# BAMDP SHAPING: A UNIFIED THEORETICAL FRAMEWORK FOR INTRINSIC MOTIVATION AND REWARD SHAPING

**Anonymous authors**
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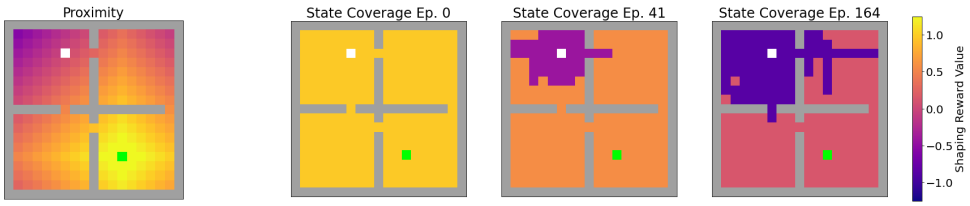
## ABSTRACT

Intrinsic motivation and reward shaping guide reinforcement learning (RL) agents by adding pseudo-rewards, which can lead to useful emergent behaviors. However, they can also exhibit unanticipated side effects – leading to reward hacking or fixation with noisy TVs. Here we provide a theoretical model which anticipates these behaviors, and provides broad criteria under which their effects can be bounded. We characterize all pseudo-rewards as reward shaping in Bayes-Adaptive Markov Decision Processes (BAMDPs), which formulates the problem of learning in MDPs as an MDP over the agent's knowledge. We can understand pseudo-rewards as guiding exploration by incentivizing RL agents to go to states with higher BAMDP value, which comprises the value of information gathered and the prior value of the physical state, while they mislead exploration when they align poorly with this value. We extend potential-based shaping theory (Ng et al., 1999) to prove only BAMDP Potential-based shaping Functions (BAMPFs) are guaranteed to preserve the optimal RL algorithm, and show empirically how a BAMPF helps a meta-RL agent learn an optimal RL agent for a Bernoulli Bandit domain. We finally prove that BAMPFs with bounded monotone potentials are also resistant to reward-hacking in MDPs. We show that it is straightforward to retrofit or design new pseudo-reward terms in this form to avoid unintended side effects, and provide an empirical demonstration in the Mountain Car environment.

## 1 INTRODUCTION

RL algorithms are known to struggle when rewards are sparse. A common solution is intrinsic motivation (IM) or reward shaping, which guides RL agents by adding pseudo-rewards to the true rewards (Schmidhuber, 1991; Dorigo & Colombetti, 1994; Barto et al., 2004). Intrinsic rewards may depend on the entire history while shaping rewards depend only on the action and previous and current MDP state. A wide variety of pseudo-rewards have been proposed and used successfully with scalable deep RL algorithms in complex environments (Pathak et al., 2017; Berseth et al., 2019; Hafner et al., 2023). However, designing them is challenging, and they can affect performance in counter-intuitive ways leading to degenerate behaviors (Taiga et al., 2021; Clark & Amodei, 2016). For instance, IM that rewards accurate prediction of the next percept may cause an agent to sit forever in front of a blank wall (Rhinehart et al., 2021), while favoring "surprise"—states where the next percept is hard to predict—causes an agent to get stuck watching a "noisy TV" that randomly flips channels, rather than encouraging exploration as one might expect (Burda et al., 2018).

Avoiding these behaviors requires understanding their root causes. We approach this by analyzing pseudo-rewards within a theoretical framework for how a rational RL agent *should* behave—the Bayes-Adaptive MDP (BAMDP) (Bellman & Kalaba, 1959; Martin, 1967), a generalization of Bayesian bandits Gittins (1979). In a BAMDP, the agent starts out not knowing which MDP it is operating in and learns more through experience. BAMDP states consist of the cumulative information observed from the actual MDP, i.e., the entire history $h$ of states, actions, and rewards, up to and including the current physical state. An RL algorithm can be viewed as a *policy* mapping the BAMDP state to an action that updates it (Duff, 2002), and optimal RL algorithms maximize the expected BAMDP return, i.e., the expected return while exploring and learning.




(a) Each state $s$ is colored by the PBSF reward for stepping there from $s_0$, i.e., $\gamma\phi(s) - \phi(s_0)$, with $\phi(s)$ the proximity to the goal (green cell).

