Improved Soft Actor-Critic: Mixing Prioritized Off-Policy Samples With On-Policy Experiences

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Abstract—Soft actor-critic (SAC) is an off-policy actor-critic (AC) reinforcement learning (RL) algorithm, essentially based on entropy regularization. SAC trains a policy by maximizing the trade-off between expected return and entropy (randomness in the policy). It has achieved the state-of-the-art performance on a range of continuous control benchmark tasks, outperforming prior on-policy and off-policy methods. SAC works in an off-policy fashion where data are sampled uniformly from past experiences (stored in a buffer) using which the parameters of the policy and value function networks are updated. We propose certain crucial modifications for boosting the performance of SAC and making it more sample efficient. In our proposed improved SAC (ISAC), we first introduce a new prioritization scheme for selecting better samples from the experience replay (ER) buffer. Second we use a mixture of the prioritized off-policy data with the latest on-policy data for training the policy and value function networks. We compare our approach with the vanilla SAC and some recent variants of SAC and show that our approach outperforms the said algorithmic benchmarks. It is comparatively more stable and sample efficient when tested on a number of continuous control tasks in MuJoCo environments.

Index Terms—Off-policy learning, on-policy learning, policy optimization, reinforcement learning (RL), soft actor-critic (SAC).

I. INTRODUCTION

REINFORCEMENT learning (RL) has shown significant growth and achieved state-of-the-art performance in diverse domains including robotics [1], [2], locomotion control [3], [4], strategy games [5], [6], multi-agent systems and control [7], [8], wireless sensor network [9], [10], and so on. In the conventional model-free RL paradigm, an agent can be trained either by learning an approximator of action-value (Q) function [11], [12] or by explicitly learning and optimizing a policy model. In particular, the class of actor-critic (AC) algorithms [13], [14] follows the later approach. In a policy optimization process, a typical AC algorithm performs three basic steps of: 1) generating samples by running current policy on environment; 2) estimating a state/action-value function from the samples; and 3) evaluating the performance of the last action and updating the current policy.

Based on how the past experiences are utilized, the AC or RL algorithms in general can be classified as either on-policy or off-policy algorithms. An on-policy algorithm continually learns a policy from the samples generated by the policy upon interacting with the environment but discards them once used. Popular examples of on-policy algorithms include vanilla policy gradient [15], trust region policy optimization [16], proximal policy optimization [17], and so on. By contrast, an off-policy algorithm learns a policy from the samples of past experiences stored in a buffer, e.g., deep deterministic policy gradient (DDPG) [18], [19], twin delayed DDPG [20] and soft actor-critic (SAC) [21]. In particular, SAC is a model-free off-policy algorithm that optimizes a stochastic policy, with the use of entropy regularization. Increase in the policy’s entropy results in more exploration and accelerates learning. SAC has so far achieved state-of-the-art performance on a number of continuous control benchmark tasks, outperforming several on-policy and off-policy algorithms. The experimental results in [21] demonstrate that SAC outperforms the benchmark algorithms in the aforementioned references [17]–[20] and soft Q-learning in [22].

As an off-policy algorithm, SAC maintains a so-called experience replay (ER) buffer and trains its policy network on the data uniformly sampled from the buffer. ER forms the basis of most off-policy algorithms where actors and/or critics are updated according to the samples from the past experiences stored in an ER buffer. Using ER greatly increases the sample efficiency of an algorithm by enabling data to be reused multiple times for training the policy. It typically needs a large number of environment-agent interactions to obtain experiences (or transition tuples) and maintain the ER buffer. Researchers have studied different approaches of leveraging the ER buffer for policy optimization in literature.

For instance, a sample efficient AC algorithm with ER [23] interleaves the on-policy learning and off-policy learning cycle where a hyperparameter controls the ratio of off-policy updates to on-policy updates. Hindsight ER [24] and its recent variants [25]–[27] aim to essentially deal with sparse reward and multi-goal RL environments. The remember and forget for ER [28] algorithm enforces the similarity between policy and the experiences in the replay buffer. It characterizes past experiences as either “near-policy” or “far-policy” based on the deviation from the importance sampling weight and calculate gradients only from “near-policy” experiences. In a different work, Schimit et al. [29] introduces a Q-function free AC paradigm where concurrent agents share their experiences.
through a common ER module and also use V-trace importance sampling [30] for variance reduction. The research shows that mixing of a proportion of on-policy experiences with off-policy experiences contributes to the improvement of the proposed algorithm’s convergence.

