Towards Improving Exploration in Self-Imitation Learning using Intrinsic Motivation

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Abstract—Reinforcement Learning has emerged as a strong alternative to solve optimization tasks efficiently. The use of these algorithms highly depends on the feedback signals provided by the environment in charge of informing about how good (or bad) the decisions made by the learned agent are. Unfortunately, in a broad range of problems the design of a good reward function is not trivial, so in such cases sparse reward signals are instead adopted. The lack of a dense reward function poses new challenges, mostly related to exploration. Imitation Learning has addressed those problems by leveraging demonstrations from experts. In the absence of an expert (and its subsequent demonstrations), an option is to prioritize well-suited exploration experiences collected by the agent in order to bootstrap its learning process with good exploration behaviors. However, this solution highly depends on the ability of the agent to discover such trajectories in the early stages of its learning process. To tackle this issue, we propose to combine imitation learning with intrinsic motivation, two of the most widely adopted techniques to address problems with sparse reward. In this work intrinsic motivation is used to encourage the agent to explore the environment based on its curiosity, whereas imitation learning allows repeating the most promising experiences to accelerate the learning process. This combination is shown to yield an improved performance and better generalization in procedurally-generated environments, outperforming previously reported self-imitation learning methods and achieving equal or better sample efficiency with respect to intrinsic motivation in isolation.

Index Terms—Reinforcement Learning, Intrinsic Motivation, Self Imitation Learning, Sparse Rewards, Generalization

I. INTRODUCTION

Reinforcement Learning has captured the attention of the research community due to the manifold applications in which this kind of learning problems can be formulated, including games [1], healthcare [2], industry [3] and robotics [4], among others. This momentum has flourished from studies reporting the proven superiority of Deep Reinforcement Learning (DRL) over humans in certain tasks [5], [6], and its potential to train generalist agents [7].

Unfortunately, the large number of samples usually required for DRL makes its application infeasible in some real-world settings. Consequently, Imitation Learning (IL) and Transfer Learning strategies have been proposed over the years to accelerate the learning process and decrease the required amount of training data [8], [9]. The same strategy of using expert demonstrations has been used to address exploration issues in problems with sparse rewards and help the agent learn without any feedback signal from the environment [10]. Nevertheless, such expert demonstrations are not always available in practice. This motivated the idea of the agent interacting with the environment and storing experiences entailing good exploration properties, namely, self-Imitation Learning (self-IL 1). Although it effectively alleviates the need for expert demonstrations, self-imitation learning methods have a high sensitivity to the discovery of sufficiently good trajectories in first instance which can be difficult to obtain depending on the scenario. On the other hand, exploration issues have been also tackled from the perspective of Intrinsic Motivation (IM), in which the agent is encouraged to interact with the environment based on its inner curiosity rather than on externally signalled information about the quality of the interaction with respect to the formulated goal.

In the absence of expert demonstrations and with the aim of maximizing the sample-efficiency in sparse rewards problems, this work proposes a framework that combines both self-IL and IM towards achieving a better management of the agent’s exploration capabilities in sparse problems. Both strategies are commonly used to address tasks demanding high exploration, yet in a separate fashion. Our research hypothesis is that these strategies can be synergistic: IM can be used to generate intrinsic rewards and foster exploration directly, so that the limitation of discovering diverse and valuable trajectories exposed by self-IL can be alleviated. At the same time, self-IL can be effectively used to replay and prioritize good experiences in the agent’s learning process. We envision that, by combining both approaches, we simultaneously boost generalizable knowledge by reinforcing those experiences attractive in term of objective as well as those novel potentially leading to better outcomes.

This is not the first time that both strategies have been mixed to see whether they are complementary [11]–[13]. Previous research studies were carried out in singleton environments [11], [12] with different kinds of prioritization strategies. Contrarily, procedurally-generated environments are created depending on specified attributes (or seeds) that govern the characteristics/dynamics of the generated environment (starting point, configuration of the objects, distance to the goal, etc) to measure the sampled efficiency and generalization capabilities. That is why, recently, hybrid IL-IM algorithms

1For the sake of clarity, in the paper we refer to this kind of methods as self-IL, whereas we use SIL to refer to the approach presented in [11].
were evaluated over these environments yet being analyzed in low to moderate difficulty tasks, leaving the open question whether such algorithms can solve harder exploration tasks [13]. Besides, in the absence of an ablation study it is difficult to determine the contribution of each element of the approach to expose their limitations. In this work we evaluate our framework in procedurally-generated environments from MiniGrid [14], where state-of-the-art algorithms and even IM-based solutions have difficulties to learn [15]. We build our approach on top of a novel self-IL approach called RAPID [16], which retains good exploration behaviors by inspecting the entire episode, and takes into account both extrinsic and intrinsic feedback signals for replay. We evaluate the performance of our proposal in procedurally-generated hard-exploration environments, beating previously reported state-of-the-art self-IL methods results, and also achieving an equal or better sample efficiency with respect to IM approaches in isolation. In addition, we identify several weaknesses that might well hinder a better performance and spur future research directions.

