On Learning Intrinsic Rewards for Policy Gradient Methods

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Abstract

In many sequential decision making tasks, it is challenging to design reward functions that help an RL agent efficiently learn behavior that is considered good by the agent designer. A number of different formulations of the reward-design problem, or close variants thereof, have been proposed in the literature. In this paper we build on the Optimal Rewards Framework of [Singh et al. 2010] that defines the optimal intrinsic reward function as one that when used by an RL agent achieves behavior that optimizes the task-specifying or extrinsic reward function. Previous work in this framework has shown how good intrinsic reward functions can be learned for lookahead search based planning agents. Whether it is possible to learn intrinsic reward functions for learning agents remains an open problem. In this paper we derive a novel algorithm for learning intrinsic rewards for policy-gradient based learning agents. We compare the performance of an augmented agent that uses our algorithm to provide additive intrinsic rewards to an A2C-based policy learner (for Atari games) and a PPO-based policy learner (for Mujoco domains) with a baseline agent that uses the same policy learners but with only extrinsic rewards. Our results show improved performance on most but not all of the domains.

1 Introduction

One of the challenges facing an agent-designer in formulating a sequential decision making task as a Reinforcement Learning (RL) problem is that of defining a reward function. In some cases a choice of reward function is clear from the designer’s understanding of the task. For example, in board games such as Chess or Go the notion of win/loss/draw comes with the game definition, and in Atari games there is a game score that is part of the game. In other cases there may not be any clear choice of reward function. For example, in domains in which the agent is interacting with humans in the environment and the objective is to maximize human-satisfaction it can be hard to define a reward function. Similarly, when the task objective contains multiple criteria such as minimizing energy consumption and maximizing throughput and minimizing latency, it is not clear how to combine these into a single scalar-valued reward function.

Even when a reward function can be defined, it is not unique in the sense that certain transformations of the reward function, e.g., adding a potential-based reward [Ng et al. 1999], will not change the resulting ordering over agent behaviors. While the choice of potential-based or other (policy) order-preserving reward function used to transform the original reward function does not change what the optimal policy is, it can change for better or for worse the sample (and computational) complexity of the RL agent learning from experience in its environment using the transformed reward function.

Yet another aspect to the challenge of reward-design stems from the observation that in many complex real-world tasks an RL agent is simply not going to learn an optimal policy because of various bounds...
(or limitations) on the agent-environment interaction (e.g., inadequate memory, representational
capacity, computation, training data, etc.). Thus, in addressing the reward-design problem one may
want to consider transformations of the task-specifying reward function that change the optimal
policy. This is because it could result in the bounded-agent achieving a more desirable (to the agent
designer) policy than otherwise. This is often done in the form of shaping reward functions that are
less sparse than an original reward function and so lead to faster learning of a good policy even if it
in principle changes what the theoretically optimal policy might be [Rajeswaran et al., 2017]. Other
examples of transforming the reward function to aid learning in RL agents is the use of exploration
bonuses, e.g., count-based reward bonuses for agents that encourage experiencing infrequently visited
states [Bellemare et al., 2016; Ostrovski et al., 2017; Tang et al., 2017].

The above challenges make reward-design difficult, error-prone, and typically an iterative process.
Reward functions that seem to capture the designer’s objective can sometimes lead to unexpected
and undesired behaviors. Phenomena such as reward-hacking [Amodei et al., 2016] illustrate this
vividly. There are many formulations and resulting approaches to the problem of reward-design
including preference elicitation, inverse RL, intrinsically motivated RL, optimal rewards, potential-
based shaping rewards, more general reward shaping, and mechanism design; often the details of
the formulation depends on the class of RL domains being addressed. In this paper we build on
the optimal rewards problem formulation of [Singh et al., 2010]. We discuss the optimal rewards
framework as well as some other approaches for learning intrinsic rewards in Section 2.

Our main contribution in this paper is the derivation of a new stochastic-gradient-based method for
learning parametric intrinsic rewards that when added to the task-specifying (hereafter extrinsic)
rewards can improve the performance of policy-gradient based learning methods for solving RL
problems. The policy-gradient updates the policy parameters to optimize the sum of the extrinsic
and intrinsic rewards, while simultaneously our method updates the intrinsic reward parameters to
optimize the extrinsic rewards achieved by the policy. We evaluate our method on several Atari games
with a state of the art A2C (Advantage Actor-Critic) [Mnih et al., 2016] agent as well as on a few
Mujoco domains with a similarly state of the art PPO agent and show that learning intrinsic rewards
can outperform using just extrinsic reward as well as using a combination of extrinsic reward and a
constant “live bonus” [Duan et al., 2016].

