Do You Need the Entropy Reward (in Practice)?

Haonan Yu 1  Haichao Zhang 1  Wei Xu 1

Abstract
Maximum entropy (MaxEnt) RL maximizes a combination of the original task reward and an entropy reward. It is believed that the regularization imposed by entropy, on both policy improvement and policy evaluation, together contributes to good exploration, training convergence, and robustness of learned policies. This paper takes a closer look at entropy as an intrinsic reward, by conducting various ablation studies on soft actor-critic (SAC), a popular representative of MaxEnt RL. Our findings reveal that in general, entropy rewards should be applied with caution to policy evaluation. On one hand, the entropy reward, like any other intrinsic reward, could obscure the main task reward if it is not properly managed. We identify some failure cases of the entropy reward especially in episodic Markov decision processes (MDPs), where it could cause the policy to be overly optimistic or pessimistic. On the other hand, our large-scale empirical study shows that using entropy regularization alone in policy improvement, leads to comparable or even better performance and robustness than using it in both policy improvement and policy evaluation. Based on these observations, we recommend either normalizing the entropy reward to a zero mean (SACZero), or simply removing it from policy evaluation (SACLite) for better practical results.

1. Introduction
Since its appearance, soft actor-critic (SAC) (Haarnoja et al., 2018) has achieved a great success as one of the state-of-the-art continuous control reinforcement learning (RL) algorithms. Compared to other contemporary RL algorithms such as PPO (Schulman et al., 2017), DDPG (Lillicrap et al., 2016), and TD3 (Fujimoto et al., 2018), SAC enjoys the best of both worlds: off-policy training for sample efficiency and a stochastic actor for training stability. One major design of SAC is to augment the task reward with an entropy reward, resulting in a maximum entropy (MaxEnt) RL formulation. Some primarily claimed benefits of MaxEnt RL are:

- encouraging the agent to visit unexplored states where the policy entropy is expected to be high (Haarnoja et al., 2018),
- smoothing the optimization landscape to make the optimization easier (Ahmed et al., 2019) and improving the training convergence and stability (Vieillard et al., 2020),
- encouraging the agent to accomplish a task while acting randomly, for robustness when deployed with environment perturbations (Eysenbach & Levine, 2021).

Compared to some prior works that merely use entropy as a regularization cost in policy improvement (Mnih et al., 2016; Schulman et al., 2017; Abdolmaleki et al., 2018), using entropy to regularize both policy improvement and evaluation seems more “aggressive” in transforming the original RL objective. Thus a natural question is, how largely will entropy as an intrinsic reward obscure the maximization of the utility? Moreover, will robustness to environment perturbations also emerge (empirically) when entropy is only used for regularizing policy improvement?

One non-negligible issue of the entropy reward arising particularly in episodic Markov decision processes (MDPs) is that, it will change the policy’s tendency of terminating an episode. The reason is that entropy bonuses are added to normal time steps but not to those post termination. This could result in overly optimistic or pessimistic policies, depending on whether the entropy is positive or negative. In this paper, we name this side effect as reward inflation. Previously, reward inflation has been largely ignored by practitioners especially when applying SAC to episodic MDPs.

Another scenario which entropy rewards could complicate is multi-objective RL. There, an interplay between several task rewards already exists in the training process, and it is often difficult to determine a good trade-off among them. Having an entropy reward on top of multiple task rewards further makes the training dynamics more unpredictable.

Of course, as pointed out by Haarnoja et al. (2018), when the entropy weight \(\alpha\) is sufficiently small (compared to the task reward scale), its MaxEnt RL objective reduces back to
the original utility objective. When $\alpha$ is tunable, this usually won’t happen until the policy becomes much deterministic, due to a high initial value of $\alpha^1$. It is best not to ignore the distortion of the utility objective by simply assuming that $\alpha$ will eventually become very small, as the training might have been affected in an irreversible way by then.

With these doubts in mind, we conduct ablation studies centering around the entropy that seems critical to SAC. Through extensive experiments on various continuous control tasks, our findings reveal that in general, entropy rewards should be applied with caution to policy evaluation. On one hand, we show that the entropy reward could sometimes obscure the task reward if its weight is not properly managed. Particularly, we show manifestations of reward inflation that hinders utility maximization especially in episodic MDPs. On the other hand, we show that entropy regularization alone in policy improvement leads to comparable or even better performance and robustness. The gain of having the entropy bonus in policy evaluation on top of this is little or sometimes negative. As a result, we recommend simply removing entropy from policy evaluation while only keeping it in policy improvement for better practical results (dubbed as SACZero). When the entropy reward is indeed needed, normalizing it to a zero mean will alleviate the reward inflation effect (dubbed as SACZero). The code for reproducing the experiment results is available at: https://github.com/hnyu/entropy_reward.

Disclaimer This paper is not arguing that the entropy-augmented return formulation in MaxEnt RL is unnecessary. Instead, it serves to bring to RL practitioners’ attention that there is a hidden cost of using an entropy reward in policy evaluation, from a perspective of intrinsic rewards. To minimize this cost, we propose to apply zero-mean normalization to the entropy reward, or better remove it from the return. While SAC is studied as a representative MaxEnt RL algorithm, some conclusions could also apply to other MaxEnt RL algorithms, for example, Haarnoja et al. (2017); Nachum et al. (2017); Schulman et al. (2018).