The rest of this manuscript is structured as follows: Section II presents the background related to IL, self-IL and IM. Next, Section III describes how self-IL and IM are combined together to foster a more efficient and synergistic exploration. Section IV follows by detailing the experimental setup. Section V examines the reported results and discusses the limitations. Finally, Section VI draws conclusions and future research work to be developed in this research line.

II. RELATED WORK

In this section we briefly review the literature related to IL and self-IL (Section II.a), IM (Section II.b) and IL+IM approaches (Section II.c) to deal with sparse reward problems from a sample-efficient perspective.

a) Imitation Learning (IL): The experience replay buffers have been employed to stabilize the learning process when using neural network in Reinforcement Learning [1]. Instead of just focusing on the whole history of experiences, different works have proposed to prioritize those samples based on the TD-error [17] or high extrinsic trajectories [18]. The goal is to sample the most promising experiences more frequently, potentially expanding and enhancing the overall knowledge learned by the agent. Following the idea of improving the sample efficiency, IL methods have resorted to expert demonstrations to accelerate the learning stage process, by forcing the agent to learn the inherent decision making hidden in those examples [19], [20]. However, collecting expert demonstrations is not easy to achieve and most of the time the agent is fed with suboptimal demonstrations that hinder the learning of an optimal policy [21], [22]. When lacking an expert capable of providing examples, self-IL was proposed so that an agent, without any kind of prior knowledge, is responsible for collecting and imitating good experiences improvised in the past [11], [23], [24]. Interestingly, self-IL approaches aim to deal with exploration-exploitation dilemma by encouraging the agent to exploit the information that has not been previously learned, so as to achieve a better exploration strategy and ultimately, a near-optimal performance. Despite their proven efficiency at hard exploration problems [11], [25], [26], these methods tend to struggle in tasks characterized by very sparse rewards due to their reduced capability to find good trajectories early in the learning process by just naive exploration [27]. This can be the reason why self-IL solutions have so far been evaluated mainly over non-procedurally-generated environments, where the generalization capabilities of the agent are not tested since the observation’s features do not change from level to level [25], [26]. Alternatively, new approaches like RAPID [16] have emerged to deal with procedurally-generated environments by ranking the episodes not only in terms of their extrinsic rewards, but also by considering exploration scores related to the level. As a result of this multi-criteria ranking, the agent can imitate those experiences and overcome the exploration needs of very sparse tasks, as opposed to other approaches that prioritize episodes based just on their achieved extrinsic reward [11].

b) Intrinsic Motivation (IM): Another research direction to enhance the exploration of the agent and thereby achieve a good overall performance for a given task is to use IM mechanisms. Some of the IM methods were not originally designed to tackle procedurally-generated environments, such as Counts [28], Random Network Distillation (RND [29]), or Intrinsic Curiosity Module (ICM [30]). Lately new approaches have emerged with the aim to learn more robust and generalized knowledge: this is the case of BeBold/NoveId [31], MADE [32], RIDE [33] or AGAC [34]. One of the common aspects to all these methods is that the generated rewards are commonly used with on-policy algorithms (i.e., A2C/A3C, PPO, IMPALA), which discard the collected experiences after their respective optimization updates. This hinders a good sample efficiency, even more so when considering disentanglement/derrailment [26] and catastrophic forgetting due to the fades of intrinsic rewards [35].

c) Combined IL+IM approaches: The idea of combining IL and IM strategies is not new. Previous works have analyzed if they are complementary to each other. However, most of them have been studied at singleton environments where the generalization capabilities have not been assessed. SIL [11] used a count-based intrinsic reward to augment the exploration capabilities in singleton Apple-Gold mazes. Similarly, DTSIL [25] employed the same environment and evaluated its generalization ability by training over 12 random mazes and by evaluating the trained agent over 6 test instances. However, it requires a hierarchical policy where they do not use any kind of IM technique: they only combine DTSIL and IM to evaluate the exploration improvements over some Atari’s (non procedurally-generated) environments. The approach presented in [12] was tested in Atari’s Montezuma, Solaris and Venture environments, in which different prioritizing strategies were studied with prioritized experience replay and IM methods. Recently, [13] evaluated its solution with SIL and BeBold in relatively easy sparse MiniGrid environments.
Nevertheless, neither [13] nor [16] address hard exploration environments as in other works related to IM [31], [34]. At this point, we note that by hard exploration we refer to different configurations of the environments that make them more difficult to be solved. For instance, using more rooms in Multiroom; larger room size in KeyCorridor; or facing ObstructedMaze. In these tasks the generalization and learning requirements are of utmost importance and call for better exploration strategies during the agent’s learning process.

d) Contribution: We formally propose the use of a self-IL strategy together with IM, showing that this combination succeeds at solving hard exploration environments. Our proposal builds upon RAPID [16], in which we combine its ranking strategy for past stored episodes with intrinsic motivation mechanisms. This manuscript steps beyond the state of the art by showing that previous procedures are discarded after the optimization step. However, self-IL methods are highly sensitive to the discovery of good samples, which lie at the heart of the proposed framework described in Section III-C.