2 Background and Related Work

Optimal rewards and reward design. Our work builds on the Optimal Reward Framework.
Formally, the optimal intrinsic reward for a specific combination of RL agent and environment is
defined as the reward which when used by the agent for its learning in its environment maximizes the
extrinsic reward. The main intuition is that in practice all RL agents are bounded (computationally,
representationally, in terms of data availability, etc.) and the optimal intrinsic reward can help
mitigate these bounds. Computing the optimal reward remains a big challenge, of course. The paper
introducing the framework used exhaustive search over a space of intrinsic reward functions and
thus does not scale. Sorg et al. [2010] introduced PGRD (Policy Gradient for Reward Design), a
scalable algorithm that only works with lookahead-search (UCT) based planning agents (and hence
the agent itself is not a learning-based agent; only the reward to use with the fixed planner is learned).
Its insight was that the intrinsic reward can be treated as a parameter that influences the outcome of
the planning process and thus can be trained via gradient ascent as long as the planning process is
differentiable (which UCT and related algorithms are). Guo et al. [2016] extended the scalability
of PGRD to high-dimensional image inputs in Atari 2600 games and used the intrinsic reward as a
reward bonus to improve the performance of the Monte Carlo Tree Search algorithm using the Atari
emulator as a model for the planning. A big open challenge is deriving a sound algorithm for learning
intrinsic rewards for learning-based RL agents and showing that it can learn intrinsic rewards fast
enough to beneficially influence the online performance of the learning based RL agent. Our main
contribution in this paper is to answer this challenge.

Reward shaping and Auxiliary rewards. Reward shaping [Ng et al., 1999] provides a general
answer to what space of reward function modifications do not change the optimal policy, specifically
potential-based rewards. Other attempts have been made to design auxiliary rewards to derive
policies with desired properties. For example, the UNREAL agent [Jaderberg et al., 2016] used
pseudo-reward computed from unsupervised auxiliary tasks to refine its internal representations. In
Hierarchical RL. Another approach to a form of intrinsic reward is in the work on hierarchical RL. For example, the recent FeUdal Networks (FuNs) [Vezhnevets et al., 2017] is a hierarchical architecture which contains a Manager and a Worker learning at different time scales. The Manager conveys abstract goals to the Worker and the Worker optimizes its policy to maximize the extrinsic reward and the cosine distance to the goal. The Manager optimizes its proposed goals to guide the Worker to learn a better policy in terms of the cumulative extrinsic reward. A large body of work on hierarchical RL also generally involves a higher level module choosing goals for lower level modules. All of this work can be viewed as a special case of creating intrinsic rewards within a multi-module agent architecture. One special aspect of hierarchical-RL work is that these intrinsic rewards are usually associated with goals of achievement, i.e., achieving a specific goal state while in our setting the intrinsic reward functions are general mappings from observation-action pairs to rewards. Another special aspect is that most evaluations of hierarchical RL show a benefit in the transfer setting with typically worse performance on early tasks while the manager is learning and better performance on later tasks once the manager has learned. In our setting we take on the challenge of showing that learning and using intrinsic rewards can help the RL agent perform better while it is learning on a single task. Finally, another difference is that hierarchical RL typically treats the lower-level learner as a black box while we train the intrinsic reward using gradients through the policy module in our architecture.

3 Gradient-Based Learning of Intrinsic Rewards: A Derivation

As noted earlier, the most practical previous work in learning intrinsic rewards using the Optimal Rewards framework was limited to settings where the underlying RL agent was a planning (i.e., needs a model of the environment) agent using lookahead search in some form (e.g., UCT). In these settings the only quantity being learned was the intrinsic reward function. By contrast, in this section we derive our algorithm for learning intrinsic rewards for the setting where the underlying RL agent is itself a learning agent, specifically a policy gradient based learning agent.

3.1 Policy Gradient based RL

Here we briefly describe how policy gradient based RL works, and then we will present our method that incorporates it. We assume an episodic, discrete-actions, reinforcement learning setting. Within an episode, the state of the environment at time step $t$ is denoted by $s_t \in S$ and the action the agent takes from action space $A$ at time step $t$ as $a_t$, and the reward at time step $t$ as $r_t$. The agent’s policy, parameterized by $\theta$ (for example the weights of a neural network), maps a representation of states to a probability distribution over actions. The value of a policy $\pi_\theta$, denoted $J(\pi_\theta)$ or equivalently $J(\theta)$, is the expected discounted sum of rewards obtained by the agent when executing actions according to policy $\pi_\theta$, i.e.,

$$ J(\theta) = E_{s_t \sim T(\cdot|s_{t-1}, a_{t-1}), a_t \sim \pi_\theta(\cdot|s_t)} \left[ \sum_{t=0}^{\infty} \gamma^t r_t \right], \quad (1) $$