2. Related Work

Entropy regularized RL Incorporating entropy regularization into RL has proved to be an effective technique for improving performance, especially in the deep RL literature (Mnih et al., 2016; Schulman et al., 2017; Abdolmaleki et al., 2018; Haarnoja et al., 2017; 2018). In contrast to using entropy for only regularizing policy improvement, the MaxEnt RL formulation (Ziebart, 2010) also uses it to regularize policy evaluation, by maximizing a combination of the task reward and the entropy reward.

To our best knowledge, there aren’t many empirical studies that compare entropy regularizing policy improvement to entropy regularizing both policy improvement and evaluation. On a small subset of six Atari games, Schulman et al. (2018) compared the two entropy use cases with an A2C backbone, where they call the two “naive” and “proper” versions of entropy-regularized RL, respectively. However, their experiment results were not very conclusive: the proper version was shown to be “the same or possibly better than” the naive version. On only CartPole and the Asterix Atari game, Viellard et al. (2020) investigated if adding entropy rewards in policy evaluation improves empirical results. There was no significant benefit observed for Asterix. For CartPole, the advantage of regularizing policy evaluation was only seen on certain hyperparameters. In contrast to these two prior works, this paper analyzes the entropy regularization from a perspective of intrinsic rewards, and presents a large-scale study on complex control tasks.

Intrinsic rewards are internally calculated by RL agents independently of the extrinsic environment rewards. They are usually for improving exploration by driving an agent to visit novel states (Pathak et al., 2017; Burda et al., 2018) or learning diverse skills (Eysenbach et al., 2019; Gehring et al., 2021) in an unsupervised way. Usually, intrinsic rewards are not exactly aligned with extrinsic rewards, and thus how to make a good trade-off between them is important (Badia et al., 2020). The entropy reward can be regarded as a special case of intrinsic rewards, where it drives an agent to visit states on which its policy produces actions randomly and thus is usually thought to be under-trained.

3. Background

The RL problem can be defined as policy search in an MDP $(S, A, p, r)$. The state space $S$ and action space $A$ are both assumed to be continuous. The environment transition probability $p(s_{t+1} | s_t, a_t)$ stands for the probability density of arriving at state $s_{t+1} \in S$ after taking an action $a_t \in A$ at the current state $s_t \in S$. It is usually unknown to the agent. For each transition, the environment outputs a reward to the agent as $r(s_t, a_t, s_{t+1})$. Sometimes, it is easier to just write the (expected) reward of the transition as $r(s_t, a_t) \triangleq \mathbb{E}_{s_{t+1}, r(s_t, a_t)} r(s_t, a_t, s_{t+1})$. We use $\pi(a_t | s_t)$ to denote the agent’s policy.

The typical RL objective is to find a policy $\pi^*$ that maximizes the expected discounted return

$$\pi^* = \arg \max_{\pi} \mathbb{E}_{\pi, R} \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t),$$

where $\gamma \in [0, 1]$ is a discount factor. For episodic settings, we assume $r(s_t, a_t) = 0$ for time steps post episode ter-
Do You Need the Entropy Reward (in Practice)?

Before our investigation starts, we’d like to first define two concepts to be used frequently in the remainder of this paper.

i) using entropy as a regularization term for policy improvement (Eq. 1), and

ii) adding entropy values as intrinsic rewards (Eq. 2) to policy evaluation, just like using other novelty-based rewards (Pathak et al., 2017; Burda et al., 2018).

When referring to “entropy regularized” RL, most works don’t differentiate in depth between the impacts of entropy on training performance from (i) and from (ii). For the former, entropy serves as a regularization term that affects only one step of policy optimization (Schulman et al., 2018), while for the latter entropy behaves as an intrinsic reward that does reward shaping to the original MDP. In the following, we will use the term entropy reward to refer to (i), while using entropy reward/bonus to refer to (ii). The occurrences of “entropy reward” prior to this section all refer to (ii).

It is tempting to treat the entropy cost as a one-step entropy bonus, for example in (Schulman et al., 2018). Although they are very similar, we believe that it is better not to confuse the two. Generally speaking, a one-step entropy bonus depends on the next state \( s_{t+1} \) and it is different for each action \( a_t \) to be taken at the current state \( s_t \), namely, it can reward actions differently. This can be achieved by setting the discount \( \gamma \) of any \( s_{t+k} \) (\( k > 1 \)) to zero. In contrast, the entropy cost regularizes the policy at \( s_t \) independent of specific \( a_t \), namely, without differentiating the actions.

5. Reward Inflation by the Entropy Reward

For now let us focus on interpreting entropy as an intrinsic reward (ii). Given the augmented reward \( r_{\text{MaxEnt}} \), one would instantly ask the question: how will the entropy reward impact the policy learning? As with any intrinsic reward, it inevitably transforms the original MDP. We know that it certainly requires the policy to make a trade-off between utility maximization and stochasticity. However, in this section we highlight a side effect orthogonal to stochasticity which we call the reward inflation of the entropy reward.