III. SYNERGISTIC EXPLORATION WITH SELF IMITATION LEARNING AND INTRINSIC MOTIVATION THROUGH RANKED EPISODES

Self-IL methods allow the agent itself to reproduce self-collected past experiences to induce a better exploration behavior in its learning process [11]. The core idea is to replay experiences that potentially improve the performance of the agent, even though that information was not persisted in the agent because experiences were not exploited enough. This makes the agent explore more effectively. This behavior is emphasized with on-policy algorithms, where samples are stored in a buffer of limited size. The criterion to keep episodes is sampled from the buffer and the policy is go one step further by strengthen its knowledge with the off-policy/supervised loss, which replays and prioritizes the most promising experiences from which to learn.

In this section we explain a self-IL and a IM approach, namely, RAPID (Section III-A) and BeBold (Section III-B), which lie at the heart of the proposed framework described in Section III-C.

A. Ranking the episodes (RAPID)

RAPID [16] was proposed to endow an agent with a more general criterion to detect good exploration behaviors. To this end, RAPID assigns episodic exploration scores to each episode’s experiences instead of relying only on state-level intrinsic rewards. The overall episodic score is calculated by a weighted sum of three scores:

\[ S = w_0 S_{\text{ext}} + w_1 S_{\text{local}} + w_2 S_{\text{global}}, \]

where \( S_{\text{ext}} \) is the total extrinsic reward of the episode, \( S_{\text{local}} \) encourages the exploration inside the episode by maximizing the diversity across visited states, and \( S_{\text{global}} \) models a long-term exploration view by using the average curiosity of the states inside the episode from a visitation count that takes not only the current episode but the whole training process into account. Based on these scores, the most promising episodes are kept in the replay buffer, so that highly ranked episodes are replayed and ultimately imitated by the agent to enhance its exploration.

B. Beyond the boundary of explored regions (BeBold)

BeBold [31] proposes an intrinsic motivation method that circumvent the short-sightedness and detachment problems by issuing a reward signal whenever the next state \( s_{t+1} \) is more novel than the current one \( s_t \):

\[ r^i_t = \max \left( \frac{1}{N(s_{t+1})}, \frac{1}{N(s_t)} \right), \]

where \( N(s_t) \) denotes the number of times the agent has visited state \( s_t \) during training. Moreover, BeBold minimizes the undesired behavior of the agent going back and forth by imposing that a state receives a reward only once per episode.

C. Proposed Framework

As stated in [36], IM-based exploration methods provide an auxiliary objective to collect more diverse data rather than learning to utilize it. Our proposed framework aims to exploit efficiently those collected diverse data during the agent’s interaction (used in the on-policy RL updates) and go one step further by strengthen its knowledge with the off-policy/supervised loss, which replays and prioritizes the most promising episodes from which to learn.

Bearing this in mind, our framework first generates an intrinsic reward \( r^i \) as in Expression (2) at each step, which is weighted by a factor \( \beta \) before being added to the extrinsic reward \( r^e \) given by the environment, yielding the overall reward \( r_t = r^i_t + \beta r^e_t \). This reward is used by the selected RL algorithm to maximize the discounted return, \( G_t = \sum_{k=1}^{\infty} \gamma^k r_k \). Then, the most promising experiences (\( s, a \)) are stored in a buffer of limited size. The criterion to keep episodes is driven by (1) an extrinsic component such as the non-biased Monte Carlo extrinsic return of the episode, \( G = \sum_{t=0}^{T} r^e_t \), and also by (2) scores that augment the exploration behavior in the episode, i.e., local and global scores exposed by RAPID as per Expression (1). After a given number of steps, a batch of experiences is sampled from the buffer and the policy is enforced to match previously executed actions by behavioral cloning\(^2\).

\(^2\)Behavioral cloning is selected for its relative simplicity [37], but other alternatives for policy matching can be equally considered.
With this proposal, the RL update will be strengthened with a intrinsic reward that promotes exploration and augments the probability of sampling good episodes for the ranking buffer, while the latter stores and persists previous highly-ranked episodes to keep improving the agent even when the on-policy updates are not enough and when its intrinsic exploration bonus vanishes. Likewise, both losses will foster exploration while maximizing the exploitation of the given task.