where $T$ denotes the transition dynamics, and the initial state $s_0 \sim \mu$ is chosen from some distribution $\mu$ over states. Henceforth, for ease of notation we will write the above quantity as $J(\theta) = E_{s_t} \left[ \sum_{t=0}^{\infty} \gamma^t r_t \right]$. The policy gradient theorem of [Sutton et al., 2000] shows that the gradient of the value $J$ with respect to the policy parameters $\theta$ can be computed as follows: from all time steps $t$ within an episode

$$ \nabla_\theta J(\theta) = E_{s_t, a_t} [G(a_t, s_t) \nabla_\theta \log \pi_\theta(a_t|s_t)], \quad (2) $$

where $G$ is the return.
where $G(s_t, a_t) = \sum_{i=t}^{\infty} \gamma^{i-t} r_i$ is the return until termination. Note that recent advances such as advantage actor-critic (A2C) learn a critic ($V_{\theta}(s_t)$) and use it to reduce the variance of the gradient and bootstrap the value after every $n$ steps. However, we present this simple policy gradient formulation (Eq 2) in order to simplify the derivation of our proposed algorithm and aid understanding.

3.2 LIRPG: Learning Intrinsic Rewards for Policy Gradient

Notation. We use the following notation throughout.

- $\theta$: policy parameters
- $\eta$: intrinsic reward parameters
- $r^{ex}$: extrinsic reward from the environment
- $r^{in} = \gamma^t r(t, a)$: intrinsic reward estimated by $\eta$
- $G^{ex}(s_t, a_t) = \sum_{i=t}^{\infty} \gamma^{i-t} r^{ex}$
- $G^{in}(s_t, a_t) = \sum_{i=t}^{\infty} \gamma^{i-t} \eta r^{in}(s_i, a_i)$
- $G^{ex+in}(s_t, a_t) = \sum_{i=t}^{\infty} \gamma^{i-t} (r^{ex} + \lambda r^{in}(s_i, a_i))$
- $J^{ex} = E_\theta[\sum_{i=0}^{\infty} \gamma^i r^{ex}]$
- $J^{in} = E_\theta[\sum_{i=0}^{\infty} \gamma^i \eta r^{in}(s_i, a_i)]$
- $J^{ex+in} = E_\theta[\sum_{i=0}^{\infty} \gamma^i (r^{ex} + \lambda r^{in}(s_i, a_i))]$
- $\lambda$: relative weight of intrinsic reward.

The departure point of our approach to reward optimization for policy gradient is to distinguish between the extrinsic reward, $r^{ex}$, that defines the task, and a separate intrinsic reward $r^{in}$ that additively transforms the extrinsic reward and influences learning via policy gradients. It is crucial to note that the ultimate measure of performance we care about improving is the value of the extrinsic rewards achieved by the agent; the intrinsic rewards serve only to influence the change in policy parameters. Figure 1 shows an abstract representation of our intrinsic reward augmented policy gradient based learning agent.

Algorithm Overview. An overview of our algorithm, LIRPG, is presented in Algorithm 1. At each iteration of LIRPG, we simultaneously update the policy parameters $\theta$ and the intrinsic reward parameters $\eta$. More specifically, we first update $\theta$ in the direction of the gradient of $J^{ex+in}$ which is the weighted sum of intrinsic and extrinsic rewards. After updating policy parameters, we update $\eta$ in the direction of the gradient of $J^{ex}$ which is just the extrinsic rewards. Intuitively, the policy is updated to maximize both extrinsic and intrinsic reward, while the intrinsic reward function is updated to maximize only the extrinsic reward. We describe more details of each step below.

Updating Policy Parameters ($\theta$). Given an episode where the behavior is generated according to policy $\pi_\theta(\cdot|s)$, we update the policy parameters using regular policy gradient using the sum of intrinsic and extrinsic rewards as the reward:

$$\theta' = \theta + \alpha \nabla_\theta J^{ex+in}(\theta)$$

$$\approx \theta + \alpha G^{ex+in}(s_t, a_t) \nabla_\theta \log \pi_\theta(a_t|s_t),$$

where Equation 4 is a stochastic gradient update.