It is intuitively known that differentiating important samples from not so important ones is beneficial to policy learning; see [31]. Prioritized experience replay (PER) is a strategy for differentiating samples in ER. In [32], the PER algorithm samples non-uniformly from the replay buffer and favors those samples which have a higher value of absolute temporal difference (TD) error. PER has also been tested with double deep Q-networks (DQNs) [33], dueling network architecture DQNs [34], and DQNs with snapshot ensembling [35], and it performs better than the non-prioritized/uniform sampling approach. As a result, PER has been adopted in many DQN extensions, e.g., [36]–[39]. In a recent DQN-PER extension, called prioritized sequence experience replay [40], the algorithm not only assigns high sampling priority to important transitions but also increases the priorities of the previous transitions that lead to important transitions. PER has also been applied to the AC type of algorithms, e.g., for DDPG [41].

Apart from using absolute TD error for sample prioritization, episodic return/episodic memory has also been used for the same purpose in a number of works [42]–[44]. For example, the asynchronous episodic DDPG [44] improves over the vanilla DDPG algorithm using two replay buffers and sampling from them with a fixed probability for training the DDPG networks. One buffer (the Memory) is just like the generic DQN-style replay buffer and the other (the HMemory) stores only those episodic experiences whose episodic reward (or score) surpasses the best score at present. The work highlights the demerits of learning the policy with episodic experiences from episodes with a “best so far” score. This approach leads to reduction in sample diversity which might result in overfitting of the learned networks and introduction of bias for the final convergence.

In this article, we aim to propose a strategy to manage an ER buffer as enhancement to the vanilla SAC algorithm to reduce the number of these environment–agent interactions and thus increase the speed of learning. The new version of SAC is named improved SAC (ISAC) throughout the article, which has two primary innovations. On one hand, we introduce a priority-based selection of better quality data from mini-batches sampled from the ER buffer. On the other hand, we strategically mix the latest on-policy experiences with the current prioritized mini-batch of samples and then train the SAC networks on the updated batch. We compare our approach with the vanilla SAC and other latest SAC versions on several MuJoco continuous control tasks and our approach shows superior performance in comparison.

The remaining sections of the article are organized as follows. In Section II, we discuss the preliminaries and motivations of our work. In Section III, we discuss in detail our proposed ISAC algorithm. Section IV contains the experiments on several MuJoco continuous control tasks with some discussion about the results with regard to compared benchmarks. Finally in Section V we conclude this article and discuss some future extensions of the work.

II. PRELIMINARIES AND MOTIVATION

The article is concerned about a Markovian dynamical system represented by a conditional probability density function \(p(s_{t+1}|s_t, a_t)\) where \(s_t \in S\) and \(a_t \in A\) are the current state and action respectively at time instant \(t = 1, 2, \ldots\), and \(s_{t+1} \in S\) represents the next state at \(t + 1\). Here, \(S\) and \(A\) represent the continuous state and action spaces, respectively. The objective is to learn a stochastic policy \(\pi_\phi(a_t|s_t)\) parameterized by \(\phi\). Now, the closed-loop trajectory distribution for the episode \(t = 1, \ldots, T\) can be represented by

\[
p_\phi(t) = p(s_1) \prod_{t=1}^{T} \pi_\phi(a_t|s_t)p(s_{t+1}|s_t, a_t)
\]

for \(\tau = (s_1, a_1, s_2, a_2, \ldots, s_T, a_T, s_{T+1})\). Denote \(r_t = R(a_t, s_{t+1})\) as the reward generated at time \(t\). The objective is to find an optimal policy, represented by the parameter \(\phi^* = \arg \max_\phi E_{\tau \sim p_\phi(\tau)} [\sum_{t=1}^{T} \gamma^t R(a_t, s_{t+1})]\)

which maximizes the objective function \(J(\phi)\), \(\gamma\) is the discount factor.

SAC uses a maximum entropy objective, formed by augmenting the typical RL objective with the expected entropy of the policy over \(p_\phi(t)\). In other words, an agent receives an additional reward at each timestep which is proportional to the policy’s entropy at that timestep, given by \(\mathcal{H}(\pi_\phi(|s_t|))\). So, the SAC’s entropy-regularized RL objective to find an optimal policy can be written as

\[
\phi^* = \arg \max_\phi E_{\tau \sim p_\phi(\tau)} [\sum_{t=1}^{T} \gamma^t (R(a_t, s_{t+1}) + \alpha \mathcal{H}(\pi_\phi)|s_t|)]
\]

where the entropy regularization coefficient \(\alpha\) determines the relative importance of the entropy term against the reward. Throughout the research in this article, we use the latest version of SAC [45] where \(\alpha\) varies over the course of training and is not fixed.

