case of random goal sampling.

With our masking approach, we are able to make the conditional independence assumption and to estimate the actual evaluation success chance for each goal by performing a small set of evaluation rollouts after each training epoch. This sample-efficient method allows us to identify the optimal “Goldilocks” conditions under which the learning performance is maximal. We quantify the optimal estimated success chance of a sampled goal to lie between 10% and 40%, depending on the experience replay mechanism and the specific task to solve. We also demonstrate that our approach is robust with respect to the optimal success rate parameter $c_g$, as long as it lies between 10% and 40%, with a reasonable value for the sharpness parameter $\kappa$.

The experiments that we performed required the simulated equivalent of more than 600 days of training on a physical robot. Therefore, we performed the experiments to find the parameters in simulation. However, Andrychowicz et al. [2], who performed the same benchmarking experiments using the same robotic simulation used for our experiments, demonstrate that using a convolutional neural network to localize the object and adding Gaussian noise to the observations during the training allow for direct transfer of the learned neural network models from simulation to a real robot.
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