Updating Intrinsic Reward Parameters ($\eta$). Given an episode and the updated policy parameters $\theta'$, we update intrinsic reward parameters. Intuitively, updating $\eta$ requires estimating the effect such a change would have on the extrinsic value through the change in the policy parameters. Our key idea is to use the chain rule to compute the gradient as follows:

$$\nabla_\eta J^{ex} = \nabla_{\theta'} J^{ex} \nabla_\eta \theta',$$

Figure 1: Inside the agent are two modules, a policy function parameterized by $\theta$ and an intrinsic reward function parameterized by $\eta$. In our experiments the policy function (A2C / PPO) has an associated value function as does the intrinsic reward function (see supplementary materials for details). As shown by the dashed lines, the policy module is trained to optimize the weighted sum of intrinsic and extrinsic rewards while the intrinsic reward module is trained to optimize just the extrinsic rewards.
where the first term \((\nabla_{\theta'} J^{ex})\) sampled as
\[
\nabla_{\theta'} J^{ex} \approx G^{ex}(s_t, a_t) \nabla_{\theta'} \log \pi_{\theta'}(a_t | s_t)
\]
is an approximate stochastic gradient of the extrinsic value with respect to the updated policy parameters \(\theta'\) when the behavior is generated by \(\pi_{\theta'}\), and the second term can be computed as follows:
\[
\nabla_{\eta} \theta' = \nabla_{\eta} \left( \theta + \alpha G^{ex+in}(s_t, a_t) \nabla_{\theta} \log \pi_{\theta}(a_t | s_t) \right) = \nabla_{\eta} \left( \alpha \log \pi_{\theta}(a_t | s_t) \right) = \alpha \lambda \sum_{i=t}^{\infty} \gamma^{t-i} \nabla_{\eta} \log \pi_{\theta}(a_t | s_t).
\]

Note that to compute the gradient of the extrinsic value \(J^{ex}\) with respect to the intrinsic reward parameters \(\eta\), we needed a new episode with the updated policy parameters \(\theta'\) (cf. Equation 6), thus requiring two episodes per iteration. To improve data efficiency we instead reuse the episode generated by the policy parameters \(\theta\) at the start of the iteration and correct for the resulting mismatch by replacing the on-policy update in Equation 6 with the following off-policy update using importance sampling:
\[
\nabla_{\theta'} J^{ex} = G^{ex}(s_t, a_t) \nabla_{\theta'} \pi_{\theta'}(a_t | s_t) \pi_{\theta}(a_t | s_t).
\]

The parameters \(\eta\) are updated using the product of Equations 10 and 11 with a step-size parameter \(\beta\); this approximates a stochastic gradient update (cf. Equation 5).

Implementation on A2C and PPO. We described LIRPG using the most basic policy gradient formulation for simplicity. There have been many advances in policy gradient methods that reduce the variance of the gradient and improve the data-efficiency. Our LIRPG algorithm is also compatible with such actor-critic architectures. Specifically, for our experiments on Atari games we used a reasonably state of the art advantage action-critic (A2C) architecture, and for our experiments on Mujoco domains we used a similarly reasonably state of the art proximal policy optimization (PPO) architecture. We provide all implementation details in supplementary material.

4 Experiments on Atari Games

Our overall objective in the following first set of experiments is to evaluate whether augmenting a policy gradient based RL agent with intrinsic rewards learned using our LIRPG algorithm (henceforth, augmented agent in short) improves performance relative to the baseline policy gradient based RL agent that uses just the extrinsic reward (henceforth, A2C baseline agent in short). To this end, we first perform this evaluation on multiple Atari games from the Arcade Learning Environment (ALE) platform [Bellemare et al., 2013] using the same open-source implementation with exactly the same

\[1\] Our implementation is available at: https://github.com/Hwhitetooth/lirpg
hyper-parameters of the A2C algorithm \cite{Mnih2016} from OpenAI \cite{Dhariwal2017} for both our augmented agent as well as the baseline agent. The extrinsic reward used is the game score change as is standard for the work on Atari games. The LIRPG algorithm has two additional parameters relative to the baseline algorithm, the parameter $\lambda$ that controls how the intrinsic reward is scaled before adding it to the extrinsic reward and the step-size $\beta$; we describe how we choose these parameters below in our results.

We also conducted experiments against another baseline which simply gave a constant positive value as a live bonus to the agent at each time step (henceforth, A2C-bonus baseline agent in short). The live bonus heuristic encourages the agent to live longer so that it will potentially have a better chance of getting extrinsic rewards.

Note that the policy module inside the agent is really two networks, a policy network and a value network (that helps estimate $G^{ex+in}$ as required in Equation \ref{equ:intrinsic_cumulative}). Similarly the intrinsic reward module in the agent is also two networks, a reward function network and a value function network (that helps estimate $G^{ex}$ as required in Equation \ref{equ:intrinsic_cumulative}).

