MULTI-CRITIC ACTOR LEARNING: TEACHING RL POLICIES TO ACT WITH STYLE

Anonymous authors
Paper under double-blind review

ABSTRACT

Using a single value function (critic) shared over multiple tasks in Actor-Critic multi-task reinforcement learning (MTRL) can result in negative interference between tasks, which can compromise learning performance. Multi-Critic Actor Learning (MultiCriticAL) proposes instead to maintain separate value-function estimators, i.e. critics, for each task being trained. This relaxes an assumption of continuity between task values and avoids interference between task-value estimates. Explicitly distinguishing between tasks also eliminates the need for critics to learn to do so. MultiCriticAL is tested in the context of multi-style learning, a special case of MTRL where agents are trained to behave with different distinct behavior styles, and yields up to 45% performance gains over the single-critic baselines and even successfully learns behavior styles in cases where single-critic approaches may simply fail to learn. As a further test of MultiCriticAL's utility, it is tested on a simulation of EA's UFC game, where our method enables a single policy function to learn and smoothly transition between multiple fighting styles.

1 INTRODUCTION

Reinforcement Learning (RL) offers an interesting means by which to develop interesting behaviors in a variety of controls settings. The work presented in this paper is primarily contextualized by our efforts to develop RL techniques for teaching RL-policies to behave with multiple distinct and specific styles for game-play. RL can be be useful in developing control policies for game-play and has been demonstrated as being capable of learning human-like or even superhuman play, most notably beating top-ranked human players in games such as Dota 2 (Berner et al., 2019), StarCraft (Vinyals et al., 2019), Chess (Silver et al., 2017), and Go (Silver et al., 2016). RL-based control in games offers a wide array of potential applications, including testing (Zhao et al., 2020; Ariyurek et al., 2021; Gordillo et al., 2021), game design (Gisslén et al., 2021), providing competition for human players (Berner et al., 2019), or simply as a means to develop more interesting game-play AI behaviors (Zhao et al., 2020; Alonso et al., 2020). RL algorithms can be notorious however for training aesthetically unappealing policies, but prior work has demonstrated that, with careful shaping of the reward functions, it is possible to derive highly specific desirable behavior (Peng et al., 2018; Mysore et al., 2021b). However, machine learning (ML) based solutions to game-play AI often represent a significant increase in compute requirements over their heuristic-based counterparts, especially when using deep learning techniques. Actor-Critic RL techniques can help alleviate some of the computational cost as only the actor functions are required for inference, while the critics can often be disregarded after training, thus reducing the computational burden at runtime. If a learned control policy were able to represent multiple desirable styles and offered a controllable way to transition between the learned styles, this could significantly reduce the total compute burden of the ML-based controller, making it more practically viable. The problem of interest then becomes about a single policy learning and transitioning smoothly between multiple different styles.

We explore the problem of *mutli-style* RL, a special case of the more commonly explored problem of multi-task RL (MTRL). Whereas MTRL techniques typically seek to solve a wide array of RL problems under a single learning campaign, multi-style RL adds the extra constraint that the 'tasks' in question all have identical system dynamics but would be characterized by different reward signals corresponding to the different desired styles of behavior. A common baseline approach to MTRL is to employ one-hot task encoding to delineate between tasks. However, when applied to a number of multi-style cases, the MTRL policies would fail to learn, despite successful training in the single-

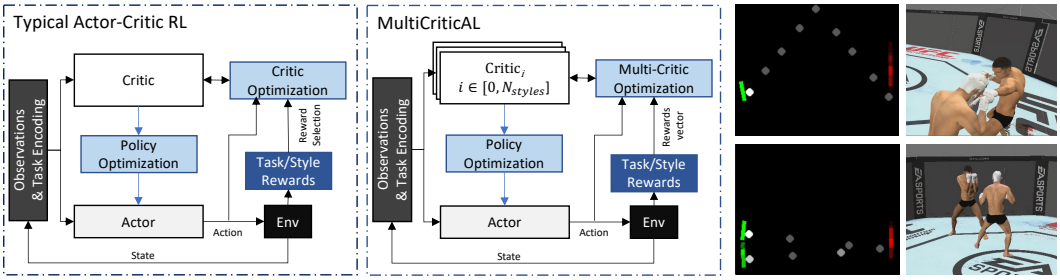

Figure 1: MultiCriticAL breaks from the common practice of using a single unified critic in MTRL and instead uses separate critics for each task learned. The proposed method is used to successfully train multiple distinct behavior styles in various games including Pong and UFC.

style case. We attributed this to the similarity of game-play states visited between each trained style interfering with each style's value optimization. In surveying existing MTRL literature for advancements in the field of multi-task Actor-Critic RL methods, we noticed a surprising hole. There are studies which employ single actors and single critics (Finn et al., 2017; Yang et al., 2020; Sodhani et al., 2021; Nichol et al., 2018), multiple actors and multiple critics (Andreas et al., 2017; Teh et al., 2017; Rusu et al., 2015; 2016; Huang et al., 2017), or multiple actors and a single critic (Yang et al., 2017; Dewangan et al., 2018). Curiously, seemingly no prior work explores the use of a single actor with multiple critics, i.e. training a single policy with distinct, per-task value estimation.

This paper proposes Multi-Critic Actor Learning (MultiCriticAL), a single-actor, multi-critic framework for multi-task Actor-Critic optimization and evaluate it on a number of multi-style learning problems. The core idea of MultiCriticAL is to maintain separate per-style (or task) critic functions for each style being learned. By separating the critic, for each learned style, MultiCriticAL is able to avoid the negative interference in the learned values for different styles. Our results demonstrate that MultiCriticAL is consistently able to train more performant policies when compared to its single-critic counterparts, succeeding in cases where the single-critic methods fail and achieving between 20-45% improvement in more traditional multi-task settings involving multi-level game-play. Additionally, we demonstrate the utility of MultiCriticAL in a use-case more reflective of real-world application, within a development environment for EA's UFC, where we successfully train policies to act with multiple specific and distinct behavior styles. This work is also amongst the first to study the efficacy of MTRL algorithms across a broad range of multi-style problems, an aspect of MTRL which has historically not received much attention.

2 Preliminaries

The core reinforcement learning (RL) problem is framed as a finite-horizon Markov decision process, $\langle S, A, P, r, \gamma \rangle$, with state transition dynamics $P : S, A \rightarrow S$, for states $s \in S$ and actions $a \in A$, and reward function $r : S, A \rightarrow \mathbb{R}$. The RL objective is to train a policy, $\pi : S \rightarrow A$ such that the expected sum of discounted rewards, $\mathbf{E}_{\tau_\pi}\left[\sum_i \gamma^i r(s_i, a_i)\right]$, with discount factor γ, is maximized for all trajectories, τ_π, sampled on policy π. RL typically assumes that both the transition dynamics and reward dynamics are encompassed by a black-box environment. RL agents interact with the environment to observe the state response and generated rewards, but where specific reward functions and transition dynamics are not assumed known. Solving the RL optimization problem requires estimating expected rewards and using these approximations to optimize the action policies.

While a number of different techniques exist for tackling the RL optimization problem, we will primarily consider Actor-Critic methods. A key characteristic of Actor-Critic algorithms is their separation of the 'actors', which represent the RL policy, and the 'critic', which represents the value-function estimator that learns to estimate discounted future rewards. This separation allows Actor-Critic RL to take advantage of the improved sample-efficiency of value-based techniques, such as Q-learning (Watkins & Dayan, 1992), while taking advantage of policy-based techniques, such as policy gradients (Sutton et al., 2000), for improved robustness to stochasticity and to enable learning in continuous action domains. Examples of prominent contemporary algorithms in this class of RL methods include TRPO (Schulman et al., 2015), PPO (Schulman et al., 2017), DDPG (Lillicrap et al., 2016), TD3 (Fujimoto et al., 2018), and SAC (Haarnoja et al., 2018).