5.1. A Toy Example in an Episodic Setting

We will first demonstrate that how an entropy reward hinders policy learning on a toy task SIMPLECHAIN in an episodic setting (Figure 1, left). The environment consists of a simple chain of length 5. For each episode, the agent always starts from the leftmost node 0. At each time step, it can choose to move left or right, and receives a reward of \(-0.05\) for node 0-3. The only way to end an episode is to reach the rightmost node 4 which gives a reward of 0. The time limit of an episode is set to 50 steps. The agent’s action space is...
When inflation in an episodic setting. Here, we only focus on the values of $\alpha H(\pi)$ in the beginning the agent will get an entropy reward of $\alpha H(\pi) = 0.2 \times \log(2) \approx 0.14$ at every step. So the overall reward it gets at a non-terminal state is roughly $0.14 - 0.05 = 0.09$. Thus due to entropy rewards, the agent’s policy becomes overly optimistic and never wants to reach the terminal state. When $\alpha$ is tunable and starts with 0.2, as Eq. 3 takes effect, if the entropy target is high, $\alpha H(\pi)$ can still be greater than 0.05 in its stable state (e.g., $\alpha$ and $H(\pi)$ settle at slightly smaller values than 0.2 and $\log(2)$, respectively). Even for a low entropy target, the policy’s tendency of termination will not flip until $\alpha H(\pi)$ decreases below 0.05. This process might take some time depending on $\alpha$’s learning rate, and thus hurt the sample efficiency.

It is important to note that there exist many more training configurations where the entropy reward makes training fail. This toy example is not special or restrictive; the absolute values of $-0.05$, $\log(2)$, and 0.2 are not important. It is the relative magnitudes of these numbers that contribute to the behavior of the entropy reward. For example, one can come up with another similar example where the agent has an $N$-dimensional action space and the immediate reward is $-0.05N$, or $\alpha = 1.0$ with an immediate reward of $-0.1$.

### 5.2. Reward Inflation and Its Remedies

The key issue SAC faces in the above is that its entropy reward inflates (in expectation) the reward function before termination while not after it, because the Q value of any step post termination is always set to zero when doing TD backup. Since an entropy reward could also be negative for a continuous distribution, it can also deflate (in expectation) the reward function\(^2\). For terminological simplicity, we will use “inflation” to refer to both cases. Reward inflation can cause a policy to be overly optimistic or pessimistic\(^3\).

\(^2\)An opposite behavior may happen if the entropy is negative initially (e.g., when the action range is small and the uniform probability density is greater than 1). In this case, the agent tends to terminate the task earlier than the optimal behavior which might be staying alive.

\(^3\)Generally speaking, any intrinsic reward could have this reward inflation in an episodic setting. Here, we only focus on the entropy reward as a special case.

One aggressive way of reducing the reward inflation is to simply discard the entropy reward but still keeping the entropy cost in policy optimization (Eq. 1). This usage of entropy has previously appeared in other actor-critic algorithms, for example A3C (Mnih et al., 2016), A2C (Schulman et al., 2018), and MPO (Abdolmaleki et al., 2018). In the following, we denote this variant of SAC by SACLite.

Another remedy is to make sure that the entropy reward have a running mean of zero. Thus when doing TD backup in Eq. 2, we propose to subtract the entropy rewards by their moving average (i.e., zero-mean normalization), resulting in a variant of SAC which we call SACZero.

### 5.3. Experiments on Episodic SIMPLECHAIN

To verify our analysis in the above, we train SAC, SACLite, and SACZero on episodic SIMPLECHAIN, and plot their training success rate curves in Figure 2, where a success is defined as the agent reaching the terminal state in 50 steps. We also plot their expected V values ($V \triangleq \mathbb{E}_{s \sim P, a \sim \pi} Q(s, a)$) during the training. Note that the hyper-parameters are all the same across the three methods, and the only difference is how each deals with entropy. Each method was run with $9$ random seeds, and the dashed lines denote the upper and lower bounds of the $95\%$ confidence interval (CI) for the solid curve with the same color\(^4\). We see that the empirical results exactly match our earlier analysis:

1) With a fixed $\alpha$, SAC hardly makes any progress because the policy never wants to terminate. Its V value keeps increasing during training, due to the entropy rewards. Both SACLite and SACZero obtain good performance, and their V values evolve reasonably, more accurately reflecting the actual returns of the task reward.

\(^4\)In the following, our training plots will all follow this convention of computing a $95\%$ CI with $9$ random seeds and using dashed lines to represent the CI, unless otherwise stated.
Average episode length

Episodic return

Figure 3. Bipedal-walker tasks. Left and Middle: example frames of the normal and hard versions. Right: one failure case of SAC (four key frames are shown), where the robot hacks entropy bonuses by doing the splits to increase episode lengths.

Figure 4. Training curves of the two bipedal-walker tasks.

2) When $\alpha$ is tunable, even though SAC eventually obtains a perfect success rate, its sample efficiency is worse. Its V value is greatly bloated by the entropy rewards before dropping to the correct level. Generally, when specifying an initial value for $\alpha$, there is a conflict between more exploration and less reward inflation.