Following the generic AC framework, SAC learns a policy \(\pi_\phi\) which takes in the current state and generates the mean and standard deviation of an action distribution (defining a Gaussian). But instead of a single \(Q\)-network, the SAC concurrently learns two \(Q\)-networks \(Q_{\phi_1}, Q_{\phi_2}\) by regressing to the values generated by a shared pair of target networks \(Q_{\phi_{\text{avg,1}}}, Q_{\phi_{\text{avg,2}}}\) [45]. SAC works on an off-policy scheme and thus uses an ER buffer to update network parameters. It alternates between a “data collection” phase and a “network parameter update” phase. In the data collection phase, SAC saves to ER buffer the transition tuples, e.g., \(d^e_t = (s_t, a_t, r_t, s_{t+1})\), where \(t = 1, \ldots, T_e, e = 1, \ldots, E\) (E is total episodes run), obtained by running the current policy in the environment.

In the network update phase, SAC samples a mini-batch \((B)\) of saved transition tuples from the ER buffer \((B \sim D)\) uniformly and updates the network parameters. For more details on SAC, please refer to [21], [45], and [46].

On the subject of improving SAC, there have been a number of recent works, where the authors have targeted different
Aspects of the SAC framework. For example, Ward et al. [47] altered the choice of policy distribution from factored Gaussian in vanilla SAC to normalized flow policies for improving exploration. Campo et al. [48] explicitly constrained the ability of the critic to learn the high-frequency components of the state-action value function through the addition of a convolutional filter.

On the contrary to these works, we target the problem of utilizing the ER buffer more efficiently such that the SAC learns a well-generalized policy, fast and thus with fewer agent–environment interactions (or samples). In this regard, [49] and [50] have experimented with introducing TD error-based prioritization (i.e., PER [32]) in vanilla SAC and achieved improved performance. The authors of [49] proposed an emphasizing recent experience (ERE) approach, where the algorithm samples more aggressively from recent experiences such that the updates from old experiences do not overwrite those from new experiences. The combination of the aforementioned algorithms, i.e., SAC + PER + ERE shows superior performance in a number of continuous control tasks. In a slightly different approach proposed by Sinha et al. [50], the algorithm works along the lines of [44], by maintaining two replay buffers. Here, one (fast) buffer stores the recent-most on-policy experiences and another (slow) buffer contains additional off-policy experiences. Next, they estimate the density ratios between near off-policy and near on-policy distribution, by minimizing an objective over a density estimator network. They use this ratio as weight over the $Q$-network update objective so as to encourage more updates over samples closer to the fast replay buffer. Although it shows superior performance in certain benchmark environments, it introduces a number of additional hyperparameters including the size of the fast replay buffer and the architecture of the density estimator network. Besides, the density ratio estimation process also adds computational complexity to the vanilla SAC.

In this article, we propose an approach to make ER buffer-based training of SAC networks more sample efficient and achieve improved performance using fewer training episodes. But instead of prioritized sampling of recent data like in [49] or calculating importance weights using multiple buffers and additional networks like [50], we introduce a different and simpler approach as elaborated below.

First, we introduce a prioritization scheme to improve the quality of off-policy samples from an ER buffer. Using an episodic return-based priority score to select better transitions, we obtain a prioritized off-policy batch for network training. Regarding the use of episodic return to prioritize ER buffer samples and checking overfitting of networks while training frequently on better performing samples, we draw a number of crucial insights from these works [41]–[44]. Second, we mix the latest on-policy experiences directly into this prioritized off-policy batch and train the SAC networks (at each timestep). An itemized list of the major contributions to the existing conventional SAC framework is summarized as follows.

1) **Sampled Data Prioritization (SDP):** We save all the transition tuples (to the ER buffer $D$) with an additional element. It is the episodic return $\rho$ (cumulative reward of an episode) of a certain transition tuple’s parent episode and serves as a goodness or priority score for a transition. At each timestep, we accumulate data or transitions from multiple mini-batches uniformly drawn from the ER buffer. From the accumulated data, we choose a prioritized batch based on the priority score. We also control prioritized selection using a semi-metric calculation of $\rho$.

2) **Mixing On/Off Policy Experiences (MO/O):** The pure off-policy with sampled and prioritized training data is then mixed with the latest on-policy transition. This mixed batch is used to train the policy and the value function networks of SAC.

3) **Delayed Infusion of Recent Experience:** We add the recent most collection of experiences/transitions to the ER buffer in a delayed fashion. This enables the SDP to calculate and assign the priority score. This also helps preserve data diversity in the ER buffer, especially for the training on mixture of on-off policy experiences.