In algorithms based on Q-learning, such as DDPG, TD3 and SAC, the policy optimization criteria J_{π_θ} for a policy, π, parameterized by θ, is proportional to the Q-value:

$$J_{\pi_\theta} \propto Q^{\pi_\theta}(s,a) = \mathbf{E}\left[R(\tau_{\pi_\theta})|s_0 = s, a_0 = a\right] = \mathbf{E}_{s'}\left[r(s,a) + \gamma Q^{\pi_\theta}(s', \pi_\theta(s'))\right] \tag{1}$$

where s' is the next state reached from state s in response to action a, and $R(\tau)$ is the discounted sum of rewards over trajectory τ. For algorithms based on a more traditional policy gradient optimization, such as TRPO and PPO, policies are optimized proportional to the the the advantage function, A^{π_θ} and a measure of policy divergence:

$$J_{\pi_\theta} \propto \log(\pi_\theta(a|s))A^{\pi_\theta}(s,a) = \log(\pi_\theta(a|s))\left(Q^{\pi_\theta}(s,a) - V^{\pi_\theta}(s)\right) \tag{2}$$

where the value-function $V^\pi(s) = \mathbf{E}_{\tau_\pi}\left[R(\tau_\pi)|s_0 = s\right] = \mathbf{E}_{s'}\left[r(s,\pi(s)) + \gamma V^\pi(s')\right]$. For critic networks parameterized by ϕ, either a state-value estimator, V_ϕ, or Q-value (state-action-value) estimator, Q_ϕ are optimized with optimization criteria $J_{V^\pi_\phi}$ or $J_{Q^\pi_\phi}$ respectively:

$$J_{V^\pi_\phi} \propto ||V^\pi_\phi(s) - (r(s,\pi(s)) + V^\pi_\phi(s' \sim P(s,\pi(s)))|| \tag{3}$$

$$J_{Q^\pi_\phi} \propto ||Q^\pi_\phi(s,a) - (r(s,a) + Q^\pi_\phi(s' \sim P(s,a), \pi(s')))|| \tag{4}$$

While specific details around how actors and critics are optimized vary between algorithms, the above represents the fundamentals of optimization criteria upon which we shall build our discussion.

3 Related Work

We broadly categorize multi-task RL (MTRL) techniques as either *single-policy*, if the same policy function activations are used to determine actions over all task, or *multi-policy*, if more separate activations (in the case of multi-headed policies) or policy functions are used. Multi-policy techniques range from training multiple policies and selecting or mixing between them (Andreas et al., 2017; Peng et al., 2018; Dewangan et al., 2018; Yang et al., 2017; Huang et al., 2017), to simultaneously or iteratively training additional policies while sharing representation between policies (Rusu et al., 2015; Teh et al., 2017; Rusu et al., 2016). Techniques requiring multiple policy networks are limited by their storage and computational costs during inference, and multi-headed policies can limit our ability to smoothly transition between behaviors, which makes them less attractive in the context of RL for game-play. We therefore focus instead on single-policy learning.

Single-policy MTRL techniques train a single policy function to solve multiple tasks, without relying on on information from previously trained policies. Model-free meta-learning techniques have been proposed to improve multi-task generalization, in the absence of task specificity (Finn et al., 2017; Nichol et al., 2018), but where explicit task distinction can be exploited, a common approach has been to exploit task encoding to distinguish between tasks. A simple, yet effective approach to this problem has been to extend state representations with one-hot task encoding (Peng et al., 2018; Yu et al., 2020; Yang et al., 2020), thus allowing policies to distinguish between individual tasks and decide actions in a task-appropriate way. Recent work has also sought to enhance performance and generalizability of such single-policy techniques through automated task encoding (Sodhani et al., 2021) or through soft-modularization (Yang et al., 2020), which encourages the development of distinct information pathways per task within actor networks.

Our work considers the special MTRL case of *multi-style* learning. Multi-style learning requires agents to learn different behaviors for highly similar states while providing potentially highly dissimilar rewards for each style. This variability in the reward signals can have an adverse impact on the quality of learned value-functions when using a single value estimator if the estimator cannot sufficiently distinguish between styles. We hypothesize that *negative interference* more strongly impacts value-function learning in multi-style tasks as task similarity may make specific style-values harder to distinguish. Multi-style learning is however an aspect of MTRL that has not received much prior consideration. Peng et al. (2018) explore the most similar setting to our work – where agents were required to learn different movement styles in animation tasks. Their work tested single-policy MTRL and found that policies were only able to learn a limited number of styles, requiring the authors to resort to a multi-policy approach.

Most works considering the Actor-Critic MTRL problem focus predominantly on how the actors, i.e the policy-functions, are optimized, with less attention given to critics. The problem of negative interference between tasks in the broader context of MTRL is one that has been highlighted and studied before (Yang et al., 2020; Parisotto et al., 2015; Teh et al., 2017; Standley et al., 2020) however, but has similarly been approached as a policy optimization problem. A number of multi-policy techniques were noted to maintain separate valuations per policy Teh et al. (2017); Andreas et al. (2017); Peng et al. (2018), though some work has also suggested that sharing critics can allow optimization to better capture useful shared knowledge to improve policy optimization (Dewangan et al., 2018; Yang et al., 2017). A similar idea dominates single-policy techniques, where all the studied methods maintain a single value-function estimator across all tasks (Nichol et al., 2018; Yu et al., 2020; Peng et al., 2018; Yang et al., 2020; Sodhani et al., 2021). While task-encoding may allow separate task-values to be learned implicitly by the critics, this was never found to be explicitly designed. Our work alternatively frames the multi-style learning framework as one that explicitly learns distinct per-style values to propose a value-learning optimization scheme that is better able to accommodate disparate reward functions.

4 Multi-Critic Actor Learning

The policy functions, i.e. the 'actor' part of Actor-Critic frameworks, represent the core decision-making processes of RL agents and the success or failure of any algorithm rests on the policies' abilities to learn useful mappings. The learned critics have limited utility after training and learned value-function estimators are also known for being a poor approximation of the true value-functions they attempt to capture (Ilyas et al., 2020), so it makes sense that prior work has focused more on how policies are constructed and trained. We hypothesize, however, that this is exactly why the specifics of value-network constructions and optimization are important to consider. As demonstrated in recent works by Mysore et al. (2021a) and Andrychowicz et al. (2021), a critical element in the performance of RL algorithms can be the representational capacity of the learned value-functions. It therefore stands to reason, that better structuring how value-networks represent the learned values can be an important component of improving value-function learning and therefore policy performance.

A common approach to how single-critic optimization is formulated in the MTRL setting involves including a task-encoding, Ω, to distinguish between learned tasks and to specify task rewards and updating the state representation $\bar{s} = \langle s, \Omega \rangle$. The optimization criteria in Equations 1-4 are correspondingly updated to use $\bar{s}$ in place of s. For resulting MTRL value-function optimization criteria typically represent rewards and learned values by scalar values. Practically, the learned value-functions are learned by a single network with a single output node, regardless of the number of tasks. Representing multiple values by a single learned value-function enforces a continuity between the learned values, which may not necessarily reflected in the true value functions and could compromise the quality of learned values and in turn adversely impact the learned policies.