5.4. Experiments on the Bipedal-walker Tasks

To further illustrate the reward inflation of entropy rewards in more natural episodic settings, we test on two representative bipedal-walker tasks (Brockman et al., 2016). In either task (Figure 3, left and middle), a bipedal robot is motivated to move forward until a far destination to collect a total reward of 300. The reward is evenly distributed on the $x$ axis to guide the robot. An episode ends with a reward of $-100$ if the robot falls. The terrain is randomly generated for each episode, and the hardcore version additionally adds random obstacles, pits, stairs, etc. to the terrain.

Again we train SAC, SACLite, and SACZero with an initial $\alpha = 1$ on both tasks and plot their training curves in Figure 4. Within 5M environment steps, SAC’s sample efficiency and final performance are greatly reduced by the reward inflation on BipedalWalker (compared to SACZero). Even with normalization, the entropy reward still hurts the performance on BipedalWalkerHardcore (SACZero vs. SACLite). Surprisingly, SACLite is already able to achieve top performance consistently even without entropy rewards.

5.5. SimpleChain with an Infinite Horizon

One would imagine that the reward inflation of entropy rewards will disappear in an infinite-horizon setting, because now there are no longer terminal states and entropy rewards will be added to all states. Theoretically, such a reward translation makes no difference to the optimal policy in an infinite-horizon setting. To verify this, we define an infinite-horizon version of SimpleChain (Figure 1, right). It has the same MDP with the episodic version, except that node 4 is not a terminal state. We train SAC, SACZero, and SACLite with a tunable $\alpha$ on it with an episode time limit of 50. Figure 5 shows the curves of steps staying at node 4, and they do match our expectation: all three methods obtain similar perfect performance. Even though the expected V value of SAC still fluctuates due to the entropy reward, for this simple task the fluctuation doesn’t hinder policy learning. However, on the other hand, the entropy reward doesn’t show any obvious benefit of encouraging exploration in this task (SAC/SACZero compared to SACLite).

So far the downside of reward inflation outweighs its advantages in episodic settings. And in a preliminary infinite-horizon case, the entropy reward (SAC/SACZero) hasn’t really been superior to the entropy cost (SACLite). Are these results due to our current test tasks being too simple or special? Will the necessity of the entropy reward, including performance improvement and policy robustness, be justified on many other tasks in general?

Figure 5. Training curves of SimpleChain with an infinite horizon. All three methods reach the optimal 47 steps at node 4.

On BipedalWalker, after evaluating an intermediate model of SAC at 2M steps when its performance still struggles to increase compared to SACLite and SACZero, we find that a failure case is that the robot does the splits on the ground without moving forward (Figure 3, right). This behavior started right after 1M steps, since when most episode lengths reached the time limit of 1600 (Figure 4, lower left). It lets the robot harvest positive entropy rewards before they decay at about 1.2M steps due to $\alpha$ (Figure 4, lower right). Even though the entropy bonus is very small at 2M steps, it still took the policy quite some time to recover from this behavior. In comparison, both SACLite and SACZero were able to quickly get rid of this sub-optimal transient behavior, because they don’t have any entropy reward or its reward inflation is reduced by zero-mean normalization.
6. A Large-scale Empirical Study

In this section we conduct a large scale of empirical study, covering various scenarios of continuous control. Again we will compare SAC, SACZero, and SACLite as introduced in Section 5.2 with an initial entropy weight $\alpha = 1$ to be tuned automatically. For some tasks, we also experiment with an initial $\alpha = 0.01$ and name the corresponding methods as SAC-a01, SACZero-a01, and SACLite-a01. All other hyperparameters are fixed given a task.

**A brief summary of our findings** The entropy cost plays a major, if not entire, role of contributing to good exploration and performance. The entropy reward is not as necessary as it is thought to be. Below we support this claim with various experiment results.

6.1. Single-objective RL

**Manipulation** We start with four challenging MuJoCo manipulation tasks (Plappert et al., 2018) that have infinite horizons and sparse rewards: FetchReach, FetchPush, FetchSlide, and FetchPickAndPlace. In each task, a robot arm is required to accomplish a goal of reaching, pushing a box, sliding a puck, or picking up a box to a desired location which will be randomly sampled. The reward is 0 when a goal is achieved and $-1$ otherwise. The time limit of each episode is 50 steps. We train each task to 10M environment steps with the same hyperparameters suggested by Plappert et al. (2018).

According to our analysis in Section 5.5, in theory the reward inflation of the entropy reward no longer exists in an infinite-horizon setting. However, Figure 6 shows that on FetchPush and FetchPickAndPlace, SAC is much worse than SACLite, clearly affected by the entropy reward. There are two hypotheses for this observation.

(a) The overall mean of the entropy reward is constantly changing because of matching to the entropy target, and this adds another layer of non-stationarity to the value learning dynamics, even though we can assume that at any moment this mean entropy reward is benign.

(b) The entropy reward, as an intrinsic reward, indeed unfortunately obscures the task reward, making the policy learn sub-optimal or task-unrelated behaviors.