(b) States colored by BAMPF rewards with potential $\phi(h) = |\{s \in h\}|$, i.e., the count of unique states visited over an RL agent's history $h$ of all observed transitions. Over the 3 episodes shown, the agent must travel further from $s_0$ to reach unvisited states and increase $\phi(h)$.

Figure 1: Examples of reward shaping based on potential functions $\phi$ of the MDP state (PBSF, 1a), and the BAMDP state (BAMPF, 1b, which can evolve over the course of training). Start and goal states (grid cells) $s_0, g$ are marked white and green; every other state is colored by the shaping reward for transitioning there directly from $s_0$ at the start of the episode. Goal proximity is defined as $\phi(s) = -\|\mathbf{s} - \mathbf{g}\|_1$. Each episode ends and the state is reset to $s_0$ every 50 steps, $\gamma = 0.99$.

Within this framework, we can understand both reward shaping and IM as *BAMDP reward shaping*, i.e., functions over BAMDP states, that guide effective exploration by incentivizing behavior that goes to more valuable BAMDP states. We decompose BAMDP state value into the value of the information collected (VOI) and the value of the physical MDP state under the prior, which we call the value of opportunity (VOO). Many IM terms, e.g., prediction error Pathak et al. (2017) or information gain (Houthooft et al., 2016), can be understood as incentivizing exploration by adding some approximation for increase in VOI into the objective. These terms can fail to help when they do not align well enough with actual VOI—for instance, watching the noisy TV yields high prediction error but no valuable information. Other kinds of pseudo-rewards attempt to steer exploration by compensating for implied priors in the initialization of RL algorithms that misestimate VOO. For example, goal proximity (Colombetti et al., 1996) and subtask completion rewards (Ng et al., 1999) compensate for overly pessimistic VOO estimates while surprise minimization (Berseth et al., 2019) and information cost (Eysenbach et al., 2021) compensate for overly optimistic VOO estimates. This yields a new, principled typology of both IM and reward shaping approaches based on the different types of BAMDP value that they signal.

Next, we prove conditions under which a broad form of pseudo-rewards cannot be "hacked", i.e., maximized to the detriment of the underlying objective, in both RL and meta-RL settings. Potential-Based reward Shaping Functions (PBSFs) take the form $\gamma\phi(s') - \phi(s)$, where potential $\phi$ encourages going to higher value states by encoding their desirability, e.g., Fig. 1a. PBSFs on the BAMDP state (BAMPFs), e.g., Fig. 1b, may encode desirability of both the physical state *and* the total information gathered. Since they may depend on the entire training history, it is easy to convert most pseudo-rewards to BAMPFs. We extend results from Ng et al. (1999) to prove that BAMPFs always preserve the optimality of RL algorithms. Thus, we can use BAMPFs to guide meta-RL without the risk of generating RL agents that are optimal for the shaped rewards but suboptimal for the underlying domain. We empirically show this by guiding a meta-RL agent to learn an optimal RL agent for a Bernoulli Bandits domain. Next, we return to the regular RL setting and prove that BAMPFs based on potential functions that are bounded and monotonic over increasing experience will eventually also preserve the optimal MDP policy, i.e., no RL algorithm can find a reward-hacking policy maximizing shaped rewards but not real rewards. We finally demonstrate the impact of our framework in the Mountain Car environment. We use the BAMDP value decomposition to inform the design of an effective potential function, and show that the resulting BAMPF improves learning efficiency while preserving optimality, whereas similar pseudo-rewards result in reward hacking.

## 2 Background

### 2.1 Markov Decision Processes

*Markov decision processes* (MDPs) are defined by tuple $M = (\mathcal{S}, \mathcal{A}, R, T, T_0, \gamma)$ with $\mathcal{S}$ a set of states, $\mathcal{A}$ a set of actions, $T(s'|s,a)$ and $R(r|s,a,s')$ the transition and reward probability functions with expected reward $R(s,a,s')$, $T_0(s_0)$ an initial state distribution, and $\gamma$ a discount factor (when

it is not critical, we write $R$ without $s'$ for brevity). MDP policies map from current states to distributions over next actions: $\pi(a|s)$. The return is defined as the discounted sum of rewards $G = \sum_{t=0}^{\infty} \gamma^t r_{t+1}$, and an optimal policy $\pi^*$ maximizes the expected return.