Framing Value Optimization for Multi-Critic Actor Learning By instead separating the learned values per style, any assumption of continuity between style-values can be dismissed. Per-style (or task) values can be learned explicitly, without relying on optimization techniques to teach critics the distinctions. We propose the style-conditioned value optimization criteria for our Multi-Critic Actor Learning (MultiCriticAL) as:

$$J_{\mathbf{V}^{\pi}_{\phi}|\Omega} \propto \left|\left|\sum_i \omega_i \left[V^{\pi}_{\phi_i}(s) - (r_i(s, \pi(\bar{s})) + V^{\pi}_{\phi_i}(s' \sim P(s, \pi(\bar{s}))\right]\right|\right| \tag{5}$$

$$J_{\mathbf{Q}^{\pi}_{\phi}|\Omega} \propto \left|\left|\sum_i \omega_i \left[Q^{\pi}_{\phi_i}(s, a) - (r_i(s, a) + Q^{\pi}_{\phi_i}(s' \sim P(s, a), \pi(\bar{s}'))\right]\right|\right| \tag{6}$$

where, for M styles, the task/style encoding, $\Omega = [\omega_0, \ldots, \omega_M]$ and $\omega_i \in [0, 1]$. The policy optimization criteria requires the value functions to be continuous with respect to the states and task encoding, and this property can be maintained by appropriately selecting the value functions when computing the policy optimization criteria. The specifics of the exact formulation of the optimization criteria would vary in accordance with the base Actor-Critic algorithm employed, with Equations 1 and 2 respecitvely being updated as:

$$J_{\pi_\theta} \propto \sum_i \omega_i Q^{\pi_\theta}_{\phi_i}(s, a) \tag{7}$$

$$\text{or } J_{\pi_\theta} \propto \log(\pi_\theta(a|\bar{s})) \sum_i \omega_i A^{\pi_\theta}_{\phi_i}(s, a) \tag{8}$$

Practically, the multi-valued critics may be represented by separate independent critic networks – multi-network (MN) MultiCriticAL – or a single base critic network with multiple heads, where each head represents a different learned value – multi-headed (MH) MultiCriticAL. While the latter allows for some learned representations to be shared between the value functions, the former may be more beneficial when sharing is likely to lead to undesirable interference. This is visually shown in Figure 1 and extended in Figure 6 in Appendix B.

5 EVALUATION

We evaluate the proposed MultiCriticAL method in a series of multi-style RL problems. We first test our method on two basic multi-style learning environments designed as simple and light-weight demonstrations of the types of problems we seek to address: (i) learning to follow simple shapes, where different styles correspond to different shapes, (ii) playing a modified game of Pong where the player's paddle is allowed to rotate and agents are trained to play aggressively or defensively against a stock AI. While relatively simple, these environments help highlight the efficacy of MultiCriticAL over the more typical single-critic MTRL framework. Additionally, we test MultiCriticAL on learning to play multiple levels of the Sega genesis games Sonic the Hedgehog, and Sonic the Hedgehog 2, where the agent is trained to play the different levels of each game, following the reward structure devised for the Gym Retro contest (Nichol et al., 2018). Finally, we demonstrate a practical use-case for MultiCriticAL in a development environment of Electronic Arts' UFC fighting game where RL agents are integrated into the game controls and trained with different fighting styles.

Baselines We train MultiCriticAL with two popular contemporary actor-critic algorithms: PPO (Schulman et al., 2017) and SAC (Haarnoja et al., 2018), which represent Actor-Critic algorithms based on both value iteration and Q-learning respectively. These are compared against Multi-task PPO (MTPPO) and Multi-task SAC (MTSAC), which augment the state information with a one-hot task encoding and were also proposed as baselines by Yu et al. (2020). While we recognize that these are not state-of-the-art MTRL algorithms, they share a common critic optimization structure with more recent advancements in policy (actor) optimization (Sodhani et al., 2021; Yang et al., 2020), and we aim to demonstrate the fundamental utility of MultiCriticAL in the absence of additional policy optimization tricks. Training code is based on OpenAI's Spinning Up (Achiam, 2018) and is provided in the Supplementary Material for the multi-style environments. As the Sonic the Hedgehog games require paid access and the development environment for UFC is proprietary, game code is not provided, though the Appendix C details how they were adapted for our purposes.

Seeding To account for the variability in RL, performance is averaged over 5 random seeds.

5.1 PATH FOLLOWING

Environment Design and Reward Shaping In the path following environment, given is current position in space, the current phase of motion $\in [0, 1]$, and an indicator on which shape to reproduce, the agent is expected to follow a trajectory that generates the desired shape. Three shapes are tested: Circle, Square and Triangle. This simple problem adds no additional complexity related to generalization or complex system dynamics and simply expects policies to learn a mapping function that encodes the desired shape. The multi-style objective is for the agents to accurately produce any of the three required shapes, given the task encoding. Agents are rewarded based on the absolute error between the agent's current and desired position in space. The rewards are cast to be positive in the range of $[0, 1]$ per step. Appendix C offers further details, with code in Supplementary Material.

Results The pathing behavior learned for each algorithm over the three shapes is show in Figure 2. While single-style SAC and PPO are able to learn to follow each shape, performance of MTSAC and MTPPO in the multi-style setting is compromised. This is most prominent with MTSAC. MTPPO fares better but performance in the multi-style setting is still notably worse. Adapted to both algorithms, MultiCriticAL demonstrates more consistently learns to follow all three shapes. It should also be noted that larger networks were needed for the PPO algorithm to solve this task, using two hidden layers with 32 neurons each, as opposed to SAC's 8 each. This likely contributes to the improved performance of PPO in the multi-task setting as the networks being used have higher relative representational capacity, but is still outperformed by MultiCriticAL.

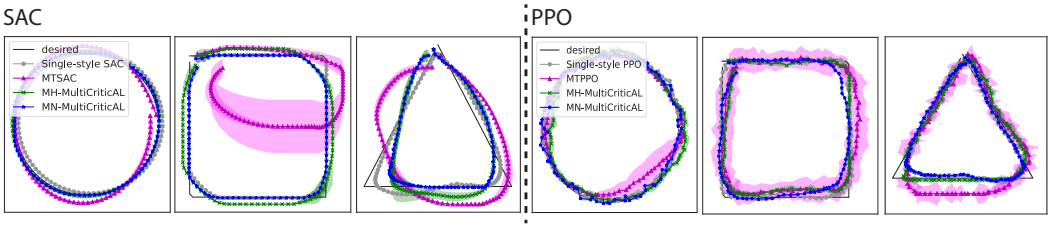

Figure 2: The path-following task requires agents to learn a Circular, Square, or Triangular path. MultiCriticAL agents can learn to follow all 3 shapes with better performance compared to the more typical single-critic multi-task value-learning frameworks of MTSAC and MTPPO.

5.2 Pong with rotatable paddles

Environment Design and Reward Shaping We use a modified game of Pong to explore a multi-style learning problem where one style is represented by a sparse reward, and the other a dense reward, anticipating that this might be a case where single-critc value-function estimation may fail. Pong typically allows only a single degree of freedom for paddle movement and does not normally command nuanced strategies. Adding an extra degree of freedom by allowing the player's paddles to rotate introduces increased complexity to the game and facilitates the training of different behavior styles. For this game, we consider two primary styles of play: (i) aggressive – with the objective of winning the game as quickly as possible, and (ii) defensive – where the objective is to avoid losing while prolonging the game as long as possible. In a real game setting, these could be analogous to hard- and easy-mode AI respectively, where the former tries to give the opponent a challenge and the latter may help the opponent learn to play. Our implementation is based on the Pong environment provided by the Pygame Learning Environment (PLE) (Tasfi, 2016). For simplicity, the basic opponent AI cannot rotate its paddle and uses a heuristic-based Pong controller provided by PLE.