4.1 Overall Performance

Figure \ref{fig:overall} shows the improvements of the augmented agents over baseline agents on 15 Atari games: Alien, Amidar, Asterix, Atlantis, BeamRider, Breakout, DemonAttack, DoubleDunk, MsPacman, Qbert, Riverraid, RoadRunner, SpaceInvaders, Tennis, and UpNDown. We picked as many games as our computational resources allowed in which the published performance of the underlying A2C baseline agents was good but where the learning was not so fast in terms of sample complexity so as to leave little room for improvement. We ran each agent for 5 separate runs each for 50 million time steps on each game for both the baseline agents and augmented agents. For the augmented agents, we explored the following values for the intrinsic reward weighting coefficient $\lambda$, \{0.003, 0.005, 0.01, 0.02, 0.03, 0.05\} and the following values for the term $\xi$, \{0.001, 0.01, 0.1, 1\}, that weights the loss from the value function estimates with the loss from the intrinsic reward function (the policy component of the intrinsic reward module). The learning rate of the intrinsic reward module, i.e., $\beta$, was set to 0.0007 for all experiments. We plotted the best results from the hyper-parameter search in Figure \ref{fig:hyperparams}. For the A2C-bonus baseline agents, we explored the value of live bonus over the set \{0.001, 0.01, 0.1, 1\} on two games, Amidar and MsPacman, and chose the best performing value of 0.01 for all 15 games. The learning curves of all agents are provided in the supplementary material.

The blue bars in Figure \ref{fig:overall} show the human score normalized improvements of the augmented agents over the A2C baseline agents and the A2C-bonus baseline agents. We see that the augmented agent outperforms the A2C baseline agent on all 15 games and has an improvement of more than ten percent on 9 out of 15 games. As for the comparison to the A2C-bonus baseline agent, the augmented agent still performed better on all games except for SpaceInvaders and Asterix. Note that most Atari games are shooting games so the A2C-bonus baseline agent is expected to be a stronger baseline.
4.2 Analysis of the Learned Intrinsic Reward

An interesting question is whether the learned intrinsic reward function learns a general state-independent bias over actions or whether it is an interesting function of state. To explore this question we used the learned intrinsic reward module and the policy module from the end of a good run (cf. Figure 2) for each game with no further learning to collect new data for each game. Figure 3 shows the variation in intrinsic rewards obtained and the actions selected by the agent over 100 thousand steps, i.e. 400 thousand frames, on 5 games. The analysis for all 15 games is in the supplementary material. The red bars show the average intrinsic reward per-step for each action. The black segments show the standard deviation of the intrinsic rewards. The blue bars show the frequency of each action being selected. Figure 3 shows that the intrinsic rewards for most actions vary through the episode as shown by large black segments, indirectly confirming that the intrinsic reward module learns more than a state-independent constant bias over actions. By comparing the red bars and the blue bars, we see the expected correlation between aggregate intrinsic reward over actions and their selection (through the policy module that trains on the weighted sum of extrinsic and intrinsic rewards).

5 Mujoco Experiments

Our main objective in the following experiments is to demonstrate that our LIRPG-based algorithm can extend to a different class of domains and a different choice of baseline actor-critic architecture (namely, PPO instead of A2C). Specifically, we explore domains from the Mujoco continuous control benchmark [Duan et al., 2016], and used the open-source implementation of the PPO [Schulman et al., 2017] algorithm from OpenAI [Dhariwal et al., 2017] as our baseline agent. We also compared LIRPG to the simple heuristic of giving a live bonus as intrinsic reward (PPO-bonus baseline agents for short). As for the Atari game results above, we kept all hyper-parameters unchanged to default values for the policy module of both baseline and augmented agents. Finally, we also conduct a preliminary exploration into the question of how robust the learning of intrinsic rewards is to the sparsity of extrinsic rewards. Specifically, we used the delayed versions of the Mujoco domains, where the extrinsic reward is made sparse by accumulating the reward for \( N = 10, 20, 40 \) time steps (or until the end of the episode, whichever comes earlier) before providing it to the agent. Note that the live bonus is not delayed when we delay the extrinsic reward for the PPO-bonus baseline agent. We expect that the problem becomes more challenging with increasing \( N \) but expect that the learning of intrinsic rewards (that are available at every time step) can help mitigate some of that increasing hardness.

Delayed Mujoco benchmark. We evaluated 5 environments from the Mujoco benchmark, i.e. Hopper, HalfCheetah, Walker2d, Ant, and Humanoid. As noted above, to create a more-challenging sparse-reward setting we accumulated rewards for 10, 20 and 40 steps (or until the end of the episode, whichever comes earlier) before giving it to the agent. We trained the baseline and augmented agents for 1 million steps on each environment.

5.1 Overall Performance

Our results comparing the use of learning intrinsic reward with using just extrinsic reward on top of a PPO architecture are shown in Figure 4. We only show the results of a delay of 20 here; the full
results can be found in the supplementary material. The dark blue curves are for PPO baseline agents. The light blue curves are PPO-bonus baseline agents, where we explored the value of live bonus over the set \{0.001, 0.01, 0.1, 1\} and plotted the curves for the domain-specific best performing choice. The red and curves are for the augmented LIRPG agents.