To the best of our knowledge, this is the first article that considers direct on- and off-policy data mixing in the context of SAC algorithm. It is also the first article that considers prioritizing data that have been uniformly sampled from the ER buffer instead of going for a prioritized sampling approach in the first place.

III. **Improved Soft Actor Critic: SAC + SDP + MO/O**

The proposed approach is called ISAC that involves mixing the latest on-policy data with a prioritized batch of off-policy data (SDP and MO/O) and training the SAC networks with it, also denoted as SAC + SDP + MO/O. The approach also includes delay in infusion of recent experiences to the ER buffer to improve the stability and for maintaining better data diversity in the ER buffer. In Fig. 1, we illustrate the overall structure of the proposed methodology. We elaborate these features in Sections III-A, III-B, and III-C, respectively.

A. **Sampled Data Prioritization (SDP)**

First, we introduce an additional element to the experience/transition tuple added to the ER buffer in conventional SAC. This element is later used for prioritizing samples. We use the episodic return ($\rho^e$) of a terminated episode $e$ as a score of goodness of all the individual transitions $(d_{t}^{e}, \ldots, d_{T}^{e})$ under that certain episode, where

$$
d_{t}^{e} = (s_{t}^{e}, a_{t}^{e}, r(a_{t}^{e}, s_{t+1}^{e}), \rho^e)\in\mathcal{D}$$

In the augmented tuple $\tilde{d}_{t}^{e} = (s_{t}^{e}, a_{t}^{e}, r(a_{t}^{e}, s_{t}^{e}), s_{t+1}^{e}, \rho^e)$, the score $\rho^e$ remains same for all the transitions of a certain episode $e$. It is worth noting that unlike conventional prioritization approaches, e.g., PER, we do not sample data from the ER buffer based on any priority.

We rather do prioritize data selection from some collected data which are first sampled uniformly from the ER buffer. We uniformly sample multiple mini-batches (with replacement) and then prioritize them based on the data in those mini-batches. More specifically, we extract $l (=2)$ of $k$ sized mini-batches from the ER buffer, i.e., $B_1 = \{d_{t_{1}}^{e_{1}}, \ldots, d_{t_{k}}^{e_{1}}\}$ and $B_2 = \{d_{t_{k+1}}^{e_{2}}, \ldots, d_{t_{2k}}^{e_{2}}\}$ for $t_{1}, \ldots, t_{2k} \in \{1, \ldots, T\}$ and $e_{1}, \ldots, e_{2k} \in \{1, \ldots, E\}$. In particular, it is noted that a
minibatch represents some random tuples rather than a certain consecutive transitions. Next, we merge the batches, i.e., $\hat{C} = B_1 \cup B_2$, resulting in $k_{\text{eff}} \leq l \times k$ transition tuples. Here, $<$ may hold if there are common elements in $B_1$ and $B_2$. Then, we pick the prioritized data $C_{\text{prior}}$ of size $k$, with $C_{\text{prior}} \subseteq \hat{C}$ and $C_{\text{test}} = \hat{C} \setminus C_{\text{prior}}$, such that $\rho^{c} \geq \rho^{\hat{c}}$ for all $\hat{c} \in C_{\text{prior}}$ and $\hat{c} \in C_{\text{test}}$. Selecting prioritized data from a comparatively larger $\hat{C}$ with a large $l$ essentially trains the networks with a higher percentage of repeated data. So using $l = 2$ gives a superior data diversity, while keeping the minibatch size and other parameters unchanged.

We also introduce mechanisms to control prioritization since learning only from better performing experiences or transition tuples may cause overfitting of the networks, as noted in, e.g., [44]. Moreover, the episodic return-based score values $(\rho^{c})$ of the transition tuples improve over time with the policy and successive episodic return values can become very similar or same in certain cases. So, as time goes the ER buffer is filled with more transition tuples with similar score values. In this situation, if we sample minibatches with similar score values then performing prioritization on the data becomes ineffective. Thus, non-prioritized samples should help train the networks better. Therefore, if the two sampled mini-batches $B_1$ and $B_2$ are similar with respect to their scores then we do not perform prioritization but use uniformly sampled mini-batch for training in that timestep.