Aggressive play is conditioned with a sparse reward: +1 on a win and -1 on loss. Agents are meant to learn that the best way to maximize cumulative discounted rewards is to win as quickly as possible. Defensive play is conditioned with dense rewards: -1 on loss, -1 for bouncing the ball against walls, +0.5 for receiving the ball, +0.1 if the opponent successfully receives the ball and +0.1 for every time-step of play. Defensive rewards encourage avoiding losing and ensuring that the opponent can receive the ball in order to prolong the game.

Results We first established baseline performance by training SAC and PPO on the *Aggressive* and *Defensive* play-styles. Figure 3 shows samples of play strategies adopted for each style, where the *Aggressive* agent exploits paddle rotation to bounce the ball off the side wall to outmaneuver the opponent. Conversely, *Defensive* agents attempt to return the ball directly to the opponent, exploiting the paddle rotation to angle the ball back towards the opponent. As desired, aggressive play yields high win-rates, with plays lasting significantly shorter than defensive play, which would win approximately half of the games but play longer games (videos in Supplementary Material).

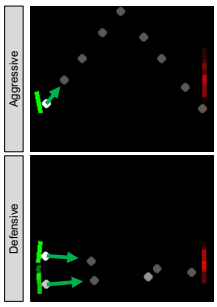

Figure 3: Behavior samples for *Aggressive* and *Defensive* play in Pong.

Multi-style performance is tested by introducing a one-hot style encoder and randomly uniformly sampling either defensive or aggressive play for each new training episode. We observed that both MTSAC and MTPPO failed to learn to properly distinguish between play-styles. MTSAC agents often defaulted to highly defensive play (likely due to the over representation of the dense defensive rewards in the replay buffers) while MTPPO agents tended to learn intermediate behavior that was neither aggressive, nor defensive. MultiCriticAL agents were however able to successfully learn to distinguish between the styles with both base algorithms, with performance comparable to single-style agents. Table 1, shows performance statistics averaged over 20 test episodes per seed for each algorithm.

We also test how MultiCriticAL agents would respond to changes in the style encoding at test time. As shown in Table 2, when provided an intermediate (0.5,0.5) encoding, the agents often presented with behavior statistics that were almost halfway between that of their aggressive and defensive statistics. This was even without explicit conditioning, when agents were trained with purely binary

Table 1: Learning different play-styles on Pong with rotatable player paddles

	Agent	Single-style	MT w/ one-hot	MN-MultiCriticAL	MH-MultiCriticAL
SAC	*Aggressive-Setting*				
	Reward ↑	0.89 ± 0.05	-0.40 ± 0.15	0.80 ± 0.02	0.79 ± 0.03
	Win-rate ↑	$93 \pm 2\%$	$30 \pm 10\%$	$85 \pm 4\%$	$84 \pm 6\%$
	Play-time ↓	300 ± 118	171 ± 84	317 ± 138	313 ± 145
	Defensive-Setting				
	Reward ↑	146.34 ± 47.65	152.68 ± 46.03	173.34 ± 12.40	149.56 ± 14.02
	Win-rate	$52 \pm 2\%$	$50 \pm 5\%$	$30 \pm 5\%$	$40 \pm 14\%$
	Play-time ↑	1383 ± 447	1446 ± 422	1637 ± 113	1350 ± 364
PPO	*Aggressive-Setting*				
	Reward ↑	0.67 ± 0.13	-0.27 ± 0.16	0.80 ± 0.11	0.5 ± 0.03
	Win-rate ↑	$82 \pm 10\%$	$37 \pm 13\%$	$90 \pm 3\%$	$75 \pm 5\%$
	Play-time ↓	523 ± 258	312 ± 119	475 ± 184	360 ± 137
	Defensive-Setting				
	Reward ↑	99.57 ± 27.94	36.16 ± 22.11	88.14 ± 25.81	74.98 ± 14.02
	Win-rate	$53 \pm 10\%$	$40 \pm 3\%$	$37 \pm 3\%$	$62 \pm 5\%$
	Play-time ↑	952 ± 190	467 ± 258	841 ± 226	826 ± 103

Table 2: Interpolating between aggressive and defensive Pong play-styles

Agent	SAC		PPO	
	MN-MultiCriticAL	MH-MultiCriticAL	MN-MultiCriticAL	MH-MultiCriticAL
Training with Binary Style Selection				
Win-rate	$70 \pm 5\%$	$63 \pm 10\%$	$68 \pm 4\%$	$75 \pm 5\%$
Play-time	773 ± 228	$785 \pm 110\%$	565 ± 264	529 ± 60
Training with Explicit Style Interpolation				
Win-rate	$75 \pm 5\%$	$73 \pm 8\%$	$70 \pm 3\%$	$71 \pm 2\%$
Play-time	852 ± 98	803 ± 120	601 ± 128	580 ± 166

style indicators. When explicitly interpolating between styles in training (by providing a multi-dimensional style-reward, with aggressive and defensive rewards scaled by their encoding weight), both MultiCriticAL SAC and PPO agents yielded performance statistics that more closely matched the mid-points between their aggressive and defensive behaviors.

5.3 Sonic the Hedgehog

Training Setup To explore the utility of MultiCriticAL in a more established multi-task setting, we tested two Sonic the Hedgehog games, using the Gym-retro wrappers designed for the games during the Gym-retro contest (Nichol et al., 2018), using the same setup configuration developed for the competition. This multi-task setting is handled by MultiCriticAL by maintaining a separate critic for each trained level. Running sufficient experiments over both games and also training independent agents for each levels required the use of CPU and GPU parallelism, which our code only supports for PPO and therefore results are only provided for PPO and compares both multi-network and multi-headed MultiCriticAL against MTPPO.

Results Performance on 17 of the main levels for each game, averaged over 10 tests per agent, per level, are presented in Figure 4, with per-level tabulated numerical rewards provided in Appendix A. Sonic the Hedgehog appears to be a game where learning shared representations over multiple levels helps overall performance, for both MultiCriticAL and MTPPO, though this observation does not hold for Sonic the Hedgehog 2, where MTPPO agents perform worse on average than agents trained on single-levels. MultiCriticAL agents tend to perform comparable or better than independently trained and MTPPO agents in almost all cases however, with 32% and 19% improvements on Sonic the Hedgehog and 45% and 31% improvement on Sonic the Hedgehog 2 of MN-MultiCriticAL and MH-MultiCriticAL over MTPPO respectively.

5.4 UFC Environment

To test MultiCriticAL in use-case that is more reflective of real-world application, we applied it to training AI fighters in an experimental build for Electronic Arts' UFC. To interface with the game, a gym-like (Brockman et al., 2016) wrapper was built for the game environment to allow the control of an RL-controlled player to play against the game's stock AI. We will note that this is not a feature of the commercially released game but is a modification made for research purposes. Given resource constraints, MultiCriticAL is primarily tested with PPO, with a multi-headed critic in this use-case.

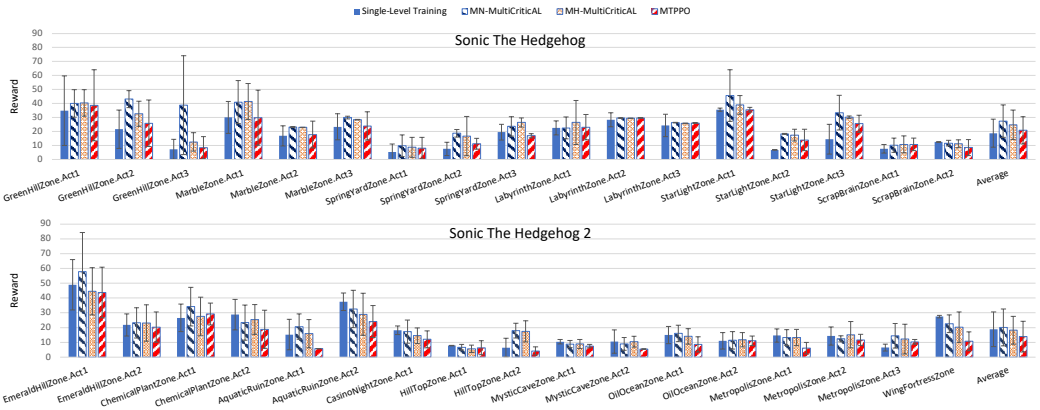

Figure 4: Evaluated over two Sonic games with 17 training levels per game, MultiCriticAL offers consistently superior performance to the single-critic baseline and achieves comparable, if not better performance to agents trained specifically for each level.