IV. EXPERIMENTAL SETUP

This section describes in depth the environments considered to evaluate the results of the proposed framework (Section IV-A), the baselines for comparison with their selected hyperparameters and neural network architectures (Section IV-B), and the adopted evaluation methodology (Section IV-C). In order to guarantee transparency and reproducibility of the experiments later discussed, software scripts and configuration files have been made available in a public GitHub repository: https://github.com/aklein1995/exploration_sil_im.

A. Environments

Performance evaluations are carried out over procedurally-generated environments, where the agent position and the configuration of objects can randomly change depending on a numerical seed. The goal is to learn a policy capable of solving unseen instances of such environments. In the present work we employ some of the hard-exploration scenarios provided in MiniGrid [14]. Environments in this benchmark are built on a grid with a discrete state/observation space. Observations are egocentric and partially observable to the agent in the form of $7 \times 7$ tiles. Moreover, each object is represented with a compact encoding of 3 values. Thus, an observation is a value tensor of size $7 \times 7 \times 3$. Moreover, 7 different actions are available to solve any given scenario: turn left, turn right, move forward, pick up (an object, e.g. keys or balls), drop the object (if carried), toggle (open doors, interact with objects) and done. Specifically, we evaluate the framework over the following scenarios (for further information about the environments and their tasks, please refer to [14]):

- MultiRoom ($\text{MN}7\text{S}8$ and $\text{MN}1\text{2S}10$).
- KeyCorridor ($\text{KS}4\text{R}3$).
- ObstructedMaze ($\text{OZD}1\text{h}$).

The criteria to select these environments relies on their difficulty as exposed in [16]. In this work $\text{MN}1\text{2S}10$ and $\text{KS}4\text{R}3$ were identified as the most difficult analyzed scenarios: the first was solved by RAPID and RIDE, while the latter remained unsolved for the given train steps by any of the baselines under consideration. In the case of [13] where the performance of SIL+BeBold was analyzed, the most difficult environments were $\text{KS}3\text{R}3$ and $\text{MN}6\text{S}$, which are more easily solvable than $\text{KS}4\text{R}3$ and $\text{MN}1\text{2S}10$. Additionally, we include another very hard exploration scenario, not considered in the aforementioned works, which possesses different characteristics and requirements than the previous environments: $\text{OZD}1\text{h}$.

B. Baselines and Hyperparameters

We select RAPID [16] and SIL [11] as self-IL methods. The intrinsic reward function proposed by BeBold [31] is chosen, in which novelty is calculated by using visitation counts $N(s)$. All strategies use PPO as RL algorithm, which uses a number of steps equal to 128 and 4 minibatches of size 32 for training (one unique agent). Each train step comprises 4 epochs, where optimization updates are carried out with a clipping factor of 0.2, a learning rate of $10^{-4}$, $\gamma = 0.99$ and $\lambda = 0.95$ for the advantages calculation with GAE. Furthermore, the loss function is weighted with an entropy coefficient of 0.01 and a value coefficient of 0.5. We employ 2 independent fully-connected layers for the actor and the critic, each with 64 neurons.

By default, we configure RAPID as in its original paper, with a buffer size of $10^4$ experiences, batch size of 256, 5 off-policy updates after each episode completion. Weights to rank the replay buffer experiences – Expression (1) – are set to $w_0 = 1$, $w_1 = 0.1$ and $w_2 = 0.001$. In the case of SIL, to be as fair as possible with respect to RAPID, we use the same replay buffer size ($10^4$) and the same off-policy update ratio (5). Moreover, we establish a loss weight of 0.1 and a value loss weight of 0.01. Regarding PER [17], we select a prioritization exponent $\alpha = 0.6$ and a bias correction factor $\beta = 0.1$. All these parameter values were chosen according to the supplementary material provided in [11], and taking into account that we target at solving hard exploration environments. On the other hand, the intrinsic reward when using BeBold is computed as described in Section III-B, using an intrinsic coefficient of 0.005. These values were tailored based on the results of a grid search carried out over scenario $\text{MN7S8}$, which can be found in the GitHub repository.

C. Evaluation Methodology

We report the mean and standard deviation of the average return computed over the past 100 episodes for each experiment, performing 3 different runs (with different seeds) to account for the statistical variability of the results.

V. RESULTS & DISCUSSION

This section is devoted to present insights about how intrinsic motivation can help self-imitation learning methods to boost their performance (Section V-A) and discuss potential limitations (Section V-B).

A. Results

Analyzing the performance of self-IL and IM techniques independently and when being combined: to begin with, Figure 1 analyzes the actual impact on the performance of the agent when using IM and self-IL techniques either independently or in combination. We observe that BeBold shows a good behavior only in 2 out of the 4 environments under consideration (namely, $\text{MN7S8}$ and $\text{KS4R3}$). However,
it completely fails when dealing with the challenging scenarios of MultiRoom and ObstructedMaze series (corr. MN12S10 and O2Dlh). When using just SIL, it performs poorly in all scenarios\(^3\).