We see that in 4 out of 5 domains learning intrinsic rewards significantly improves the performance of PPO, while in one game (Ant) we got a degradation of performance. Although a live bonus did help on 2 domains, i.e. Hopper and Walker2d, LIRPG still outperformed it on 4 out of 5 domains except for HalfCheetah on which LIRPG got comparable performance. We note that there was no domain-specific hyper-parameter optimization for the results in this figure; with such optimization there might be an opportunity to get improved performance for our method in all the domains.

**Training with Only Intrinsic Rewards.** We also conducted a more challenging experiment on Mujoco domains in which we used only intrinsic rewards to train the policy module. Recall that the intrinsic reward module is trained to optimize the extrinsic reward. In 3 out of 5 domains, as shown by the green curves denoted by ‘PPO+LIRPG($R^{in}$)’ in Figure 4 using only intrinsic rewards achieved similar performance to the red curves where we used a mixture of extrinsic rewards and intrinsic rewards. Using only intrinsic rewards to train the policy performed worse than using the mixture on Hopper but performed even better on HalfCheetah. It is important to note that training the policy using only live-bonus reward without the extrinsic reward would completely fail, because there would be no learning signal that encourages the agent to move forward. In contrast, our result shows that the agent can learn complex behaviors solely from the learned intrinsic reward on MuJoCo environment, and thus the intrinsic reward captures far more than a live bonus does; this is because the intrinsic reward module takes into account the extrinsic reward structure through its training.

### 6 Discussion and Conclusion

Our experiments on using LIRPG with A2C on multiple Atari games showed that it helped improve learning performance in all of the 15 games we tried. Similarly using LIRPG with PPO on multiple Mujoco domains showed that it helped improve learning performance in 4 out 5 domains (for the version with a delay of 20). Note that we used the same A2C / PPO architecture and hyper-parameters in both our augmented and baseline agents. While more empirical work needs to be done to either make intrinsic reward learning more robust or to understand when it helps and when it does not, we believe our results show promise for the central idea of learning intrinsic rewards in complex RL domains.

In summary, we derived a novel practical algorithm, LIRPG, for learning intrinsic reward functions in problems with high-dimensional observations for use with policy gradient based RL agents. This is the first such algorithm to the best of our knowledge. Our empirical results show promise in using intrinsic reward function learning as a kind of meta-learning to improve the performance of modern policy gradient architectures like A2C and PPO.
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References

Satinder Singh, Richard L Lewis, Andrew G Barto, and Jonathan Sorg. Intrinsically motivated reinforcement learning: An evolutionary perspective. *IEEE Transactions on Autonomous Mental Development*, 2(2):70–82, 2010.

Andrew Y Ng, Daishi Harada, and Stuart J Russell. Policy invariance under reward transformations: Theory and application to reward shaping. In *Proceedings of the Sixteenth International Conference on Machine Learning*, pages 278–287. Morgan Kaufmann Publishers Inc., 1999.

Aravind Rajeswaran, Kendall Lowrey, Emanuel V Todorov, and Sham M Kakade. Towards generalization and simplicity in continuous control. In *Advances in Neural Information Processing Systems*, pages 6553–6564, 2017.

Marc Bellemare, Sriram Srinivasan, Georg Ostrovski, Tom Schaul, David Saxton, and Remi Munos. Unifying count-based exploration and intrinsic motivation. In *Advances in Neural Information Processing Systems*, pages 1471–1479, 2016.

Georg Ostrovski, Marc G Bellemare, Aäron Oord, and Rémi Munos. Count-based exploration with neural density models. In *International Conference on Machine Learning*, pages 2721–2730, 2017.

Haoran Tang, Rein Houthooft, Davis Foote, Adam Stooke, OpenAI Xi Chen, Yan Duan, John Schulman, Filip DeTurck, and Pieter Abbeel. # exploration: A study of count-based exploration for deep reinforcement learning. In *Advances in Neural Information Processing Systems*, pages 2750–2759, 2017.

Dario Amodei, Chris Olah, Jacob Steinhardt, Paul Christiano, John Schulman, and Dan Mané. Concrete problems in ai safety. *arXiv preprint arXiv:1606.06565*, 2016.

Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In *International Conference on Machine Learning*, pages 1928–1937, 2016.

Yan Duan, Xi Chen, Rein Houthooft, John Schulman, and Pieter Abbeel. Benchmarking deep reinforcement learning for continuous control. In *International Conference on Machine Learning*, pages 1329–1338, 2016.

Jonathan Sorg, Richard L Lewis, and Satinder Singh. Reward design via online gradient ascent. In *Advances in Neural Information Processing Systems*, pages 2190–2198, 2010.

Xiaoxiao Guo, Satinder Singh, Richard Lewis, and Honglak Lee. Deep learning for reward design to improve monte carlo tree search in atari games. *arXiv preprint arXiv:1604.07095*, 2016.