Table 3: Multi-headed MultiCriticAL-PPO on UFC

Style	Style Rewards (mean)				Action Probability (%)				Win Rate (%)
	Aggressive	Defensive	Blocking	Moving	No-action	Strike	Block	Move	
Aggressive	**0.900**	0.00	0.056	0.356	0.30	**15.20**	16.10	68.40	90
Defensive	0.00	**17.3**	**3.53**	**1.96**	0.45	4.02	**31.71**	63.82	0 (40% ties)
Neutral	0.499	3.28	0.501	0.638	**0.56**	10.68	24.15	64.62	90
Blocking	0.479	2.40	0.640	0.00	0.37	13.35	18.74	67.54	90
Moving	0.491	3.58	0.00	1.50	0.46	7.67	21.98	**68.89**	90

Environment design and Reward Shaping The RL agent observes information about the player's and opponent's position, velocity, health, and actions being taken, stacked over 8 steps. The RL-agent is able to control 11 basic discrete high-level actions including forward and backward movement, high or low blocking, left or right attacking (with straights, uppercuts or hooks), and is also allowed to take no action. The RL-agent is conditioned over 2 sets of 2 playing styles: aggressive or defensive and blocking or moving. During training, aggression vs. defensiveness, and blocking vs. moving are set on $[0, 1]$ scales with $(0.5, 0.5)$ representing a neutral style which is meant to balance behavior from both scales. For all styles, the agent is rewarded for winning and is penalized for every strike request. For the aggressive style, the agent is additionally rewarded for reducing the opponent health. For the defensive style, the agent gets a small positive reward for each step that it remains alive, is penalized for losing health and is rewarded for reducing the opponent's health (though not as much as with the aggressive style). For the blocking style, the agent is rewarded for every successful block and for the moving style, the agent is rewarded for maintaining a positive velocity. More specifics on the state and action spaces, specifics on reward tuning, and training are provided in Appendix C.3.

Results MultiCriticAL allows PPO agents to successfully learn and smoothly transition between the different fighting styles. The behavior styles are distinguished visually and Figure 5 attempts to capture this through frames from captured gameplay with videos included in the Supplementary Material. Average behavior statistics for each style are presented in Table 3. Aggressive and defensive play are the most distinct but there are also observable differences between control that prioritizes blocking and moving, with the blocking-style conditioning agents to hold their ground while moving prompts agents to move around the ring more. Defensive play was noted to achieve the highest Blocking and Moving rewards which was due to defensive play lasting longer without a clear victory (as designed), thus achieving higher cumulative totals, whereas blocking and moving play still try to win the fights, as reflected in their action distributions.

5.5 Discussion

While explicit separation of the learned value functions per style under the MultiCriticAL framework offers a demonstrable and consistent improvement over the single-critic baselines, it must be noted that MTSAC and MTPPO baselines do not necessarily reflect the state-of-the-art in MTRL, but they

Figure 5: We show 8 seconds of play with one representative frame per second for the different styles of play for the MultiCriticAL agent trained to play UFC. The RL agent has black hair while the stock AI has white hair. All styles are captured for the same RL agent, trained to play with multiple behavior styles. As desired, the agent more frequently goes on the offensive when set to *Aggressively*, prioritizes constant blocking and avoiding damage on *Defensive*, standing its ground and blocking incoming attacks on *Blocking* and moving around the ring for *Moving*.

do reflect how value optimization is typically handled in contemporary literature. It is likely that utilizing some of the improvements to policy optimization techniques discussed in Section 3, may contribute to improved performance of policies trained using single-critic value-optimization, however the same may also further improve the performance of agents trained with MultiCriticAL and remains to be studied. Curiously, MN-MultiCriticAL consistently outperformed MH-MultiCriticAL on all the tested tasks, which calls into question the idea that shared representation is important and/or useful (Dewangan et al., 2018; Yang et al., 2017) and is an aspect that may warrant further study. An interesting extension could be to extend modularization (Yang et al., 2020; Andreas et al., 2017) to value-function optimization. Learning with curricula (Bengio et al., 2009; Graves et al., 2017; Mysore et al., 2019; Andreas et al., 2017) has also been demonstrated to (sometimes dramatically) improve RL performance and multi-style/task curricula also seem like a potential natural fit for multi-critic optimizaiton. Recent work (Mysore et al., 2021a; Andrychowicz et al., 2021; Ilyas et al., 2020) has also demonstrated that value function capacity can be a key bottleneck in RL performance. Increasing the network capacity of a single-critic value-function may improve the efficacy of the critic, but this is not guaranteed and there are few principled ways to determine what a sufficient network capacity may be. Significantly increased computational resources may be required for the learnability of the multi-style problems under a single-critc framework. MultiCriticAL also requires increased compute during training, particularly MN-MultiCriticAL, but MH-MultiCriticAL allows for a bounded increase to computational load with an acceptable compromise in relative performance while still outperforming single-critic value learning.

6 Conclusion

We study Actor-Critic optimization in multi-style RL problems, where agents are required to behave with different styles in the same environments, our work represents one of the first explorations of the application of RL to a wider array of multi-style problems. We hypothesized that limitations of single-actor, single-critic MTRL frameworks may result in interference between the reward signals for different styles due to high similarity in visited states and to mitigate this, we proposed Multi-Critic Actor Learning (MultiCriticAL), which separates critics into per-task value-function estimators, thus avoiding interference between style rewards and reduces learning complexity by not requiring critics to learn to distinguish between tasks. MultiCriticAL consistently outperforms the single-critic MTRL baselines, achieving up to 45% improvement in multi-task performance and successfully learning multiple behavior styles where single-critic methods would fail.

REPRODUCIBILITY STATEMENT

As noted in Section 5, training code is based upon the open-source OpenAI Spinning Up code-base (Achiam, 2018), with modifications made to support MultiCriticAL for PPO and SAC. The modified code-base is included in the Supplementary Material for this paper, along with the code for the custom environments for Path Following (presented in Section 5.1) and Pong with rotatable paddles (presented in Section 5.2). The README files included with the code detail installation and use of the code. For the Sonic the Hedgehog games, reproducing results would require acquiring the games' ROM files and linking them to an install of gym-retro, as detailed by Nichol et al. (2018). Also included Appendices C and D are additional details for the setup of the training environments discussed in the main body of the paper as well as training configurations used. We recognize that tests on the UFC environment may not be independently reproducible due to requiring access to proprietary development software and we therefore mainly discuss it as a demonstration of the practical utility for our proposed MultiCriticAL method, rather than as a benchmark task.

REFERENCES

Joshua Achiam. Spinning Up in Deep Reinforcement Learning. 2018.

Eloi Alonso, Maxim Pete, David Goumard, and Joshua Romoff. Deep reinforcement learning for navigation in aaa video games. *NeuriPS Workshop on Challenges of Real-World RL*, 2020.

Jacob Andreas, Dan Klein, and Sergey Levine. Modular multitask reinforcement learning with policy sketches. In *International Conference on Machine Learning*, pp. 166–175. PMLR, 2017.