We additionally train SAC-a01, SACZero-a01, and SACLite-a01 and add their curves to Figure 6. On FetchPush, (a) seems primary because SACZero is comparable to SACLite (with zero-mean normalization (a) is no longer present). However, (b) cannot be completely ruled out because on FetchSlide and FetchPickAndPlace, SACZero is clearly worse than SACLite. With a smaller initial $\alpha$, SACZero-a01 is closer to SACLite and SACLite-a01, indicating that the performance gets improved if the zero-mean entropy reward is less weighted from the beginning. Both hypotheses seem to account for the results on FetchPickAndPlace, given that SACLite > SACZero > SAC. Note that a smaller initial $\alpha$ will not eradicate the issues faced by SAC, as shown by FetchPush.

**Box2D** The next four Box2D control tasks (Brockman et al., 2016) to be evaluated are episodic. BipedalWalker and BipedalWalkerHardcore have been partially evaluated in Section 5.4, but here we additionally test SAC-a01, SACZero-a01, and SACLite-a01 on them for further analysis. The other two tasks are LunarLanderContinuous and CarRacing. In LunarLanderContinuous, a lander is rewarded for resting on a landing pad and penalized for crashing during the landing process. In CarRacing, a racing car is rewarded for each tile visited on the track and penalized for being too far away from the track. Both tasks have an episode time limit of 1000 steps. Figure 7 shows that while sometimes an initial $\alpha = 0.1$ helps alleviate the side effects of the entropy reward in SAC (BipedalWalker and LunarLanderContinuous), it can hurt the performance of SACLite (BipedalWalkerHardcore) and SACZero (CarRacing) if they obtain good results with $\alpha = 1$. In other words, to achieve top results, sufficient exploration by a large $\alpha$ is necessary for some tasks. Note that SACLite is able to perform well consistently with $\alpha = 1$. 

---

**Figure 6.** Training curves of four MuJoCo manipulation tasks. "FetchPP" stands for FetchPickAndPlace. $x$ axis: training environment steps; $y$ axis: episodic return.

**Figure 7.** Training curves of four Box2D tasks. "BWHardcore" stands for BipedalWalkerHardcore and "LLContinuous" stands for LunarLanderContinuous. $x$ axis: training environment steps; $y$ axis: episodic return.

**Figure 8.** Training curves of four locomotion tasks. $x$ axis: training environment steps; $y$ axis: episodic return.
Do You Need the Entropy Reward (in Practice)?

**Figure 9.** Training curves of eight DM control tasks. 

x axis: training environment steps; y axis: episodic return.

**Figure 10.** Training curves of the Safety Gym POINT tasks. Odd columns are the goal success rate curves. Even columns are the averaged per-step constraint curves, where the red dashed line represents the constraint threshold of $5 \times 10^{-4}$. On all tasks, SACLite and SACZero are both able to satisfy the threshold approaching the end of training. SAC has some difficulty in constraint satisfaction on POINTPush1/2. x axis represents training environment steps.

**Figure 11.** Training curves of the reward robustness experiments. 

x axis: training environment steps; y axis: gap (the smaller the better) between the evaluated returns of task and adversarial rewards.

We also consider DeepMind control suite (Tassa et al., 2020) and choose eight tasks that are in different domains with the MuJoCo ones. All tasks require the robot to achieve some (randomized) goal state configuration starting from a distribution of initial states, for example, moving the end effector of a robot arm to a location. A reward of $+1$ is given only when the current state satisfies the goal condition, or for some tasks the reward decreases smoothly from 1 to 0 as the state deviates more from the goal state. The eight tasks are all infinite-horizon with a time limit of 1000. We train each task to 3M environment steps with every step repeating an action twice. Figure 9 shows that SACLite is much better than SAC on PENDULUM:SWINGUP, SWIMMER:SWIMMER6 and FINGER:TURN_HARD, and almost the same on the other tasks. Zero-mean normalization does not result in better performance (SACZero vs. SAC), indicating that the hypothesis (b) is the cause.

**6.2. Multi-objective RL**

The next scenario is multi-objective RL. Specifically, we’d like to know what impact the entropy reward will have on the performance when multiple task rewards are already competing with each other. Particularly, we choose a safe RL scenario where the agent needs to improve its utility while satisfying a pre-defined constraint (in expectation). We test on six customized Safety Gym (Ray et al., 2019) tasks of POINT. Each task has an infinite horizon with an episode time limit of 1000. In each episode, the robot is required to achieve a random goal while avoiding obstacles, distraction objects, and/or moving gremlins. An episode will not terminate when a constraint is violated or when a goal is achieved. We set the constraint threshold to be $-5 \times 10^{-4}$ per step, meaning that the agent is allowed to violate any constraint only once every 2k steps or 2 episodes in expectation. Note that since the agent does not have any prior knowledge about safety (it has to learn the concept from scratch), constraint satisfaction can only be asymptotic. A success is defined as achieving the goal before timeout.