Max Jaderberg, Volodymyr Mnih, Wojciech Marian Czarnecki, Tom Schaul, Joel Z Leibo, David Silver, and Koray Kavukcuoglu. Reinforcement learning with unsupervised auxiliary tasks. *arXiv preprint arXiv:1611.05397*, 2016.

Deepak Pathak, Pulkit Agrawal, Alexei A Efros, and Trevor Darrell. Curiosity-driven exploration by self-supervised prediction. In *International Conference on Machine Learning (ICML)*, volume 2017, 2017.

Jürgen Schmidhuber. Formal theory of creativity, fun, and intrinsic motivation (1990–2010). *IEEE Transactions on Autonomous Mental Development*, 2(3):230–247, 2010.

Bradly C Stadie, Sergey Levine, and Pieter Abbeel. Incentivizing exploration in reinforcement learning with deep predictive models. *arXiv preprint arXiv:1507.00814*, 2015.
Pierre-Yves Oudeyer and Frederic Kaplan. What is intrinsic motivation? a typology of computational approaches. *Frontiers in Neurorobotics*, 1:6, 2009.

Alexander Sasha Vezhnevets, Simon Osindero, Tom Schaul, Nicolas Heess, Max Jaderberg, David Silver, and Koray Kavukcuoglu. Feudal networks for hierarchical reinforcement learning. In *International Conference on Machine Learning*, pages 3540–3549, 2017.

Richard S Sutton, David A McAllester, Satinder Singh, and Yishay Mansour. Policy gradient methods for reinforcement learning with function approximation. In *Advances in neural information processing systems*, pages 1057–1063, 2000.

Marc G Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *J. Artif. Intell. Res.(JAIR)*, 47:253–279, 2013.

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

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

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, 2015.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

John Schulman, Philipp Moritz, Sergey Levine, Michael Jordan, and Pieter Abbeel. High-dimensional continuous control using generalized advantage estimation. *arXiv preprint arXiv:1506.02438*, 2015.
A Implementation Details

A.1 Atari Experiments

**Episode Generation.** As in Mnih et al. [2015], each episode starts by doing a no-op action for a random number of steps after restarting the game. The number of no-op steps is sampled from 0 to 30 uniformly. Within an episode, each action chosen is repeated for 4 frames, before selecting the next action. An episode ends when the game is over or the agent loses a life.

**Input State Representation.** As in Mnih et al. [2015], we take the maximum value at each pixel from 4 consecutive frames to compress them into one frame which is then rescaled to a $84 \times 84$ gray scale image. The input to all four neural networks is the stack of the last 4 gray scale images (thus capturing frame-observations over 16 frames). The extrinsic rewards from the game are clipped to $[-1, 1]$.

**Details of the Two Networks in the Policy Module.** Note that the policy module is unchanged from the OpenAI implementation. Specifically, the two networks are convolutional neural networks (CNN) with 3 convolutional layers and 1 fully connected layer. The first convolutional layer has thirty-two $8 \times 8$ filters with stride 4. The second convolutional layer has sixty-four $4 \times 4$ filters with stride 2. The third convolutional layer has sixty-four $3 \times 3$ filters with stride 1. The fourth layer is a fully connected layer with 512 hidden units. Each hidden layer is followed by a rectifier non-linearity. The value network (that estimates $G_{ex+in}$) shares parameters for the first four layers with the policy network. The policy network has a separate output layer with an output for every action through a softmax non-linearity, while the value network separately outputs a single scalar for the value.

**Details of the Two Networks in the Intrinsic Reward Module.** The intrinsic reward module has two very similar neural network architectures as the policy module described above. It again has two networks, a “policy” network that instead of a softmax over actions produces a scalar reward for every action through a tanh nonlinearity to keep the scalar in $[-1, 1]$; we will refer to it as the intrinsic reward function. The value network to estimate $G_{ex}$ has the same architecture as the intrinsic reward network except for the output layer that has a single scalar output without a non-linear activation. These two networks share the parameters of the first four layers.

**Hyper-Parameters for Policy module.** We keep the default values of all hyper-parameters in the original OpenAI implementation of the A2C-based policy module unchanged for both the augmented and baseline agents.

**Hyper-Parameters for Intrinsic Reward module in Augmented Agent.** We use RMSProp to optimize the two networks of the intrinsic reward module. The decay factor used for RMSProp is 0.99, and the $\epsilon$ is 0.00001. We do not use momentum. Recall that there are two parameters special to LIRPG. Of these, the step size $\beta$ was initialized to 0.0007 and annealed linearly to zero over 50 million time steps for all the experiments reported below. We did a small hyper-parameter search for $\lambda$ for each game (this is described below in the caption of Figure 5). As for the A2C implementation for the policy module we clipped the gradient by norm to 0.5 in the intrinsic reward module.