Marcin Andrychowicz, Anton Raichuk, Piotr Stańczyk, Manu Orsini, Sertan Girgin, Raphaël Marinier, Leonard Hussenot, Matthieu Geist, Olivier Pietquin, Marcin Michalski, Sylvain Gelly, and Olivier Bachem. What matters for on-policy deep actor-critic methods? a large-scale study. In *International Conference on Learning Representations*, 2021.

S. Ariyurek, A. Betin-Can, and E. Surer. Automated video game testing using synthetic and human-like agents. *IEEE Transactions on Games*, 13(1):50–67, 2021. doi: 10.1109/TG.2019.2947597.

Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. Curriculum learning. In *Proceedings of the 26th annual international conference on machine learning*, pp. 41–48, 2009.

Christopher Berner et al. Dota 2 with large scale deep reinforcement learning. *CoRR*, abs/1912.06680, 2019.

Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. Openai gym. *arXiv:1606.01540*, 2016.

Parijat Dewangan, S Phaniteja, K Madhava Krishna, Abhishek Sarkar, and Balaraman Ravindran. Digrad: Multi-task reinforcement learning with shared actions. *arXiv preprint arXiv:1802.10463*, 2018.

Prafulla Dhariwal, Christopher Hesse, Oleg Klimov, Alex Nichol, Matthias Plappert, Alec Radford, John Schulman, Szymon Sidor, Yuhuai Wu, and Peter Zhokhov. Openai baselines. `https://github.com/openai/baselines`, 2017.

Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *International Conference on Machine Learning*, pp. 1126–1135. PMLR, 2017.

Scott Fujimoto, Herke Hoof, and David Meger. Addressing function approximation error in actor-critic methods. In *International Conference on Machine Learning*, pp. 1587–1596, 2018.

Linus Gisslén, Andy Eakins, Camilo Gordillo, Joakim Bergdahl, and Konrad Tollmar. Adversarial reinforcement learning for procedural content generation. *IEEE Conference on Games*, 2021.

Camilo Gordillo, Joakim Bergdahl, Konrad Tollmar, and Linus Gisslén. Improving playtesting coverage via curiosity driven reinforcement learning agents. *IEEE Conference on Games*, 2021.

Alex Graves, Marc G Bellemare, Jacob Menick, Remi Munos, and Koray Kavukcuoglu. Automated curriculum learning for neural networks. In *international conference on machine learning*, pp. 1311–1320. PMLR, 2017.

Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, and Sergey Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. *International Conference on Machine Learning (ICML)*, 2018.

Zhewei Huang, Shuchang Zhou, BoEr Zhuang, and Xinyu Zhou. Learning to run with actor-critic ensemble. *arXiv preprint arXiv:1712.08987*, 2017.

Andrew Ilyas, Logan Engstrom, Shibani Santurkar, Dimitris Tsipras, Firdaus Janoos, Larry Rudolph, and Aleksander Madry. A closer look at deep policy gradients. In *International Conference on Learning Representations*, 2020.

Timothy P. Lillicrap, Jonathan J. Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. *International Conference on Learning Representations*, 2016.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *nature*, 518(7540):529–533, 2015.

Siddharth Mysore, Robert Platt, and Kate Saenko. Reward-guided curriculum for robust reinforcement learning. In *Workshop on Multi-task and Lifelong Reinforcement Learning at ICML*, 2019.

Siddharth Mysore, Bassel Mabsout, Renato Mancuso, and Kate Saenko. Honey, i shrunk the actor: A case study on preserving performance with smaller actors in actor-critic rl. *IEEE Conference on Games*, 2021a.

Siddharth Mysore, Bassel Mabsout, Kate Saenko, and Renato Mancuso. How to train your quadrotor: A framework for consistently smooth and responsive flight control via reinforcement learning. *ACM Transactions on Cyber-Physical Systems (TCPS)*, 5(4):1–24, 2021b.

Alex Nichol, Vicki Pfau, Christopher Hesse, Oleg Klimov, and John Schulman. Gotta learn fast: A new benchmark for generalization in rl. *arXiv preprint arXiv:1804.03720*, 2018.

Emilio Parisotto, Jimmy Lei Ba, and Ruslan Salakhutdinov. Actor-mimic: Deep multitask and transfer reinforcement learning. *arXiv preprint arXiv:1511.06342*, 2015.

Xue Bin Peng, Pieter Abbeel, Sergey Levine, and Michiel van de Panne. Deepmimic: Example-guided deep reinforcement learning of physics-based character skills. *ACM Transactions on Graphics (TOG)*, 37(4):1–14, 2018.

Andrei A Rusu, Sergio Gomez Colmenarejo, Caglar Gulcehre, Guillaume Desjardins, James Kirkpatrick, Razvan Pascanu, Volodymyr Mnih, Koray Kavukcuoglu, and Raia Hadsell. Policy distillation. *arXiv preprint arXiv:1511.06295*, 2015.

Andrei A Rusu, Neil C Rabinowitz, Guillaume Desjardins, Hubert Soyer, James Kirkpatrick, Koray Kavukcuoglu, Razvan Pascanu, and Raia Hadsell. Progressive neural networks. *arXiv preprint arXiv:1606.04671*, 2016.

John Schulman, Sergey Levine, Pieter Abbeel, Michael Jordan, and Philipp Moritz. Trust region policy optimization. In *Proceedings of the 32nd International Conference on Machine Learning*, Lille, France, 07–09 Jul 2015.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv:1707.06347*, 2017.

David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *nature*, 529(7587):484–489, 2016.

David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, et al. Mastering chess and shogi by self-play with a general reinforcement learning algorithm. *arXiv preprint arXiv:1712.01815*, 2017.

Shagun Sodhani, Amy Zhang, and Joelle Pineau. Multi-task reinforcement learning with context-based representations. *arXiv preprint arXiv:2102.06177*, 2021.

Trevor Standley, Amir Zamir, Dawn Chen, Leonidas Guibas, Jitendra Malik, and Silvio Savarese. Which tasks should be learned together in multi-task learning? In *International Conference on Machine Learning*, pp. 9120–9132. PMLR, 2020.

Richard S Sutton, David A McAllester, Satinder P Singh, and Yishay Mansour. Policy gradient methods for reinforcement learning with function approximation. In *Advances in neural information processing systems*, 2000.

Norman Tasfi. Pygame learning environment. `https://github.com/ntasfi/PyGame-Learning-Environment`, 2016.

Yee Whye Teh, Victor Bapst, Wojciech Marian Czarnecki, John Quan, James Kirkpatrick, Raia Hadsell, Nicolas Heess, and Razvan Pascanu. Distral: Robust multitask reinforcement learning. *arXiv preprint arXiv:1707.04175*, 2017.

Oriol Vinyals, Igor Babuschkin, Wojciech M Czarnecki, Michaël Mathieu, Andrew Dudzik, Junyoung Chung, David H Choi, Richard Powell, Timo Ewalds, Petko Georgiev, et al. Grandmaster level in starcraft ii using multi-agent reinforcement learning. *Nature*, 575(7782):350–354, 2019.

Christopher JCH Watkins and Peter Dayan. Q-learning. *Machine learning*, 8(3-4):279–292, 1992.

Ruihan Yang, Huazhe Xu, Yi Wu, and Xiaolong Wang. Multi-task reinforcement learning with soft modularization. *arXiv preprint arXiv:2003.13661*, 2020.

Zhaoyang Yang, Kathryn E Merrick, Hussein A Abbass, and Lianwen Jin. Multi-task deep reinforcement learning for continuous action control. In *IJCAI*, volume 17, pp. 3301–3307, 2017.