Given the constraint threshold, we employ the Lagrangian method (Ray et al., 2019) to automatically adjust the weight $\lambda$ of the constraint reward. When computing the loss for $\lambda$, instead of comparing the constraint $V$ values to the accumulated discounted violation budget, we directly compare

**Locomotion** We study four MuJoCo locomotion tasks that were evaluated by SAC (Haarnoja et al., 2018): HOPPER, ANT, WALKER2D, and HALF CHEETAH. Generally, each task rewards the robot for moving forward on the x axis as fast as possible. All tasks except HALF CHEETAH have an early termination condition when the robot is considered no longer “healthy”, and thus are episodic. The healthiness of a robot is determined by checking its body/joint positions. The time limit of each episode is 1000 steps. We train each task with the same hyperparameters suggested by Haarnoja et al. (2018). Unlike the manipulation and Box2D tasks, Figure 8 presents very close curves of SAC, SACZero, and SACLite. SACZero is better than SAC only on HALF CHEETAH, while SACLite doesn’t have an obvious overall advantage over SAC or vice versa.
the violation rate of a rollout sample batch with the per-step threshold following Yu et al. (2022). We train SAC, SACZero, and SACLite for 5M steps on each task.

The experiment results are in Figure 10. On the Goal and Button tasks, SAC’s sample efficiency is worse than SACLite and SACZero, although its final success rates are comparable. On the Push tasks, SAC struggles to improve the success rates within 5M steps and still does not satisfy the constraint threshold at the end. At the same time, SACZero is comparable to SACLite on average. Thus compared to the manipulation results (Section 6.1), SAC’s worse results seem to solely result from the hypothesis (a). This is reasonable given that with the Lagrangian method adjusting the two task reward weights and causing non-stationarity in the Q values already, the extra non-stationarity by the entropy reward will further challenge the training.

7. Entropy Cost Alone Promotes Robustness

Eysenbach & Levine (2021) shows (both theoretically and empirically) that MaxEnt RL trains policies that have both dynamics robustness and reward robustness. In this section, we provide preliminary empirical evidence of the entropy cost alone also resulting in these two types of robustness.

Dynamics robustness We first define a similar 2D navigation task (Figure 12, left) following the one in Eysenbach & Levine (2021). The agent (blue circle) is situated in an 8 × 8 2D environment. In each episode of up to 50 steps, the agent starts from the top-left corner to reach the goal (green circle) at the bottom-right corner. The reward is defined as the deceased L2 distance to the goal compared to the previous step. However, the agent will get a penalty of −1 every time it enters either of the two red regions. Thus the optimal return will be roughly √((8 - 1.5)^2 + 8^2) = 10.3. The L-shaped obstacle in purple does not exist during training, but will be enabled when evaluating a trained policy, thus adding dynamics perturbations. The agent has a 2D observation as its current (x, y) coordinate and a 2D action (dx, dy) ∈ [-1, 1]^2. We train SAC and SACLite on this navigation task. Figure 12 (right) shows the training curves of SAC and SACLite, with SACLite being slightly more sample efficient than SAC. After this, we enable the L-shaped obstacle on the map and evaluate either trained policy by sampling actions from it. Averaged over 500 episodes, we obtained an episodic return of 9.46 and 9.68 for SAC and SACLite, respectively. This result questions the necessity of the entropy reward for dynamics robustness in this task.

Reward robustness Next we test if SACLite (trained with the task reward but not the entropy reward) can simultaneously obtain good “worst-case” adversarial rewards ϋ(s, a) = ω(s, a) − α log π(a|s) as defined in Eysenbach & Levine (2021). We use a fixed α = 0.1 to ensure that the second term does not fade as training proceeds. For reference, we also train SAC with the same α. The return gap between the task reward and the adversarial reward is plotted in Figure 11. It is clear that even trained with the task reward only, SACLite still achieves desirable performance when evaluated in an adversarial setting, showing a large degree of reward robustness.

8. Discussions, Limitations, and Conclusions

Through illustrative examples and extensive experiments, we have shown that entropy for regularizing policy evaluation is not “icing on the cake”. There is a certain cost involved by adding an entropy reward to the task reward. We have identified a side effect of the entropy reward which we call reward inflation, inflating/deflating reward function before but not after episode terminations. Reward inflation could obscure or completely change the original MDP in an episodic setting. Even for an infinite horizon, the non-stationarity of Q values caused by a decaying entropy reward also poses a challenge to policy optimization. Moreover, the fact that SACZero is worse than SACLite on some tasks demonstrates that even after removing reward inflation, the entropy reward could still obscure the task reward by changing the relative importance of every transition. With a tunable α, the entropy reward usually vanishes after some time and MaxEnt RL reduces to standard RL. However, by then α is very small and exploration can hardly be done. The policy may have got stuck in a local optimum.

We have also shown that the properties of good exploration, training convergence and stability, and policy robustness of MaxEnt RL, result more from entropy regularizing policy improvement than from entropy regularizing policy evaluation. A theoretical explanation of this might be helpful for better understanding our results in the future.

It is impractical for us to evaluate all continuous control RL tasks available out there. Our evaluation has selected representative tasks that can be approached by SAC reasonably while still posing challenges. Our goal is to at least bring some side effects of the entropy reward to RL practitioners’ attention. We believe that this work can shed some light on how to better harness entropy as an intrinsic reward to improve entropy-regularized RL training in practice.
Do You Need the Entropy Reward (in Practice)?

Acknowledgements

We thank the Horizon AIDI platform team for computational infrastructure support, and the group members for help discussions.

References

Abdolmaleki, A., Springenberg, J. T., Tassa, Y., Munos, R., Heess, N., and Riedmiller, M. Maximum a posteriori policy optimisation. In ICLR, 2018.