### 2.2 Intrinsic Motivation and Reward Shaping

*Intrinsic motivation* (IM) is a method for guiding RL algorithms (Barto, 2013) by adding pseudo-rewards to the original reward at each step, generating composite reward signal: $r'_t = r_t + F(h_t)$, where $F$ denotes the IM function which can depend on the entire training history $h_t = s_0 a_0 r_1 s_1 ... a_{t-1} r_t s_t$ (and thus also the algorithm's internal state or beliefs). *Reward shaping functions* are restricted to the form $F(s_t, a_t, s_{t+1})$, resulting in shaped reward function $R'(s_t, a_t, s_{t+1})$ (whereas IM does not generally lead to a valid MDP reward function of this form). The optimal policy for the shaped MDP, i.e. maximizing the composite return, is generally not optimal for the original MDP. *Potential-based shaping functions* (PBSFs) take the form $F(s_t, a_t, s_{t+1}) = \gamma\phi(s_{t+1}) - \phi(s_t)$ and preserve optimal policies in all MDPs (Ng et al., 1999).

### 2.3 Formulation of RL Problems as BAMDPs

We formulate RL problems as BAMDPs, for which RL algorithms are policies. We use overlines, e.g., $\bar{M}$, to denote the BAMDP version of any object. Our conventions are inspired by Zintgraf et al. (2019) and Guez et al. (2012).

RL algorithms learn to maximize return in an MDP by repeatedly updating an internal state (e.g., a Q-function estimate) while selecting actions and receiving observations. We denote them by $\bar{\pi} : \mathcal{S} \times \mathcal{H} \to \mathcal{A}$, where $\mathcal{H}$ is the set of histories ($h_t = s_0 a_0 r_1 s_1 ... a_{t-1} r_t s_t$, representing the sequence of all transitions observed so far). We measure performance in MDP $M$ by expected return *while learning*: $\mathcal{J}_M(\bar{\pi}) = \mathbb{E}_{M,\bar{\pi}}[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)]$.[1] A Bayes-optimal RL algorithm for an RL problem maximizes the expected performance in MDPs sampled from prior $p(M)$: $\mathcal{J}(\bar{\pi}) = \mathbb{E}_{p(M)}[\mathcal{J}_M(\bar{\pi})]$ (Singh et al., 2009), where $p(M)$ represents the domain, i.e., the distribution of MDPs that the algorithm will encounter (e.g., MiniGrid mazes (Chevalier-Boisvert et al., 2023) or Atari games).

For clarity of exposition, we assume all possible MDPs in $p(M)$ share the same $\mathcal{S}, \mathcal{A}, \gamma$, so only $R, T, T_0$ are initially uncertain.[2] $p(M|h_t)$ is the posterior after updating $p(M)$ on the evidence in history $h_t$, i.e., $p(M|h_t) \propto p(h_t|M)p(M)$.

A BAMDP is a tuple $\bar{M} = (\bar{\mathcal{S}}, \mathcal{A}, \bar{R}, \bar{T}, \bar{T}_0, \gamma)$ where:

- $\bar{\mathcal{S}}$ is an augmented state space $\mathcal{S} \times \mathcal{H}$, so $\bar{s} = \langle s, h \rangle$. This encapsulates all the information $\bar{\pi}$ could use when choosing an action—though typically it maintains a lossy memory of $h$.
- $\mathcal{A}$ and $\gamma$ are shared with the underlying MDPs, although internally $\bar{\pi}$ may sample its actions from the MDP policy that it learnt: $\pi_t = \bar{\pi}(\bar{s}_t)$, so that $\bar{\pi}(a|\bar{s}_t) = \pi_t(a|s_t)$.
- $\bar{R}(\bar{s}_t, a) = \mathbb{E}_{p(M|h_t)}[R(s_t, a)]$, the expected reward under the current posterior.
- $\bar{T}(\bar{s}_{t+1}|\bar{s}_t, a_t) = \mathbb{E}_{p(M|h_t)}[T(s_{t+1}|s_t, a_t)R(r_{t+1}|s_t, a_t)\mathbb{1}[h_{t+1} = h_t a_t r_{t+1} s_{t+1}]]$
- $\bar{T}_0(\langle s_0, h_0 \rangle) = \mathbb{E}_{p(M)}[T_0(s)]\mathbb{1}[h_0 = s_0]$.