Tianhe Yu, Deirdre Quillen, Zhanpeng He, Ryan Julian, Karol Hausman, Chelsea Finn, and Sergey Levine. Meta-world: A benchmark and evaluation for multi-task and meta reinforcement learning. In *Conference on Robot Learning*, pp. 1094–1100. PMLR, 2020.

Y. Zhao, I. Borovikov, F. de Mesentier Silva, A. Beirami, J. Rupert, C. Somers, J. Harder, J. Kolen, J. Pinto, R. Pourabolghasem, J. Pestrak, H. Chaput, M. Sardari, L. Lin, S. Narravula, N. Aghdaie, and K. Zaman. Winning is not everything: Enhancing game development with intelligent agents. *IEEE Transactions on Games*, 12(2), 2020. doi: 10.1109/TG.2020.2990865.

A ADDITIONAL RESULTS

A.1 SONIC THE HEDGEHOG

Table 4: Rewards achieved on Sonic the Hedgehog (1)

Level	Single-level Policy	MTPPO	MN-MultiCriticAL	MH-MultiCriticAL
GreenHillZone.Act1	34.88 ± 24.84	38.70 ± 25.44	40.01 ± 9.82	$\mathbf{40.36 \pm 9.44}$
GreenHillZone.Act2	21.60 ± 13.66	25.82 ± 16.62	$\mathbf{43.13 \pm 6.07}$	32.67 ± 9.01
GreenHillZone.Act3	7.23 ± 7.07	8.37 ± 7.93	$\mathbf{38.85 \pm 35.28}$	12.53 ± 6.54
MarbleZone.Act1	30.06 ± 11.45	29.80 ± 19.70	40.93 ± 15.35	$\mathbf{41.43 \pm 12.85}$
MarbleZone.Act2	16.86 ± 7.23	17.79 ± 9.63	$\mathbf{23.10 \pm 0.37}$	22.92 ± 0.11
MarbleZone.Act3	23.31 ± 9.36	23.94 ± 10.04	$\mathbf{29.93 \pm 0.98}$	28.50 ± 0.17
SpringYardZone.Act1	5.29 ± 5.78	8.07 ± 7.70	$\mathbf{9.77 \pm 7.75}$	8.70 ± 7.14
SpringYardZone.Act2	7.55 ± 4.73	11.15 ± 3.85	$\mathbf{18.74 \pm 2.71}$	16.67 ± 14.06
SpringYardZone.Act3	19.47 ± 5.69	16.99 ± 1.48	23.62 ± 6.97	$\mathbf{26.43 \pm 3.27}$
LabyrinthZone.Act1	22.51 ± 4.98	23.04 ± 9.00	22.50 ± 7.78	$\mathbf{26.45 \pm 15.77}$
LabyrinthZone.Act2	28.28 ± 5.03	$\mathbf{29.65 \pm 0.19}$	29.59 ± 0.31	29.46 ± 0.06
LabyrinthZone.Act3	24.30 ± 8.06	26.04 ± 0.09	$\mathbf{26.33 \pm 0.13}$	25.82 ± 0.19
StarLightZone.Act1	35.53 ± 1.09	35.52 ± 1.66	$\mathbf{45.67 \pm 18.48}$	38.99 ± 6.68
StarLightZone.Act2	6.81 ± 0.14	13.91 ± 7.62	$\mathbf{18.25 \pm 0.30}$	17.31 ± 4.21
StarLightZone.Act3	14.47 ± 10.61	25.57 ± 6.08	$\mathbf{33.40 \pm 12.39}$	30.11 ± 0.88
ScrapBrainZone.Act1	7.56 ± 3.05	10.73 ± 4.52	10.23 ± 5.11	$\mathbf{10.74 \pm 6.11}$
ScrapBrainZone.Act2	12.52 ± 0.00	8.54 ± 5.67	$\mathbf{11.61 \pm 1.99}$	11.25 ± 2.81
Average	18.72 ± 10.01	20.80 ± 9.74	$\mathbf{27.39 \pm 11.65}$	24.73 ± 10.51

Table 5: Rewards achieved on Sonic the Hedgehog 2

Level	Single-level Policy	MTPPO	MN-MultiCriticAL	MH-MultiCriticAL
EmeraldHillZone.Act1	48.98 ± 17.00	43.72 ± 17.08	$\mathbf{57.81 \pm 26.48}$	44.59 ± 15.97
EmeraldHillZone.Act2	21.82 ± 7.47	20.34 ± 10.19	$\mathbf{23.21 \pm 10.27}$	23.05 ± 12.28
ChemicalPlantZone.Act1	26.58 ± 9.29	29.21 ± 7.36	$\mathbf{34.16 \pm 12.98}$	27.50 ± 13.06
ChemicalPlantZone.Act2	28.82 ± 10.32	18.84 ± 12.90	23.38 ± 11.85	$\mathbf{25.50 \pm 10.00}$
AquaticRuinZone.Act1	15.27 ± 10.31	5.85 ± 0.00	$\mathbf{20.61 \pm 8.56}$	15.92 ± 9.54
AquaticRuinZone.Act2	37.55 ± 5.89	24.12 ± 10.85	$\mathbf{32.61 \pm 12.60}$	28.95 ± 14.23
CasinoNightZone.Act1	18.18 ± 2.97	12.08 ± 5.71	$\mathbf{17.24 \pm 7.81}$	14.57 ± 5.19
HillTopZone.Act1	7.82 ± 0.20	6.36 ± 4.72	6.71 ± 1.85	5.65 ± 2.57
HillTopZone.Act2	6.44 ± 6.33	4.22 ± 2.81	$\mathbf{17.98 \pm 4.96}$	17.40 ± 7.18
MysticCaveZone.Act1	10.45 ± 1.53	7.42 ± 1.14	8.86 ± 2.44	$\mathbf{8.90 \pm 3.07}$
MysticCaveZone.Act2	10.57 ± 7.91	5.47 ± 0.00	8.92 ± 4.32	$\mathbf{10.47 \pm 3.69}$
OilOceanZone.Act1	14.96 ± 5.87	8.66 ± 5.18	$\mathbf{16.10 \pm 5.58}$	14.04 ± 5.28
OilOceanZone.Act2	11.01 ± 5.55	11.07 ± 3.21	11.42 ± 5.86	$\mathbf{11.82 \pm 4.82}$
MetropolisZone.Act1	14.64 ± 4.55	6.06 ± 3.94	13.29 ± 5.28	$\mathbf{13.33 \pm 5.52}$
MetropolisZone.Act2	14.34 ± 6.18	11.59 ± 3.83	12.44 ± 2.07	$\mathbf{15.17 \pm 8.86}$
MetropolisZone.Act3	6.49 ± 2.27	10.31 ± 1.59	$\mathbf{14.44 \pm 8.29}$	12.24 ± 10.06
WingFortressZone	27.43 ± 0.88	10.79 ± 6.41	$\mathbf{22.61 \pm 5.98}$	20.31 ± 10.25
Average	18.90 ± 11.71	13.89 ± 10.46	$\mathbf{20.11 \pm 12.44}$	18.20 ± 9.45

B MULTI-NETWORK VS. MULTI-HEADED TRAINING FRAMEWORK OVERVIEW

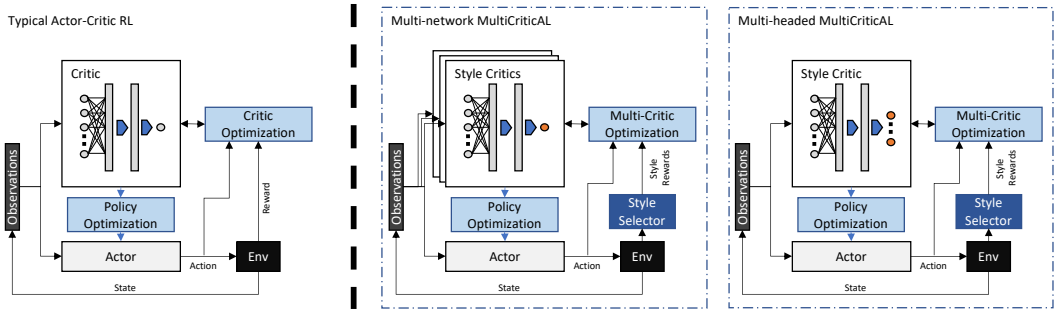

Figure 6: MN-MultiCriticAL and MH-MultiCriticAL frameworks compared.