With reference to RAPID, it is capable of solving MultiRoom environments (as expected), but struggles over KS4R3 and O2Dlh, which are assumed to have larger state spaces and an increasing difficulty from the perspective of exploration. On top of the self-IL approaches, BeBold fosters the exploration and consequently renders some valuable learning when using SIL. However, results are worse than using BeBold in isolation, which suggests that the SIL prioritization mechanisms are not working properly. Contrarily, results are outstanding when combined with RAPID, reducing drastically the number of samples to achieve the same performance and attaining a better overall learning when compared to using RAPID in its naïve version. Besides these improvements, it is interesting to notice that the benefits of using IM remain even when the latter is not enough to learn in isolation: BeBold does not capture any knowledge over MN12S10 and O2Dlh, but it augments the capabilities of RAPID when used in those scenarios.

![Fig. 1: Results over multiple procedurally-generated hard exploration environments in MiniGrid. Both RAPID and SIL always achieve better results when combined with BeBold.](image1)

**Evaluation of RAPID with other IM strategies:** A key aspect of this work is the capacity of IM to enhance the agent’s exploration while learning. Therefore, it is of utmost importance to assess the sensitivity of the proposed self-IL+IM combination with respect to the selection of the IM approach. With that in mind, and considering that the current implementation is based on BeBold’s tabular version (see Section III-B), we now evaluate the agent’s performance with other two visitation counts strategies: \textit{counts} (i.e. \(r_i = 1/\sqrt{N(s)}\)) and \textit{counts1st}, which is the same as \textit{counts} but with episodic restriction. This second set of experiments allows comparing very similar IM strategies that have proven to have different results due to their intrinsic reward generation schema [15], [31].

The results provided in Figure 2 suggest that there is a high relationship between what the agent can learn with IM (without self-IL) and what it actually does by combining them altogether. This can be regarded as a measure of the effectiveness of IM methods when implemented in isolation, where their base functionality of exploring is not wide-spread with the self-IL counterpart. At this point, by just inspecting the results reported in [15], [31], it is clear that \textit{counts} is the worst method, followed by \textit{counts1st} and BeBold. Differences between \textit{counts1st} and BeBold are unclear: most of the contribution seems to be related to the episodic restriction part. However, going beyond the boundaries of already explored regions seems to be promising as well, as it yields better results when compared to RND with episodic restriction [31]. The same comparative performance between IM methods holds when combining them with the ranking replay strategy, where RAPID+\textit{counts} performs slightly better or equal to RAPID in isolation yet being the worst out of the 3 IM options. What is more, the choice of one IM strategy over another can actually deteriorate the performance of the agent, as observed in KS4R3. Nevertheless, when selecting demonstrably good IM strategies, the agent combining self-IL+IM improves its performance even when it was not able to do it just with the IM strategy in isolation.

![Fig. 2: Performance comparison of RAPID when combined with multiple IM methods (counts, counts1st and BeBold).](image2)

\(^3\)As mentioned in Section II and Section IV-A, other works have analyzed how complementary SIL and some IM techniques were, but at sparse reward problems that are not so hard as the ones herein considered [13].

Exploration-exploitation parameters in self-IL+IM: by introducing IM into the on-policy loss, the agent has to deal
with multiple objectives (exploration-exploitation) in various stages: 1) on-policy by balancing the extrinsic and intrinsic rewards; and 2) off-policy by keeping in the buffer the most promising experiences parameterized by the extrinsic, local and global scores. In this regard, Figure 3 depicts the evolution of some representative values concerning how the exploration is carried out during a training run. Initially $G_i(s) > G_e(s)$ shows how the agent explores in the absence of extrinsic signals from the environment, yet eventually this gains more importance for the agent’s ability to complete the task. Similarly, the impact of the $w_0$ score in Expression (1) – that promotes the exploitation of highly extrinsic rewarded episodes – quickly increases. However, the selection criterion is also subject to the $w_1$ local score, which aims to maximize the diversity of observations inside the episode. In a much lower scale, the global scale $w_2$ also plays its role in the selection criterion, which can be helpful during the initial learning stages, when there are no success episodes to complete the task, and also to untie when two episodes require the same amount of steps for the task completion.

We proceed by evincing how the on-policy:off-policy ratio $\xi$ between the number of on-policy and off-policy updates change over the curse of training. On-policy optimization steps are executed once a trajectory has been finished, and it remains equal during the whole training. Off-policy updates are instead applied once an episode finishes, which varies depending on the maximum steps per episode configured for each environment, and also on the optimality of the agent’s policy at that moment. The decision to execute off-policy updates at the end of the episode was retrieved from the original paper where RAPID was proposed [16]. Such ratio

4Refers to the episodic discounted intrinsic and extrinsic returns calculated as described in Section III-C.