To be precise, we do the prioritization step (SDP) and obtain a prioritized off-policy batch, i.e., $C = C_{\text{prior}}$, if the condition $\zeta \leq \zeta_{\text{th}}$ is satisfied, where $\zeta$ is a calculated similarity value between the two mini-batches and $\zeta_{\text{th}}$ is a preset threshold hyperparameter. Otherwise, we choose any one batch randomly from the sampled mini-batches $B_1, B_2$, i.e.,

$$C = \begin{cases} C_{\text{prior}}, & \zeta \leq \zeta_{\text{th}} \leq B \in \{B_1, B_2\}, \zeta > \zeta_{\text{th}}. \end{cases}$$

We calculate a cosine similarity measure $(\zeta)$ of the sampled mini-batches $(B_1, B_2)$ using their respective episodic return score vectors, i.e., $v_{B_1} = \{\rho_1, \ldots, \rho_k\}$ and $v_{B_2} = \{\rho_1, \ldots, \rho_k\}$. In particular, the cosine similarity is given by the following expression:

$$\zeta = \frac{v_{B_1} \cdot v_{B_2}}{\|v_{B_1}\| \|v_{B_2}\|}$$

where $\|v_{B_i}\|$ and $\|v_{B_j}\|$ are the Euclidean norms of the corresponding vectors. The closer the $\zeta$ value to 1, the greater the match between the vectors and the more similar the batches are to one another. Setting a higher threshold value $\zeta_{\text{th}}$ allows more prioritization of the sampled data, leading the networks to learn on a higher percentage of better performing transition tuples. We examined the effect of varying the value of $\zeta_{\text{th}}$ on the performance of ISAC and the results are presented in Section IV.

### B. Mixing On/Off Policy Experiences (MO/O)

During the parameter update phase, the conventional SAC trains its networks by sampling one mini-batch per gradient step, from the ER buffer. This mini-batch thus contains samples of experiences collected over past iterations of the policy. We make changes to the sampled data by including the latest on-policy experiences into them and train the networks with the revised data. In our approach, after the prioritization phase (SDP) we obtain a batch $C$ and then include the latest on-policy experiences to it. We replace a random tuple $y \in C$ with the latest on-policy transition tuple $q_t$, which gives us the final batch to train the SAC networks for the current timestep, i.e., $M = (C \setminus \{y\}) \cup \{q_t\}$. 

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Fig. 1. Simplified illustrations of (a) vanilla SAC [45] and (b) proposed ISAC. The target $Q$ network(s) are not shown in the diagram for clarity.
MO/O improves the performance of the policy by ensuring that the networks are trained using the latest on-policy samples mixed with the prioritized off-policy batch. It plays an important role in ISAC. As mentioned in Section III-A with the goodness score $\rho$, we need to wait for at least one episode to generate the score, add the score to the relevant transition tuples, and then save the augmented transition tuples to the ER buffer. During the episode length, no new latest transitions or experiences are added to the ER buffer and so the learning process will continue on the samples drawn from a collection of relatively older experiences. But inclusion of the latest experiences in the off-policy samples on the go resolves this issue. We have studied the performance of SAC without the MO/O type data mixing and the empirical results show slow policy learning without the MO/O artifact. The detailed results are discussed in Section IV.

**C. Delayed Infusion of Recent Experiences**

The SDP scheme needs to generate episodic return-based scores $\rho$ for use in prioritization. Assigning $\rho$ to the transitions collected over an episode is based on the cumulative rewards (episodic return) accumulated over that episode. So, at least we need to wait through one episode to generate and assign the $\rho$ score. To enable this process, we add the recent on-policy experiences to the ER buffer in a delayed fashion contrary to the conventional practice of implementing it per timestep. The other reason for delayed infusion of data to the ER buffer is to retain its data diversity. Using MO/O, we train the networks with a mixture of the latest on-policy experiences and the sampled past experiences. If we simultaneously add the same latest experiences to the buffer, then we increase the probability of the networks seeing more of the same data, especially in the beginning when the ER buffer is relatively empty. Thus, delaying the data addition process aids in building and retaining the data diversity of the off-policy samples drawn from the ER buffer.

The detailed procedure of delayed infusion of recent experiences is elaborated as follows. During the data collection phase of the conventional SAC framework, one on-policy experience tuple (latest interaction with the environment) is added to the ER buffer at each timestep. We delay this addition of the latest experiences to the buffer, then we increase the probability of the networks seeing more of the same environment–agent interactions or training samples to reach high performance.

The detailed procedure of delayed infusion of recent experiences is elaborated as follows. During the data collection phase of the conventional SAC framework, one on-policy experience tuple (latest interaction with the environment) is added to the ER buffer at each timestep. We delay this addition of the latest experiences to the ER buffer. Specifically, at the episode $e$, we save the recent experiences from the environment into a temporary buffer $D_{\text{temp}}$ for $\xi$ episodes, i.e., $D_{\text{temp}} = \{(d_{1}^{e-\xi}, \ldots, d_{\xi}^{e-\xi}), \ldots, (d_{\xi}^{e-1}, \ldots, d_{\xi}^{e-1})\}$, and then push the whole data accumulated over the last $\xi$ episodes to the ER buffer, i.e., $D \leftarrow D_{\text{temp}}$, for every $\xi$ episodes. The temporary buffer is reset after every transfer.