We illustrate the basic concepts of BAMDPs using the *caterpillar domain* shown in Fig. 2. Here, $p(M)$ represents how butterflies usually lay eggs on the best food source in the area, but 10% of the time a more rewarding source is nearby; upon hatching on the weed, the caterpillar does not know which MDP it is in and must decide whether exploring the neighboring bush is worth the energy and opportunity cost. The bush's reward varying across possible MDPs manifests as stochastic BAMDP dynamics at the transition where the caterpillar first observes it (e.g., taking the highlighted *eat* action). After observing the reward, $p(M|h_t)$ collapses to the underlying MDP and all dynamics become deterministic (e.g., at the transitions marked with red arrows).

[1] We can convert settings with episodic environments or train/test regimes to infinite-horizon MDPs by augmenting the state space, e.g., with within-episode step indices or train/test indicators.

[2] This formulation can be extended to POMDPs and for distributions over $\mathcal{S}, \mathcal{A}, \gamma$ without any conceptual changes—the agent receives observations $o_t$, and expectations are taken over additional variables as needed.

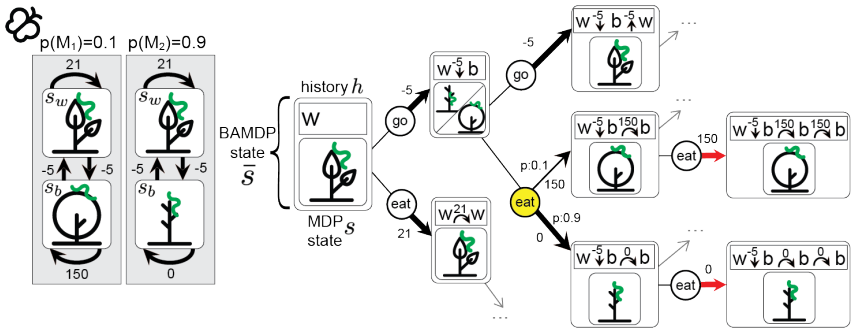



Figure 2: The caterpillar domain formulated as a BAMDP. Left: prior $p(M)$ is a categorical distribution over MDPs $M_1$ and $M_2$; in both, all transitions are deterministic, with the curved and straight arrows corresponding to *eat* and *go* actions respectively. The caterpillar hatches at state $s_w$, and must decide whether to *eat* for guaranteed reward 21, or spend $-5$ to *go* to $s_b$. Right: truncated BAMDP transition diagram, arrows are labeled with rewards (and transition probabilities when $p < 1$). The stochastic transitions (from the highlighted *eat* action) are due to the uncertainty over the MDP; all future transitions (the highlighted arrows) become deterministic once its identity is revealed.

The value of an RL algorithm is its value as a policy in the BAMDP, or, more explicitly, its expected BAMDP return is its expected return while learning in initially unknown MDP $M \sim p(M)$:

$$\begin{aligned}\mathbb{E}_{\bar{\pi}}[\bar{G}] &= \mathbb{E}_{\bar{T}_0}\left[\bar{V}^{\bar{\pi}}(\bar{s}_0)\right] = \mathbb{E}_{\bar{T}_0,\bar{T}}\left[\sum_{t=0}^{\infty}\gamma^t \bar{R}(\bar{s}_t, \bar{\pi}(\bar{s}_t))\right] \\ &= \mathbb{E}_{p(M)}\left[\mathbb{E}_M\left[\sum_{t=0}^{\infty}\gamma^t R(s_t, \bar{\pi}(\bar{s}_t))\right]\right] = \mathbb{E}_{p(M)}\left[\mathcal{J}_M(\bar{\pi})\right] = \mathcal{J}(\bar{\pi}).\end{aligned}$$

Thus, the optimal policy for the BAMDP, $\bar{\pi}^*$ maximizing $\mathbb{E}_{\bar{\pi}}[\bar{G}]$, explores optimally for the problem, i.e., it is the Bayes-optimal RL algorithm with respect to prior $p(M)$.[3] Since $\mathbb{E}_{\bar{\pi}}[\bar{G}]$ is calculated over future beliefs, $\bar{\pi}^*$ must *plan through its own learning*. E.g., in Fig. 2 with large enough $\gamma$, the optimal caterpillar would deem $s_b$ worth exploring because it can stay there if it finds food, otherwise it will learn that $s_b$ is empty and use this knowledge to go back to $s_w$ and never return.

## 3 Pseudo-Rewards Correct BAMDP Value Misestimation

We first use our framework to explain how IM and reward shaping can incentivize effective exploration by signalling the value of BAMDP states.

