Multi-Scale Reward Shaping via an Off-Policy Ensemble

(Extended Abstract)

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ABSTRACT

We propose a potential-based reward shaping architecture that is able to reduce learning speed, with no prior tuning and extra environment samples required, via considering an off-policy ensemble of value functions learning on a variety of heuristics with a variety of scales.

Categories and Subject Descriptors

I.2.6 [Artificial Intelligence]: Learning

Keywords

reinforcement learning, potential-based reward shaping, horde

1. INTRODUCTION

We are interested in methods that are capable of aiding reinforcement learning (RL) [9] with as little extra maintenance as possible. Potential-based reward shaping (PBRS) is a simple framework for integrating domain knowledge into RL, particularly attractive for its policy invariance guarantees [8]. The efficacy of PBRS in reducing learning speed, while repeatedly demonstrated in practice [3], is conditioned on precise knowledge of both quality heuristics and their magnitudes, which together define the potential function. Recent literature in both active [1, 2] and latent [4] settings has argued and demonstrated the benefits of maintaining ensembles of policies shaped with simple-heuristic-based potentials, rather than limiting to a single (but complex) one. In this work we take this intuition further, to remove the second requirement of knowing correct value magnitude for the potentials,¹ which is typically found via behind-thescenes tuning. The assumption of an ability to do so is unrealistic, and defeats the purpose of a method intended to reduce learning speed. By removing this assumption, we achieve a PBRS architecture, that reduces learning speed at no extra sample cost. Together with previous work [1, 4,

2], this allows the designer to benefit from a handful of simple heuristics, with no requirements on their quality, and no additional tuning steps introduced, making the architecture practical to use out of the box.

2. APPROACH

We assume the usual RL framework [9]. PBRS [8] augments the reward function R with an additional reward $F = \gamma \Phi' - \Phi$, where Φ is the potential function over the state(-action) space. We assume an off-policy *latent* learning setup, and maintain our Horde [10] of shapings as a set \mathcal{D} of Greedy-GQ(λ)-learners [6]. Given a set of potential functions $\mathbf{\Phi} = \{\Phi_1, \dots \Phi_\ell\}$, a range of scaling factors $\mathbf{c}^i = \langle c_1^i, \dots c_{k_i}^i \rangle$ for each Φ_i , and the base reward function R, the ensemble reward function is a vector:

$$\mathbf{R} = R + \langle F_{c_1^1}^{\Phi_1}, F_{c_2^1}^{\Phi_1}, \dots, F_{c_{k_\ell}^{\ell}}^{\Phi_{\ell}} \rangle$$
(1)

where $F_{c_j}^{\Phi_i}$ (or simply F_j^i) is the potential-based shaping reward w.r.t. the potential function Φ_i , scaled with the factor c_j^i . Adopting the terminology of Sutton et al. [10], we refer to individual agents within Horde as *demons*. Each demon d_j^i learns a greedy policy π_j^i w.r.t. its reward $R + F_j^i$. Our latent setting implies a fixed behavior policy π_b , with all π_j^i learning in parallel from the experience generated by π_b . Because each policy π_j^i is available separately at each step, an *ensemble* policy π_E can be devised by collecting votes on action preferences from the demons d_j^i , or any other suitable ensemble technique [2].

3. EXPERIMENTS

We evaluate² our approach in two common benchmark problems: mountain car [9] and cart-pole [7]. We empirically show that an indiscriminate ensemble of simple heuristics on general scaling ranges performs as well as one with cherry-picked components. The behavior π_b is a uniform distribution over all actions at each time step. Evaluation is done by interrupting learning every z episodes and executing the queried greedy policy π_j^i or ensemble policy π_E once. We report our results w.r.t. rank voting [11].

¹Brys et al. [2] address the issue of *relative* scalings within an ensemble, while our focus is the unknown absolute scale for each heuristic.

Appears in: Proceedings of the 14th International Conference on Autonomous Agents and Multiagent Systems (AA-MAS 2015), Bordini, Elkind, Weiss, Yolum (eds.), May, 4-8, 2015, Istanbul, Turkey.

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²For experiment details, see the full version of this paper [5].

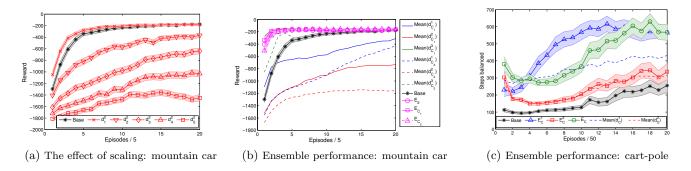


Figure 1: (a) Each curve corresponds to the performance of a demon shaped with Φ_2 , with a scaling factor from the range C_1 . (b),(c) The solid and dashed lines denote the *mean* performance of the demons w.r.t. a single shaping on a scale range, serving as reference for the performance of the ensemble components. Note that there is no single demon with this performance.

Mountain Car

We define 3 shaping potentials, corresponding to the position (Φ_1) , height (Φ_2) , and speed (Φ_3) of the car. We consider two scaling ranges $C_1 = \langle 20, 40, 60, 80, 100 \rangle$ and $C_2 = \langle 1, 10, 10^2, 10^3, 10^4 \rangle$, with the first being a reasonably close range to the optimal scales c_1, c_2, c_3 , and the second being a general sweep, with no intuition or knowledge of the optimal scale. Fig. 1(a) presents a comparison of the performance of Φ_2 over the (reasonable) scaling range C_1 , illustrating the dramatic effect small differences in scale can have on a shaping's performance. Now let E_{C_1} and E_{C_2} be the ensembles w.r.t. all three shapings on C_1 and C_2 , resp., each totaling in 16 demons (including the base learner), and let E be the ensemble w.r.t. the three shapings on tuned scalings c_1, c_2, c_3 . E_{C_1} and E_{C_2} are both statistically the same (p > 0.05) as the *tuned* ensemble E, despite their components having a much wider range of performance (Fig. 1(b)).

Cart-Pole

We define 2 shaping potentials, corresponding to the angle (Φ_1) and angular speed (Φ_2) of the pole. We consider a general scaling range $C = \langle 1, 10, 10^2, 10^3, 10^4 \rangle$, and three ensembles: E_C^1 resp. E_C^2 only comprised of the demons shaped w.r.t. Φ_1 resp. Φ_2 across C (5 demons each), and E_C containing all 11 demons (including the base learner). All ensembles improve over the base learner (Fig. 1(c)). The performance of E_C^2 matches that of its average, as all of its components perform similarly, while E_C^1 does much better than the corresponding average. The global ensemble E_C correctly identifies both which shaping to follow: its performance lies between the average of Φ_1 across C and E_C^1 , always outperforming Φ_2 , and on what scales: its final performance matches that of E_C^1 , significantly improving over the average of Φ_1 across C.

4. CLOSING REMARKS

We described a PBRS architecture that, through the use of an ensemble, can speed up learning by leveraging information from just a handful of imperfect heuristics, with no prior tuning required. In realistic settings, where little information is available a priori and environment samples are costly, this is the first practical reward shaping method, readily usable off-the-shelf. Note that the added computational expense is only linear in the number of non-zero features: Horde has been demonstrated to be able to learn thousands of policies in real time [10].

5. ACKNOWLEDGMENTS

Anna Harutyunyan is supported by the IWT-SBO project MIRAD (grant nr. 120057). Tim Brys is funded by a Ph.D grant of the Research Foundation-Flanders (FWO).

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