A.2 Mujoco Experiments

**Details of the Two Networks in the Policy Module.** Note that the policy module is unchanged from the OpenAI implementation; we provide details for completeness. The policy network is a MLP with 2 hidden layers, too. The input to the policy network is the observation. The first two layer are fully connected layers with 64 hidden units. Each hidden layer is followed by a tanh non-linearity. The output layer outputs a vector with the size of the dimension of the action space with no non-linearity applied to the output units. Gaussian noise is added to the output of the policy network to

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\[2\] We use 16 actor threads to generate episodes. For each training iteration, each actor acts for 5 time steps. For training the policy, the weighting coefficients of policy-gradient term, value network loss term, and the entropy regularization term in the objective function are 1.0, 0.5, and 0.01. The learning rate $\alpha$ for training the policy is set to 0.0007 at the beginning and anneals to 0 linearly over 50 million steps. The discount factor $\gamma$ is 0.99 for all experiments.
encourage exploration. The variance of the Gaussian noise was a input-independent parameter which was also trained by gradient descent. The corresponding value network (that estimates \( G_{ex} \)) has a similar architecture with the policy network. The only difference is that output layer outputs a single scalar without any non-linear activation. These two networks do not share any parameters.

**Details of the Two Networks in the Intrinsic Reward Module.** The intrinsic reward function networks are quite similar to the two networks in the policy module. Each network is a multi-layer perceptron (MLP) with 2 hidden layers. We concatenated the observation vector and the action vector as the input to the intrinsic reward network. The first two layer are fully connected layers with 64 hidden units. Each hidden layer is followed by a tanh non-linearity. The output layer has one scalar output. We apply tanh on the output to bound the intrinsic reward to \([-1, 1]\). The value network to estimate \( G_{ex} \) has the same architecture as the intrinsic reward network except for the output layer that has a single scalar output without a non-linear activation. These two networks do not share any parameters.

**Hyper-Parameters for Policy Module** We keep the default values of all hyper-parameters in the original OpenAI implementation of PPO unchanged for both the augmented and baseline agents.

**Hyper-Parameters for Intrinsic Reward Module** We use Adam [Kingma and Ba, 2014] to optimize the two networks of the intrinsic reward module. The step size \( \beta \) was initialized to 0.0001 and was fixed over 1 million time steps for all the experiments reported below. The mixing coefficient \( \lambda \) was fixed to 1.0 and instead we multiplied the extrinsic reward by 0.01 cross all 5 environments. The PPO implementation clips the gradient by norm to 0.5. We keep this part unchanged for the policy network and clip the gradients by the same norm for the reward network. We used generalized advantage estimate (GAE) [Schulman et al., 2015] for both training the reward network and the policy network. The weighting factor for GAE was 0.95.

**B More Experimental Results**

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\(^3\)For each training iteration, the agent interacts with the environment for 2048 steps. The learning rate \( \alpha \) for training the policy is set to 0.0003 at the beginning and was fixed over training. We used a batch size of 32 and swept over the 2048 data points for 10 epochs before the next sequence of interaction. The discount factor \( \gamma \) is 0.99 for all experiments.
Figure 5: The x-axis is time steps during learning. The y-axis is the average game score over the last 100 training episodes. The blue curves are for the baseline architecture. The red curves are for our LIRPG based augmented architecture. The dark curves are the average of four runs with different random seeds. The shaded areas show the standard errors of 5 individual runs.

Hyper-parameter Search: We explored the following values for the intrinsic reward weighting coefficient $\lambda$, \{0.003, 0.005, 0.01, 0.02, 0.03, 0.05\}. We explored the following values for the term $\xi$, \{0.001, 0.01, 0.1, 1\}, that weights the loss from the value function estimates with the loss from the intrinsic reward function (the policy component of the intrinsic reward module).
Figure 6: Intrinsic reward variation and frequency of action selection. We selected a good run for each game from the runs shown in Figure 5, and used the learned intrinsic reward module and the associated policy module for the selected run without any further learning to play the game for 100 thousand steps, i.e. 400 thousand frames, to collect data. For each game/plot the x-axis shows the index of the actions that are available in that game. The red bars show the means and standard deviations of the intrinsic rewards associated with each action. The blue bars show the frequency of each action being selected.
Figure 7: The x-axis is time steps during learning. The y-axis is the average reward over the last 100 training episodes. Each column corresponds to a domain labeled at the top. Each row corresponds to the delay labeled on the left hand side (for 10, 20, and 40 steps from the top row to the bottom row). The blue curves are for the baseline PPO architecture. The red curves are for our LIRPG based augmented architecture. The dark curves are the average of 10 runs with different random seeds. The shaded area shows the standard errors of 10 runs.