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-the-scenes 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.

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

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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:

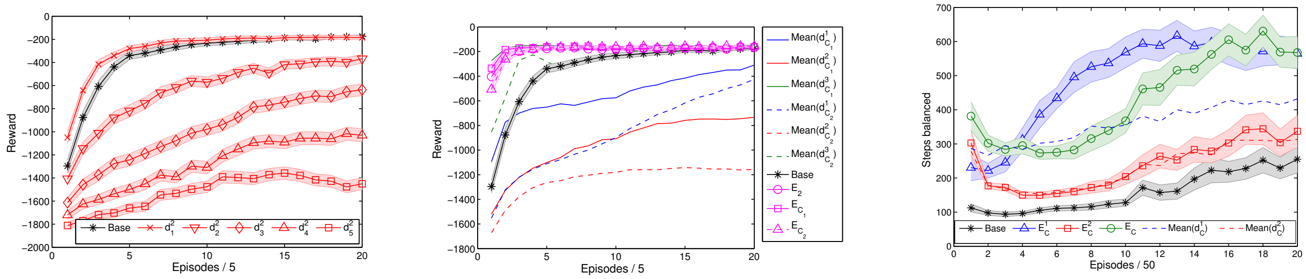
$$\mathbf{R} = R + \langle F_{c_1^1}^{\Phi_1}, F_{c_2^1}^{\Phi_1}, \dots, F_{c_{k_\ell}^\ell}^{\Phi_\ell} \rangle \tag{1}$$

where $F_{c_j^i}^{\Phi_i}$ (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 evaluate[2] 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].

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



(a) The effect of scaling: mountain car (b) Ensemble performance: mountain car (c) Ensemble performance: cart-pole

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^1_C resp. E^2_C 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^2_C matches that of its average, as all of its components perform similarly, while E^1_C 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^1_C, always outperforming Φ_2, and on *what scales*: its final performance matches that of E^1_C, 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

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6. REFERENCES

[1] T. Brys, A. Harutyunyan, P. Vrancx, M. E. Taylor, D. Kudenko, and A. Nowé. Multi-objectivization of reinforcement learning problems by reward shaping. In *Proc. of IEEE IJCNN*, 2014.

[2] T. Brys, A. Nowé, D. Kudenko, and M. E. Taylor. Combining multiple correlated reward and shaping signals by measuring confidence. In *Proc. of AAAI*, 2014.

[3] S. Devlin, D. Kudenko, and M. Grzes. An empirical study of potential-based reward shaping and advice in complex, multi-agent systems. *Advances in Complex Systems (ACS)*, 14(02):251–278, 2011.

[4] A. Harutyunyan, T. Brys, P. Vrancx, and A. Nowé. Off-policy shaping ensembles in reinforcement learning. In *Proc. of ECAI*, pages 1021–1022, 2014.

[5] A. Harutyunyan, T. Brys, P. Vrancx, and A. Nowé. Off-policy reward shaping with ensembles. Technical report, arXiv:1502.03248, 2015.

[6] H. Maei and R. Sutton. GQ(λ): A general gradient algorithm for temporal-difference prediction learning with eligibility traces. In *Proc. of AGI*, 2010.

[7] D. Michie and R. A. Chambers. Boxes: An experiment in adaptive control. In *Machine Intelligence*. 1968.

[8] A. Y. Ng, D. Harada, and S. Russell. Policy invariance under reward transformations: Theory and application to reward shaping. In *In Proc. of ICML*, 1999.

[9] R. Sutton and A. Barto. *Reinforcement learning: An introduction*, volume 116. Cambridge Univ Press, 1998.

[10] R. Sutton, J. Modayil, M. Delp, T. Degris, P. Pilarski, A. White, and D. Precup. Horde: A scalable real-time architecture for learning knowledge from unsupervised sensorimotor interaction. In *Proc. of AAMAS*, 2011.

[11] M. Wiering and H. van Hasselt. Ensemble algorithms in reinforcement learning. *Systems, Man, and Cybernetics, Part B: Cybernetics*, 38(4):930–936, 2008.