### 3.1 The Relationship Between Value Misestimation and Regret

RL algorithms typically act, implicitly or explicitly, to maximize a value prediction estimated from the history, which we denote by $\hat{Q}(\bar{s}_t, a)$. Applying the performance difference lemma (Kakade & Langford, 2002) at the BAMDP level tells us that algorithmic regret is directly related to how these estimates differ from the Bayes-Optimal value over their trajectory:

**Lemma 3.1.** *The Bayesian regret (Ghavamzadeh et al., 2015) of algorithms acting on estimate $\hat{Q}(\bar{s}_t, a)$ can be expressed as:*

$$\mathbb{E}_{\bar{\pi}^*}[\bar{G}] - \mathbb{E}_{\bar{\pi}}[\bar{G}] = \mathbb{E}_{\bar{\pi}}\left[\sum_t \gamma^t \left(\bar{V}^*(\bar{s}_t) - \bar{Q}^*\left(\bar{s}_t, \arg\max_a \hat{\bar{Q}}(\bar{s}_t, a)\right)\right)\right], \tag{1}$$

Thus, if we can add pseudo-rewards that nudge the value estimates of RL agents $\hat{Q}$ such that they select actions with higher BAMDP value $\bar{Q}^*$, they will explore more optimally.

[3] Note that, since $\bar{\pi}^*$ explores only when exploration is expected to increase return, exploring enough to find and settle on an optimal MDP policy $\pi^*$ is not generally Bayes-optimal. E.g., in Fig. 2 with small enough $\gamma$, immediate expected reward dominates $\mathbb{E}_{\bar{\pi}}[\bar{G}]$, so $\bar{\pi}^*$ eats at $s_w$ rather than risking delaying rewards by checking $s_b$ (see appendix J.1 for full calculations). Thus, optimal RL algorithms do not necessarily converge to optimal policies for the underlying MDP. Conversely, RL algorithms that *do* have this property may be over-exploring.

### 3.2 BAMDP VALUE DECOMPOSITION

We can now understand the role of pseudo-rewards as directly incentivizing RL agents to go to more valuable BAMDP states. IM terms that reward novel observations or diverse actions encode the value of the information in the BAMDP state $h_t$; these are popular because commonly used RL algorithms do not inherently account for the value of information (see appendix C). RL agents can also misestimate the value of physical states due to incorrect *initial* beliefs; many other pseudorewards compensate for this type of misestimated value, typically when there is significant prior knowledge about how to maximize rewards, e.g., it is advantageous for a ball-dribbling robot to be closer to the ball (Ji et al., 2023). This is helpful to express as a pseudo-reward because it can be difficult to program such prior knowledge into non-tabular (e.g., deep RL) algorithms before they begin learning. We decompose the BAMDP value function into these two values, which we call the Value of Information and Value of Opportunity, respectively.

**Definition 3.1** (Value of Information)**.** The Value of Information (VOI) from state $\bar{s}_t$ is the increase in $\bar{\pi}^*$'s expected return from $s_t$ due to the information in $h_t$ compared to its initial beliefs:

$$\bar{V}^*_I(\langle s_t, h_t \rangle) = \bar{V}^*(\langle s_t, h_t \rangle) - \bar{V}^*(\langle s_t, h_0 \rangle). \tag{2}$$

E.g, after watching TV $h_t$ may contain more information than $h_0$, but that information wouldn't help $\bar{\pi}^*$ get higher return, so $\bar{V}^*_I$ would be zero. Meanwhile, exploring a new maze section, even if it contains no rewards, helps $\bar{\pi}^*$ focus its search on a smaller remaining area, so $\bar{V}^*_I$ would be positive.

**Definition 3.2** (Value of Opportunity)**.** The Value of Opportunity (VOO) to $\bar{\pi}$ from state $\bar{s}_t$ is the expected optimal value of state $s_t$ without having learnt anything, i.e.:

$$\bar{V}^*_O(\langle s_t, h_t \rangle) = \bar{V}^*(\langle s_t, h_0 \rangle). \tag{3}$$

E.g., if there is always a reward at a known goal state $s_g$, then $s_t$ that are fewer steps from it have higher VOO. But RL agents with misspecified priors may underestimate the value of $s_t$ before first discovering the reward at $s_g$. Conversely, if walking near a cliff edge has a high chance of injury, then $s_t$ there have lower VOO, but RL agents may overestimate their value before the first fall.