Ahmed, Z., Roux, N. L., Norouzi, M., and Schuurmans, D. Understanding the impact of entropy on policy optimization. In ICML, 2019.

Badia, A. P., Sprechmann, P., Vitvitskyi, A., Guo, Z. D., Piot, B., Kapturowski, S., Tieleman, O., Arjovsky, M., Pritzel, A., Bolt, A., and Blundell, C. Never give up: Learning directed exploration strategies. In ICLR, 2020.

Bohez, S., Abdolmaleki, A., Neunert, M., Buchli, J., Heess, N., and Hadsell, R. Value constrained model-free continuous control. arXiv, 2019.

Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., and Zaremba, W. Openai gym, 2016.

Burda, Y., Edwards, H., Storkey, A., and Klimov, O. Exploration by random network distillation. In ICLR, 2018.

Eysenbach, B. and Levine, S. Maximum entropy rl (probably) solves some robust rl problems. arXiv, 2021.

Eysenbach, B., Gupta, A., Ibarz, J., and Levine, S. Diversity is all you need: Learning skills without a reward function. In ICLR, 2019.

Fujimoto, S., van Hoof, H., and Meger, D. Addressing function approximation error in actor-critic methods. In ICML, 2018.

Gehring, J., Synnaeve, G., Krause, A., and Usunier, N. Hierarchical skills for efficient exploration. In NeurIPS, 2021.

Haarnoja, T., Tang, H., Abbeel, P., and Levine, S. Reinforcement learning with deep energy-based policies. In ICML, 2017.

Haarnoja, T., Zhou, A., Hartikainen, K., Tucker, G., Ha, S., Tan, J., Kumar, V., Zhu, H., Gupta, A., Abbeel, P., and Levine, S. Soft actor-critic algorithms and applications. arXiv, abs/1812.05905, 2018.

Kingma, D. P. and Ba, J. Adam: A method for stochastic optimization. In ICLR, 2015.

Lillicrap, T. P., Hunt, J. J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., Silver, D., and Wierstra, D. Continuous control with deep reinforcement learning. In ICLR, 2016.

Mnih, V., Badia, A. P., Mirza, M., Graves, A., Lillicrap, T. P., Harley, T., Silver, D., and Kavukcuoglu, K. Asynchronous methods for deep reinforcement learning. In ICML, 2016.

Nachum, O., Norouzi, M., Xu, K., and Schuurmans, D. Bridging the gap between value and policy based reinforcement learning. In NeurIPS, 2017.

Pathak, D., Agrawal, P., Efros, A. A., and Darrell, T. Curiosity-driven exploration by self-supervised prediction. In ICML, 2017.

Plappert, M., Andrychowicz, M., Ray, A., McGrew, B., Baker, B., Powell, G., Schneider, J., Tobin, J., Chociej, M., Welinder, P., Kumar, V., and Zaremba, W. Multi-goal reinforcement learning: Challenging robotics environments and request for research, 2018.

Ray, A., Achiam, J., and Amodei, D. Benchmarking Safe Exploration in Deep Reinforcement Learning. 2019.

Schulman, J., Wolski, F., Dhariwal, P., Radford, A., and Klimov, O. Proximal policy optimization algorithms. arXiv, 2017.

Schulman, J., Chen, X., and Abbeel, P. Equivalence between policy gradients and soft q-learning. arXiv, 2018.

Tassa, Y., Tunyasuvunakool, S., Muldal, A., Doron, Y., Liu, S., Bohez, S., Merel, J., Erez, T., Lillicrap, T., and Heess, N. dm_control: Software and tasks for continuous control, 2020.

Vieillard, N., Kozuno, T., Scherrer, B., Pietquin, O., Munos, R., and Geist, M. Leverage the average: an analysis of kl regularization in rl. In NeurIPS, 2020.

Yu, H., Xu, W., and Zhang, H. Towards safe reinforcement learning with a safety editor policy. arXiv, 2022.

Ziebart, B. D. Modeling purposeful adaptive behavior with the principle of maximum causal entropy. PhD thesis, Carnegie Mellon University, 2010.
A. Hyperparameters

Here, we briefly list the most important hyperparameters for each experiment in the paper. These hyperparameter values were selected as the best practices on these tasks in our daily research, and they generally ensure that SAC is able to achieve reasonably good performance. For more details, please refer to our released code (Section 1).

A.1. Common

We first describe the common hyperparameters that are adopted in each experiment. They are fixed across experiments unless otherwise stated. We initially collect 10k environment steps in the replay buffer before the training starts. The smoothing coefficient of the target Q network is $5 \times 10^{-3}$, and the soft target update happens every training iteration. The training interval is 1 environment step. The hidden nonlinear activations of all networks are ReLU. The discount factor $\gamma$ is set to 0.99. We use the Adam optimizer (Kingma & Ba, 2015) with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 10^{-7}$ for training.

A.2. SimpleChain

Only one actor is used for collecting experiences. Both the actor and critic networks have only one hidden layer of size 100. The initial number of environment steps collected in the replay buffer is 5k. The total number of training environment steps is 50k which is also the replay buffer size. The entropy target for each action dimension is $-1$. We use a learning rate of $10^{-4}$ with a mini-batch size of 256.