Fig. 3: Summary of the evolution of different critical values that impact the learning for a given seed in all the scenarios, using RAPID+BeBold. Plots in the first row denote the average extrinsic reward. Plots in the second row depict the difference between the discounted extrinsic ($G_{ext}$) and intrinsic ($G_{int}$) returns used in the on-policy update (RL-loss). The third row of figures shows the influence of each component/score of the ranking buffer ($w_0, w_1, w_2$) when sampling from its collected experiences. Finally, plots in the last row indicate the average number of off-policy updates per 10 on-policy updates (ratio of updates, $\xi$). All depicted data correspond to the average value in the given time slots.
ξ can change from 1:1 to 1:3 in MultiRoom environments, and more dramatically in other scenarios like KS4R3, which initially implies a ratio of 4:1 and can evolve up to a 4:13 relation. In words, the off-policy loss can undergo a big shift between both methods. In fact, in IL this ratio is usually balanced by either using a weight when combining both losses or by selecting the frequency update [12], [19].

\[ \text{rollout size is} \]

\[ \text{policy (rows 5 & 7). We also report those values when the} \]

\[ \text{conclusions hold when analyzing} \]

\[ \text{with a better sample-efficiency and optimal solutions. Similar} \]

\[ \text{conclusions can also be inferred when using BeBold, but} \]

\[ \text{degrade the learned knowledge in the long term. These} \]

\[ \text{learning process in hard exploration tasks, it can eventually} \]

\[ \text{reduce of the frequency of the off-policy updates, which} \]

\[ \text{This fact is also observed when using a more conservative ratio} \]

\[ \text{better than a more frequent update of the off-policy part (1:1).} \]

\[ \text{original adopted schema with a ratio of 4:1 performs much} \]

\[ \text{more dramatically in other scenarios like} \]

\[ \text{environments,} \]

\[ \text{critical importance in the agent's learning process, as it would} \]

\[ \text{turn to optimize what is stored in the buffer rather than what} \]

\[ \text{is actually experiencing (or vice versa). This generates in turn} \]

\[ \text{a big shift between both methods. In fact, in IL this ratio} \]

\[ \text{is usually balanced by either using a weight when combining} \]

\[ \text{both losses or by selecting the frequency update [12], [19].} \]

\[ \text{Scheduling the self-IL updates. To shed further light on} \]

\[ \text{the importance of the aforementioned ratio, we now fix the} \]

\[ \text{off-policy loss to be constant and subject directly to the} \]

\[ \text{on-policy updates. We then analyze how the performance} \]

\[ \text{varies under several values for this ratio. Figure 4 summarizes} \]

\[ \text{the results obtained for this study. In the family of} \]

\[ \text{MultiRoom scenarios, the agent is very sensitive to a} \]

\[ \text{reduction of the frequency of the off-policy updates, which} \]

\[ \text{can eventually make the agent fail when increasing their} \]

\[ \text{complexity (10:1 in MN12S10). Contrarily, in KS4R3 the} \]

\[ \text{original adopted schema with a ratio of 4:1 performs much} \]

\[ \text{better than a more frequent update of the off-policy part (1:1).} \]

\[ \text{This fact is also observed when using a more conservative ratio} \]

\[ \text{of 10:1, suggesting that, although a higher off-policy update} \]

\[ \text{frequency can be beneficial at initial stages to bootstrap the} \]

\[ \text{learning process in hard exploration tasks, it can eventually} \]

\[ \text{degrade the learned knowledge in the long term. These} \]

\[ \text{conclusions can also be inferred when using BeBold, but} \]

\[ \text{with a better sample-efficiency and optimal solutions. Similar} \]

\[ \text{conclusions hold when analyzing O2Dlh.} \]

\[ \text{Addressing inter-episode variance. So far, the} \]

\[ \text{selected ratio seems to be decisive for the success and} \]

\[ \text{sample-efficiency of the training process. However, the} \]

\[ \text{obtained outcomes are very noisy and barely close to optimal} \]

\[ \text{results, which can be due to one of the two losses being} \]

\[ \text{unstable. While the seminal work presenting RAPID used} \]

\[ \text{PPO with a rollout size\textsuperscript{5} of nstep} = 128, \text{other similar} \]

\[ \text{works considering the same environment used a larger time} \]

\[ \text{horizon nstep} = T = 2048, \text{with better and more stable} \]

\[ \text{results [15], [34]. As mentioned in Section IV-A, each episode} \]

\[ \text{is configured differently depending on the selected seed.} \]

\[ \text{Consequently, by training the agent with less episodes in a} \]

\[ \text{single update, it might get biased to learn specific features} \]

\[ \text{present in that subset of episodes, rather than getting the} \]

\[ \text{required high level skills to solve the desired task in the} \]

\[ \text{whole possible episode distribution. Hence, the increment of} \]

\[ \text{the rollout size implies that the agent will be trained (in the} \]

\[ \text{on-policy update) with a larger set of episodes (see Table I} \]

\[ \text{to check for episode lengths) which forces the algorithm to} \]

\[ \text{extract generalizable knowledge in this wider set of slightly} \]

\[ \text{different environments, preventing from a by-heart learning.} \]

\[ \text{Furthermore, this also reduces the variance of the on-policy} \]

\[ \text{update) with a larger set of episodes (see Table I} \]

\[ \text{results [15], [34]. As mentioned in Section IV-A, each episode} \]

\[ \text{is configured differently depending on the selected seed.} \]