C ADDITIONAL ENVIRONMENT SETUP DETAILS

C.1 PATH FOLLOWING

Observed State Agents observe a 4-dimensional state with the current (x,y) coordinates of the agent in space and the current phase $\rho \in [0, 1]$ represented by $[\sin(2\rho\pi), \cos(2\rho\pi)]$

Goal generation Goals, g are generated based on the current phase of motion. The are as follows for:

- Circle: $g(\rho) = [\sin(2\rho\pi), \cos(2\rho\pi)] \;\; \forall \rho \in [0, 1]$
- Square: $g(\rho) = \begin{cases} [4\rho - 0.5, 0.5] & \rho \leq 0.25 \\ [0.5, 1.5 - 4\rho] & 0.25 \leq \rho \leq 0.5 \\ [2.5 - 4\rho, -0.5] & 0.5 \leq \rho \leq 0.75 \\ [-0.5, 4\rho - 3.5] & 0.75 \leq \rho \leq 1 \end{cases}$
- Triangle: $g(\rho) = \begin{cases} [1.5\rho, 0.5 - 3\rho] & \rho \leq 1/3 \\ [1.5 - 3\rho, -0.5] & 1/3 \leq \rho \leq 2/3 \\ [-1.5 + 1.5\rho, 1.5\rho - 1.5] & 2/3 \leq \rho \leq 1 \end{cases}$

Reward design For current state s and desired state g: $r = 1 - \log(|s - g|)/\log(\max(\Delta s))$ where $\max(\Delta s)$ is the difference between the extents of the space bounds.

C.2 SONIC THE HEDGEHOG

Reward scaling As recommended by Nichol et al. (2018), we scale rewards by a factor of 0.01 in order to encourage more stable learning with PPO.

C.3 EA UFC DEVELOPMENT ENVIRONMENT

Environment The UFC environment is an experimental build of UFC. During training simulation, superfluous elements of the game, such as audio, spectators, etc. are disabled. Socket communication is used to interface between the game-code and the python-based RL algorithms. The environment wrapper controls the game simulation and extracts and processes state information before communicating it through the socket to the python RL code and interprets requests from the python code to trigger inputs in the game. During training, agents are trained for 240 epochs with 4000 sample interactions collected per epoch. Training is run in increments of 30 epochs to improve simulation and memory management stability. Episodes are terminated when the agent runs out the max episode length or if the health differential between the agent and opponent is over 40 units.

State and Action Space for the UFC environment The environment returns the following data as 30-dimensional observations for the RL agent:

- Position: (X,Z) coordinates in the ring
- Velocity: scalar of trajectory velocity
- Health: [0,100] float value
- Action active: high-level action indicator
- Strike type: indicator of type of strike performed
- Strike segment: indicates the current stage of striking
- Ticks to event: time until next event in game ticks
- Target hit location: the region of the opponent's body the agent is targeting (upper or lower)
- Block successful: indicates when a strike is successfully blocked

The agent is allowed to take the following actions:

- No action
- (Strike) Straight: left or right, single request
- (Strike) Uppercut: left or right, single request
- (Strike) Hook: left or right, single request
- Block: high or low, needs to be held to sustain blocking
- Move: forward or backward relative to current opponent position

Reward Design The reward breakdown for the environment is as follows:

- Standard to all styles – Victory reward: +1; Strike request penalty: -0.001
- Aggressive style – successful attack reward: $+|\Delta\text{Health}_{\text{opponent}}|/100$
- Defensive style – survival reward: +0.02 per step; attack reward: $+|\Delta\text{Health}_{\text{opponent}}|/200$, health loss penalty: $-\Delta\text{Health}_{\text{agent}}/50$
- Blocking style – block reward: +0.01 per successful block
- Movement style – velocity reward: $+0.05v$

D TRAINING CONFIGURATION

Training code is based on OpenAI's Spinning Up (Achiam, 2018) and is provided in the zip folder included as additional supplementary material with our main paper submission.

With the exception of hidden layer configuration, we use the same default hyperparameters for each of the algorithms used. Different hidden layer configurations were selected for each environment such that they would not be needlessly large but would consistently solve the problem in the single-style cases

Hidden layer configurations for both the actors and critics per environment:

- Path following: PPO [64,64], SAC [8,8]
- Pong: PPO [64,64], SAC [32,32]
- Sonic the Hedgehog 1 and 2: PPO [128,128]. Note additionally that the CNN feature extractor is shared between the actors and all critics in any particular training run, though they are not shared between separate training runs. The CNN feature extractor was configured based on the the extractor used by Mnih et al. (2015) as it is the same configuration used in the Retro-contest (Nichol et al., 2018).

Additionally, a frame wrapper is used with Pong and the Sonic games to augment state information with infromation from the last 4 observed states. This wrapper is based on the FrameStack wrapper provided in OpenAI Baselines (Dhariwal et al., 2017).

Training time was determined by running training until performance plateaued, with an additional buffer given to multi-task training to account for the multi-task problem setting, with initial tests conducted to ensure that performance indeed plateaued.

Configurations for training per environment are as follows:

Path following

- Single-style PPO – Trained for 100 epochs with 4000 steps per epoch and 90 steps per episode
- Single-style SAC – Trained for 50 epochs with 4000 steps per epoch and 90 steps per episode
- Multi-style MTPPO – Trained for 300 epochs with 4000 steps per epoch and 90 steps per episode
- Multi-style MTSAC – Trained for 150 epochs with 4000 steps per epoch and 90 steps per episode
- Multi-style MultiCriticAL-PPO – Trained for 300 epochs with 4000 steps per epoch and 90 steps per episode
- Multi-style MultiCriticAL-SAC – Trained for 150 epochs with 4000 steps per epoch and 90 steps per episode

Pong with rotatable paddles

- Single-style PPO – Trained for 150 epochs with 4000 steps per epoch and variable length episodes
- Single-style SAC – Trained for 50 epochs with 4000 steps per epoch and variable length episodes
- Multi-style MTPPO – Trained for 250 epochs with 4000 steps per epoch and variable length episodes
- Multi-style MTSAC – Trained for 150 epochs with 4000 steps per epoch and variable length episodes
- Multi-style MultiCriticAL-PPO – Trained for 150 epochs with 4000 steps per epoch and variable length episodes
- Multi-style MultiCriticAL-SAC – Trained for 150 epochs with 4000 steps per epoch and variable length episodes

Sonic the Hedgehog (both 1 and 2)

- Single-style PPO – Trained for 30 epochs with 10000 steps per epoch and up to 2500 steps per episode, or until Sonic's death, whichever occurs first
- Multi-style MTPPO – Trained for 300 epochs with 10000 steps per epoch and up to 2500 steps per episode, or until Sonic's death, whichever occurs first
- Multi-style MultiCriticAL-PPO – Trained for 300 epochs with 10000 steps per epoch and up to 2500 steps per episode, or until Sonic's death, whichever occurs first