Regarding the choice of the parameter $\xi$, we consider two extreme cases. If $\xi = 1$, then as explained above frequently adding past (one episode worth) on-policy data to the buffer while running the MO/O style training will lead to the learned policy being overfitted. On the contrary, if $\xi$ is very high, e.g., >20, then learning of the network becomes very slow since we do not add new data to the ER buffer for a longer time and the networks learn mostly from the samples of very old experiences. We pick a reasonable value of $\xi = 10$ for the experiments discussed in the next section.

**IV. MuJoco Experiments**

We run experiments on three MuJoco [51] continuous control tasks, InvertedPendulum-v2, Reacher-v2, and Swimmer-v2, implemented in OpenAI Gym [52]. The objective is to compare our proposed ISAC (SAC + SDP + MO/O) algorithm with three SAC variants, namely the vanilla SAC [45], SAC + PER [32], and SAC + PER + ERE [49]. In particular, we aim to verify that ISAC can attain early convergence to improved performance and ISAC requires substantially fewer environment–agent interactions or training samples to reach high performance.

We use the same neural network architecture, hyperparameters, replay buffer size, etc., in all the algorithms for fair comparison. The important design parameters are provided in Table I. The code repository [53] is used for the implementation of all the algorithms. After a policy is trained for every certain steps (called one training unit for convenience), its performance is immediately evaluated by running the corresponding deterministic policy (i.e., the mean policy) for five consecutive episodes. One training unit is 1000 steps for InvertedPendulum-v2 and Swimmer-v2, and it is 500 steps for Reacher-v2. Totally, we run $N = 100, 400, 500$ training units (the corresponding total training steps are 0.1, 0.2, 0.5 million) for InvertedPendulum-v2, Reacher-v2, and Swimmer-v2, respectively. The average return over the five evaluation episodes is regarded as the episodic performance.
return $R_n^{\text{w}}$ for the training unit $n = 1, \ldots, N$. For each algorithm, this process is repeated for five times with $\tau = 1, \ldots, 5$. Each repeated run is performed with a different random seed. The same set of five random seeds are used to compare all the algorithms in a certain environment.

The evolution curves of the episodic return versus the number of training units (in terms of the total number of training steps) are plotted in the figures in this section. A solid curve indicates the mean of the five repeated runs, i.e., $\bar{R}_n = \sum_{i=1}^{5} R_n^{i}/5$ and the shaded area shows the confidence interval of the repeats representing the corresponding standard deviation $\sigma_n$. It is worth mentioning that each curve is smoothed using its moving average of 20 training units for clarity of understanding. The experiments were run on a computer of a six-core Intel(R) Core(TM) i7-8750H CPU @ 2.20 GHz. The results for the three different environments are discussed in the following subsections.

A. InvertedPendulum-v2

1) Environment: The task in this environment is to balance a pole hinged to a cart that sits on a rail and is moved by externally applied force. The 4-D state space consists of the position and velocity of the cart and the angle and angular velocity of the pole. The 1-D continuous action space $a_t \in [-3, 3]$ represents the horizontal force applied by the cart’s actuator. The reward is $+1$ per timestep until an episode completes. An episode is defined as a specified number of steps, e.g., 1000 in our experiments. The episode terminates prematurely if the pole topples in the sense that the angle between the pole and the vertical reference line exceeds 0.2 rad or the cart runs out of the rail. So, the maximum possible episodic return is 1000 in this task.

2) Ablation Evaluation of ISAC: The effect of the SDP threshold value $\zeta_{\text{th}}$ on the performance of ISAC is demonstrated in Fig. 2(a). We can see that a high threshold value ($\zeta_{\text{th}} = 0.9$) leads to an overfitted/myopic performance of the policy. After similar hyperparameter exploration, we found that $\zeta_{\text{th}} = 0.5$ works best for all the environments.

The individual contributions of the SDP and MO/O functions of ISAC are presented in Fig. 2(b). It is observed that only running SDP type prioritization on SAC without MO/O based on-policy data mixing (i.e., SAC + SDP) leads to slow learning of the policy. Though SDP is able to reach early peaks in reward, it fluctuates and takes a longer time to approach stable performance. Whereas adding the MO/O artifact, i.e., SAC + SDP + MO/O, substantially speeds up the performance as it ensures the current on-policy data (i.e., the latest experience) is always included in the policy training.