A.3. Manipulation

The hyperparameters of this experiment closely followed those in Plappert et al. (2018). We use 38 actors to collect experiences in parallel. Both the actor and critic networks have three hidden layers of sizes (256, 256, 256). The discount factor is set to 0.98. The total number of training environment steps is 10M, and the replay buffer size is $38 \times 20k = 0.96M$. The smoothing coefficient of the target Q network is 0.05, and the soft target update happens every 40 training iterations. The training interval is 47.5 (1900/40) environment steps. We set the entropy target for each action dimension to about $-0.916$, which roughly assumes that the target action distribution has a probability mass concentrated on $\frac{1}{5}$ of the support $[-1, 1]$. We use a learning rate of $10^{-3}$ with a mini-batch size of 4864. We normalize the task reward by its running average and standard deviation, and clip the normalized reward to $[-1, 1]$.

A.4. Box2D

**BipedalWalker** and **BipedalWalkerHardcore** We use 32 actors to collect experiences in parallel. Both the actor and critic networks have two hidden layers of sizes (256, 256). The total number of training environment steps is 5M, and the replay buffer size is $32 \times 100k = 3.2M$. The training interval is 128 environment steps. We set the entropy target for each action dimension to about $-1.609$, which roughly assumes that the target action distribution has a probability mass concentrated on $\frac{1}{10}$ of the support $[-1, 1]$. We use a learning rate of $5 \times 10^{-4}$ and a mini-batch size of 4096.

**LunarLanderContinuous** We use only one actor for collecting experiences. Both the actor and critic networks have two hidden layers of sizes (256, 256). The total number of training environment steps is 100k, and the replay buffer has the same size. The entropy target is set in the same way as **BipedalWalker**. We use a learning rate of $10^{-4}$ with a mini-batch size of 256.

**Carracing** We use 16 actors to collect experiences in parallel. Four gray-scale contiguous frames are stacked as the input observation for each step. The initial number of environment steps collected in the replay buffer is 50k. Both the actor and critic networks have a CNN configured as [(32, 8, 4), (64, 4, 2), (64, 3, 1)], where each triplet represents channels, kernel size, and stride. The CNN is followed by two hidden layers of sizes (256, 256). The total number of training environment steps is 10M, and the replay buffer size is $16 \times 100k = 1.6M$. The training interval is 80 environment steps. The entropy target is set in the same way as **BipedalWalker**. We use a learning rate of $3 \times 10^{-4}$ with a mini-batch size of 256. Additionally, 7-step TD learning is employed to speed up training.

We normalize the task reward of every Box2D task by its running average and standard deviation, and clip the normalized reward to $[-5, 5]$.

A.5. MuJoCo locomotion

The hyperparameters of this experiment closely followed those in Haarnoja et al. (2018). We use only one actor to collect experiences. Both the actor and critic networks have two hidden layers of sizes (256, 256). The total number of
training environment steps is 3M, and the replay buffer size is 1M. The initial number of environment steps collected is the replay buffer is 50k. The entropy target for each action dimension is $-1$. We use a learning rate of $3 \times 10^{-4}$ with a mini-batch size of 256.

### A.6. DM control suite

We use 10 actors to collect experiences in parallel. Each action is repeated twice at every step. Both the actor and critic networks have two hidden layers of sizes $(256, 256)$. The total number of training environment steps is 3M, and the replay buffer size is $10 \times 100k = 1M$. The training interval is 10 environment steps. The entropy target is set in the same way as the manipulation tasks. We use a learning rate of $3 \times 10^{-4}$ with a mini-batch size of 256. Additionally, 5-step TD learning is employed to speed up training. We didn’t normalize the task reward as it is already in a good range of $[0, 1]$.

### A.7. Multi-objective RL

Following Yu et al. (2022), we customized the Safety Gym (Ray et al., 2019) environment to enable a natural lidar of 64 bins to replace the default pseudo lidar of 16 bins for generating observations, as the natural lidar gives more information about the object shapes in the environment. We found that rich shape information is necessary for the agent to achieve a low constraint threshold. A separate lidar vector of length 64 is produced for each obstacle type or goal. All lidar vectors and a vector of the robot status are concatenated together to produce a flattened observation vector.

We use 32 actors to collect experiences in parallel. Since the two Button tasks contain moving gremlins to be avoided, we stack four observations as the input observation for each step. This frame stacking is adopted for all six tasks. Both the actor and critic networks have three hidden layers of sizes $(256, 256, 256)$. The total number of training environment steps is 5M, and the replay buffer size is $32 \times 50k = 1.6M$. The training interval is 160 environment steps. The entropy target is set in the same way as BipedalWalker. We use a learning rate of 0.01 for the Lagrangian method and $3 \times 10^{-4}$ for the rest of the algorithm, with a mini-batch size of 1024. Additionally, 7-step TD learning is employed to speed up training. Following Bohez et al. (2019), when using the Lagrangian multiplier $\lambda > 0$ to combine the two Q values, we use the normalized weights $\frac{1}{1+\lambda}$ and $\frac{\lambda}{1+\lambda}$. This makes the combined Q value bounded. We normalize the task reward vector by its running average and standard deviation, and clip the normalized vector to $[-10, 10]$. 