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\[ \text{single update, it might get biased to learn specific features} \]

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\[ \text{extract generalizable knowledge in this wider set of slightly} \]

\[ \text{different environments, preventing from a by-heart learning.} \]

\[ \text{Furthermore, this also reduces the variance of the on-policy} \]

\[ \text{updates through the neural network, as the minibatch size} \]

\[ \text{itself will be larger. However, the agent will perform less} \]

\[ \text{optimization steps during the training process for the same} \]

\[ \text{amount of steps/frames.} \]

\[ \text{In this context, how does the use of larger rollout size} \]

\[ \text{impact on the on-policy update regarding the performance} \]

\[ \text{of 10:1, suggesting that, although a higher off-policy update} \]

\[ \text{frequency can be beneficial at initial stages to bootstrap the} \]

\[ \text{learning process in hard exploration tasks, it can eventually} \]

\[ \text{degrade the learned knowledge in the long term. These} \]

\[ \text{conclusions can also be inferred when using BeBold, but} \]

\[ \text{with a better sample-efficiency and optimal solutions. Similar} \]

\[ \text{conclusions hold when analyzing O2Dlh.} \]

\[ \text{The rollout size is directly related with the number and minibatch size.} \]

\[ \text{The increment of the first implies that the minibatch size is also incremented} \]

\[ \text{for the same number of minibatches).} \]
and the stabilization of the learned knowledge? The answer to this question can be found by analyzing Figure 5. The on-policy update is substantially improved, which can be seen in how BeBold performs without being corrupted by off-policy updates, being such IM solution able to solve all the environments with the expected optimal steps and obtaining the best result in both KS4R3 and O2D1h. Contrarily, RAPID performs worse, and its contribution when combined with BeBold is also not as good as it has been observed in the previous analysis.

The reason for such bad results is also connected to what we have previously highlighted: the ratio $\xi$. By increasing the rollout size and making the off-policy updates be subject to the episode completion, the off-policy loss grows up to be $14\times$, $8\times$, $4\times$ and $4\times$ more frequent than the on-policy counterpart in MN7S8, MN12S10, KS4R3 and O2D1h, respectively, just at the start of the training process (Table I). As we have already seen in Figure 4, those kind of ratios does not necessarily mean to foster a better learning. Thus, when adjusting the ratio again with the new rollout size the performance of both RAPID and RAPID+BeBold drastically changes, as seen in Figure 6. In first instance, it can be seen a better sample-efficiency when using a more conservative ratio (1:1) in both KS4R3 and O2D1h. This also happens when decreasing the off-policy updates up to a 10:1 ratio, where the convergence speed can be affected although it manages to achieve the optimal policy in less steps (the 1:1 ratio struggles more to finally achieve it). In contrast, when using the criteria of applying those updates at the end of the episode, which corresponds with approximately a 1:4 ratio initially in KS4R3 and O2D1h (Table I), the results get worse, just surpassed by the BeBold approach. These behaviors strengthen our claim: the off-policy loss can help to improve the learning process, although using it in excess can be counter-productive. This is related to what is actually aiming to replay and if it is worth the value that update for the agent at that moment. Concerning MultiRoom environments, increasing the number of off-policy updates seems to be a good strategy, which is difficult to be beaten even by other state-of-the-art solutions. In fact, decreasing the frequency of the replayed experiences has a negative impact that can lead the agent to not learning in the absence of intrinsic rewards.

Fig. 5: Results on multiple hard exploration procedurally-generated environments in MiniGrid when increasing the time horizon up to 2048 in on-policy (RL-loss) updates. Off-policy (supervised/imitation) updates remain with fixed batch size of 256.

Fig. 6: Same interpretation of ratios as in Fig 4 but when increasing the rollout size up to 2048. Recall the default ratio is dynamically adjusted based on when the episode finishes (see Table I).