While running ISAC without SDP-based prioritization (i.e., SAC + MO/O), the performance of the policy does not show high performance. In particular, we can see that MO/O by mixing on-policy data learns faster than the conventional SAC. But it is unable to improve the performance over time, since it uses the conventional scheme of random sampling from the ER buffer and lacks any kind of prioritization during sampling (e.g., in SAC + PER) or prioritization of the sampled data (i.e., in SAC + SDP + MO/O).

3) Comparison With Benchmarks: From the performance plots in Fig. 3(a), it is clear that ISAC significantly outperforms the other three benchmark algorithms. The crucial characteristics of ISAC is its fast rise to improved performance, during the early stage of learning. The performance also includes good stability of the training progresses that keep on improving gradually with minor fluctuations. The comparison is also quantitatively shown in Tables II and III. In Table II, we present the maximum attained episodic return averaged over the five repeats, i.e., $\bar{R}_n^{\text{max}} = \max_{n=1}^{N}(\bar{R}_n)$, that demonstrates the ability of an algorithm in achieving the peak performance. In the table, we also present the average of the standard deviation of the five repeats for the full training period, i.e., $\bar{\sigma} = \frac{\sum_{n=1}^{N} \sigma_n}{N}$ that demonstrates the robustness of the performance.

Let $T^*$ be the number of training steps taken by a certain algorithm to reach a set target score. The target score is set as the average episodic return of the SAC benchmark over its final $N_f$ units, i.e., $R_{\text{target}} = \frac{\sum_{n=N_f-N_r}^{N_f} (\bar{R}_n)}{N_f}$, where we use $N_f = 50, 100, 50$ for InvertedPendulum-v2, Reacher-v2, and Swimmer-v2, respectively, all corresponding 0.05 million steps of training. In Table III, we present the average and standard deviation of $T^*$ for the five repeats $\tau = 1, \ldots, 5$, as a measure of an algorithm’s sample efficiency to reach improved performance.

As the maximum possible episodic return is 1000 in this task, there is no difference in the index $\bar{R}_n^{\text{max}}$. ISAC is at the
The dynamic model is described in an eleven-dimensional state space which consists of the position and velocity of the center of body (4), the angle and angular velocity of the two joints (2), and the angle and angular velocity of the center of body (4), the angle and angular velocity of the two joints (2). The 2-D action space consists of the torques applied on the two actuators. The action value of each actuator is continuous in time within the range $[-1, 1]$. The control objective is to make the end-effector of the arm reach the randomly generated target as fast as possible within 50 steps, called one episode. The environment is reset every 1000 steps, called one episode, the environment is reset. There is no premature termination condition applied to an episode.

Top the list with average standard deviation $= 30.578$ while the next best value is 72.783 for SAC + PER + ERE. In Table III, we can see that ISAC takes significantly fewer training steps to reach a set target score. Again SAC + PER + ERE scores the second best which took 600 more steps in average but with more than three times larger standard deviation.

### B. Reacher-v2

1) Environment: Reacher-v2 represents an environment of a two degree-of-freedom robotic arm anchored to the center of a square arena and a randomly generated target. The arm consists of two links of equal length and two actuated joints. The dynamic model is described in an eleven-dimensional state space which consists of joint angles (4-D), coordinates of the target (2), end-effector’s velocity (2), and coordinates of the vector from the target to the end-effector (3). The 2-D action space is for the torques applied to the two actuators. The action value of each actuator is continuous in time within the range $[-1, 1]$. The control objective is to make the end-effector of the arm reach the randomly generated target as fast as possible within 50 steps, i.e., one episode. The reward function consists of two reward components as follows.

   1) r-distance: Reward based on how close the end-effector is to the target.
   2) r-action: Reward based on the torques used by the actuators to manipulate the arm, that is,
      $$ R(a_t, s_{t+1}) = -\|d_{x+1}\|_2^2 - \|a_t\|_2^2 $$
      where $d_{x+1}$, the distance between the end-effector and the target, is a function of the state vector $s_{t+1}$, and $a_t$ is the action vector.

2) Comparison With Benchmarks: As seen in the comparison plots in Fig. 3(b), the performance of ISAC is superior to the compared benchmarks. It achieves $\bar{R}_{\text{max}}$ of $-3.673$ while its nearest rival SAC + PER + ERE scores $-3.757$ and SAC’s performance is further down at $-3.790 \pm 0.962$; see Table II. The average standard deviation for ISAC is also smaller than the three benchmarks. As shown in Table III, ISAC and SAC + PER can reach improved performance using fewer training steps than the other two algorithms. SAC + PER marginally beats ISAC on average, but with a higher standard deviation.