B. Discussion

1) Environment dependant requirements: So far we have seen outstanding results in either [16] and the current work for MultiRoom, although such benefits are not so clear in other scenarios. We hypothesize that this due to the understandings and latent knowledge that is needed to interact with the environment to accomplish the task; this is, what the agent actually has to learn in each environment to accomplish the task. On the one hand, in MultiRoom’s environments the agent independently of the destination has always to move forward until finding a door (any color), open it and continue until reaching the goal. Hence, the agent has to discover that the way to solve the task is to find the next door as soon as possible and open it with the consequent action, which may well be inferred and faster learnt when exploiting past episodes as all that information does not indeed change from one level to other. On the other hand, in KS4R3 and O2D1h the agent has to learn how to interact with multiple objects (door can be closed or locked), the relation between objects...
and their utility (key is used to open lock doors) and the information given by the colors (the key of a given color only unlocks the door of that same color). Furthermore, the location of doors, keys and also the destination change from level to level so exploiting past good episodes do not necessarily mean to be the best strategy, because the stored episodes might be biased to certain patterns that can bias the agent’s intuition (i.e. blue doors represent the best strategy to achieve the goal) and hinder what it has to actually learn.

Aside from the environment requirements, it is not straightforward to determine what episodes to replay and when to do it, as what the agent learns changes over the curse of the training. By replaying just a certain portion of all the possible steps to solve the environment and hinder what it has to actually learn.

2) Intra/Inter Level Diversity: The first is related to the diversity across episodes. Diversity in the buffer is desired when the environment evolves during the training, thus maximizing the probability of having something useful in the buffer for the agent’s learning at the moment. Rapid hyper-parameterization selection will be decisive for the buffer configuration prioritizing either the emulation of past levels with high intra-episodic diversity of states through local bonus or long-term exploration via global bonus. However, none of them was originally designed to control the diversity across different levels (inter-level). In addition, being these scored weighted statically and with no prior insights about what the agent actually manages to solve makes it impossible to assure that the buffer contents will be advantageous to learn convenient generalized knowledge. As a consequence, the agent would be forced to imitate levels that do not hold any guarantees to be useful when exploiting generalization.

3) Suboptimal demonstration replay: The second is referred to how the sparse extrinsic reward is calculated in procedurally-generated environments. Such function is commonly designed taking into account the number of steps until achieving the goal; particularly in MiniGrid it is calculated as $R(t) = 1 - 0.9 \cdot t/t_{\max}$, being $t$ the number of steps to solve the environment and $t_{\max}$ the maximum number of steps that can be taken in an episode before being reset. Nevertheless, the levels have a minimum number of optimal steps based on the sorted configuration. Hence, the same reward at different levels would not necessarily have to represent the same optimality. Consequently, the agent will be more prone to learn from suboptimal demonstrations of those “easy” configured levels just because solving them suboptimally takes less steps than doing it optimally in other levels. Furthermore, the agent can become greedy and bias its learning to those “easy” levels that do not necessarily represent the whole level distribution of the given task and fail in generalization. What is more, even in the case that the stored episodes are optimal, it exist the risk that the agent just focuses on those episodes that might not well ensure the needed diversity as explained above (see an example in Figure 7). Obviously, using the extrinsic reward for prioritization is just a criteria for classifying good episodes that is not mandatory, although it has been broadly adopted as it is one the most important (if not the main) performance metric used to evaluate a RL algorithm.

The hyper-specialization of the buffer may turn the off-policy learning poor whatever the quantity of levels processed. In that sense, the off-policy updates could be dynamically scheduled to maximize the contribution along the training. Ideally, those updates should be selected from a buffer which fairly matches the optimal scores across levels.

VI. CONCLUSIONS

This work has postulated that the use of intrinsic motivation can improve the sample efficiency of self-imitation learning approaches in those sparse reward scenarios where the exploration needs hinder the collection of good episodes to be replayed. Based on this research hypothesis, a framework combining RAPID and BeBold has been proposed, exposing experimentally an equal or better sample efficiency when compared to RAPID, BeBold or SIL approaches on their own, when solving challenging tasks formulated in MiniGrid’s procedurally-generated environments. We have shown that this advantage holds as long as the selected IM method is efficient enough. Furthermore, we highlight the necessity of scheduling correctly the on-policy and off-policy updates, as well as the use of a rollout size that considers multiple episodes in the same optimization step to reduce the variance and achieve an optimal policy. Finally, we have discussed the reasons why the

$^6$In this work, for the sake of comparison, parameters are set with the same values as in the original paper [16].
off-policy updates do not necessarily have to be helpful due to 1) the environment requirements; 2) the diversity between the stored episodes; and 3) the way in which prioritization is applied, being subject to a reward function that does not distinguish between optimal solutions across levels due to the different steps required to solve them.

In the future we aim to extend this study to continuous-state spaces, examining whether our insights herein offered can be extrapolated to other procedurally-generated benchmarks. Moreover, we plan to overcome the aforementioned limitations related to the off-policy updates, so that the agent’s learning process can be accelerated without requiring a manual setup of the on-policy/off-policy schedule and the definition of the reward function itself.

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