### C. Swimmer-v2

1) Environment: Swimmer-v2 represents a planar robot swimming in a viscous fluid. It is made up of three links (head, body, and tail) and two actuated joints connecting them. The system dynamics can be described in a 10-D state space, which consists of the position and velocity of the center of body (4), the angle and angular velocity of the center of body (2), and the angle and angular velocity of the two joints (4). The 2-D action space consists of the torques applied on the two actuators. The objective in this experiment is to stimulate the maximal forward velocity (the positive $x$-axis) by actuating the two joints, with the reward function defined as follows:

   $$ R(a_t, s_{t+1}) = v_{x+1}^2 - 0.0001 \|a_t\|_2^2 $$
   where $v_{x+1}^2$ (an element of $s_{t+1}$) is the forward velocity and $a_t$ the 2-D action torques. The value of each action torque is continuous in time within the range $[-1, 1]$, out of which the value is clipped to its maximum or minimum value. For every 1000 steps, called one episode, the environment is reset and the swimmer starts at a new random initial state. There is no premature termination condition applied to an episode.

2) Comparison With Benchmarks: Similarly, ISAC performs better compared to the benchmarks as shown in Fig. 3(c). In particular, it achieves the highest $\bar{R}_{\text{max}}$ score of 108.969 in Table II. The second best score of 87.751 is achieved by SAC but with a better standard deviation.

### Table II

| Environment   | InvertedPendulum-v2 | Reacher-v2       | Swimmer-v2       |
|---------------|---------------------|------------------|------------------|
| SAC           | 1000, 79.704        | $-3.790, 0.962$  | 87.751, 31.821   |
| SAC + PER     | 1000, 94.213        | $-3.843, 0.969$  | 62.990, 13.124   |
| SAC + PER + ERE| 1000, 72.783        | $-3.757, 0.980$  | 57.626, 13.645   |
| ISAC          | 1000, 30.578        | $-3.673, 0.859$  | 108.969, 19.119  |

### Table III

| Environment   | InvertedPendulum-v2 | Reacher-v2       | Swimmer-v2       |
|---------------|---------------------|------------------|------------------|
| Target score  | 954.467             | $-4.735$         | 53.223           |
| SAC           | 9, 200 ± 1,720      | 30, 100 ± 3,878  | 34, 660 ± 34,719 |
| SAC + PER     | 9, 200 ± 3,249      | 26, 100 ± 7,742  | 57, 000 ± 27,224 |
| SAC + PER + ERE| 7, 400 ± 2,416      | 33, 500 ± 13,311 | 51, 200 ± 28,491 |
| ISAC          | 6, 800 ± 748        | 26, 500 ± 5,630  | 19, 600 ± 8,616  |
We have proposed an improved SAC algorithm, i.e., ISAC by introducing two major enhancements to the existing SAC framework. ISAC trains conventional SAC networks using prioritized samples from the ER buffer which are also augmented with the latest on-policy sample at each timestep. The episodic return-based prioritization scheme (SDP) and augmentation of samples with the latest on-policy experiences (MO/O) are simple to implement on the existing SAC framework. It does not require any special data structure to implement ISAC, unlike SAC + PER whose implementation requires a priority tree. ISAC attains superior results on a number of test environments when compared to other recent variants of SAC. Our experiments have shown that, compared to some benchmarks, ISAC achieves higher episodic return and reaches improved performance using fewer training steps. It is interesting to test the new algorithm for more challenging environments of higher dimensional states and action spaces in the future work. Further improvement of the prioritization method, e.g., to ensure that networks are trained from a higher percentage of newer or “less seen before data” samples from the ER buffer, is also to be studied.

V. CONCLUSION AND FUTURE WORK

We have proposed an improved SAC algorithm, i.e., ISAC by introducing two major enhancements to the existing SAC framework. ISAC trains conventional SAC networks using prioritized samples from the ER buffer which are also augmented with the latest on-policy sample at each timestep. The episodic return-based prioritization scheme (SDP) and augmentation of samples with the latest on-policy experiences (MO/O) are simple to implement on the existing SAC framework. It does not require any special data structure to implement ISAC, unlike SAC + PER whose implementation requires a priority tree. ISAC attains superior results on a number of test environments when compared to other recent variants of SAC. Our experiments have shown that, compared to some benchmarks, ISAC achieves higher episodic return and reaches improved performance using fewer training steps. It is interesting to test the new algorithm for more challenging environments of higher dimensional states and action spaces in the future work. Further improvement of the prioritization method, e.g., to ensure that networks are trained from a higher percentage of newer or “less seen before data” samples from the ER buffer, is also to be studied.

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BANERJEE et al.: IMPROVED SAC: MIXING PRIORITIZED OFF-POLICY SAMPLES WITH ON-POLICY EXPERIENCES 3129

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