**Lemma 3.2** (BAMDP Value Decomposition)**.** *The optimal BAMDP value can be decomposed into the Value of Information and the Value of Opportunity:*

$$\bar{V}^*(\bar{s}_t) = \bar{V}^*_I(\bar{s}_t) + \bar{V}^*_O(\bar{s}_t). \tag{4}$$

We can now categorize IM and reward shaping terms by which of these components they signal (see Table 1). We can also understand the failure of pseudo-rewards to effectively guide RL algorithms as a result of them aligning poorly with the true BAMDP value. For example, negative surprise (Berseth et al., 2019) signals the prior knowledge that unpredictable parts of the environment have lower $\bar{V}^*_O$. This is well-aligned for environments with dangerous dynamics, but fails in safe environments where unpredictability correlates poorly with negative outcomes, causing agents to stare at a wall rather than exploring (Rhinehart et al., 2021). Meanwhile, Entropy Bonus (Szepesvári, 2010; Mnih, 2016; Haarnoja et al., 2017) signals that more $\bar{V}^*_I$ can be gained by trying a wider spread of actions. This breaks down if the scale of the pseudo-rewards is too high, because overly random behavior is unlikely to reach interesting novel states, so it must be carefully balanced with the scale and frequency of the extrinsic rewards (Hafner et al., 2023). See appendix B for more in-depth discussion of these and more examples.

## 4 PRESERVING OPTIMALITY WITH BAMDP POTENTIAL-BASED SHAPING

Section 3 explained how IM and reward shaping guide suboptimal RL algorithms to explore more effectively. As our algorithms become more powerful, another issue is that they find ways to "reward-hack", i.e., maximize their shaped rewards without also maximizing the underlying rewards we care about. This can be avoided by using pseudo-rewards that *preserve optimality*, i.e., guarantee that any behavior maximizing shaped rewards also maximizes underlying rewards. Using our framework, we define a form of pseudo-reward which makes it easy to retrofit IM terms, or design new terms, which preserve optimality: BAMDP potential-based shaping functions (BAMPFs). We prove that the use of BAMPFS can avoid reward-hacking in both RL (i.e., optimizing over the MDP policy) and meta-RL (i.e., optimizing over the RL algorithm) settings.

Table 1: Typology of IM and reward shaping terms based on the value components signalled. Attractive signals increase with metrics that correlate with under-estimated value, and repulsive signals decrease with metrics warning of over-estimated value.

| | **No $\bar{V}_O^*$ Signal** | **Attractive $\bar{V}_O^*$ Signal** | **Repulsive $\bar{V}_O^*$ Signal** |
|---|---|---|---|
| **No $\bar{V}_I^*$ Signal** | | • Goal proximity (57; 28)<br>• Subgoal reaching (60; 76)<br>• Ball possession (40) | • Negative surprise (8)<br>• Information cost (22)<br>• Joint angle violation penalty (40) |
| **Attractive $\bar{V}_I^*$ Signal** | • Prediction error (59; 10)<br>• Counts-based (6; 10)<br>• Entropy bonus (78; 54)<br>• Skill discovery (71; 82)<br>• Info gain (37; 72) | • Optimism bonuses (75; 61)<br>• Unlocking subtasks (34) | • Empowerment (44; 30)<br>• Information Capture (62) |

### 4.1 Definition of BAMDP Potential-Based Shaping Functions

Classic potential-based shaping guides RL agents towards more valuable MDP states by encoding their desirability with the potential function $\phi(s)$ (e.g., when the potential is proximity to the goal, Fig. 1a). A BAMDP Potential-Based Shaping Function (BAMPF) can guide RL agents by encoding the desirability of BAMDP states $\phi(\bar{s})$ (or equivalently, $\phi(h)$), which includes not only the physical state value (corresponding to VOO), but also the value of the information accumulated (VOI), encouraging exploration to gather valuable experiences.

**Definition 4.1.** (BAMPF) Let any $\bar{\mathcal{S}}, \mathcal{A}, \gamma$ be given. Function $F$ is a **BAM**DP **P**otential-Based Shaping **F**unction if there exists a real-valued function $\phi$ such that for all realizable $h_t$,

$$F(h_t) = \gamma\phi(h_t) - \phi(h_{t-1}), \tag{5}$$

where $h_{t-1}$ is the first $t-1$ timesteps of $h_t$. See Fig. 1b for an example of a simple BAMPF based on the size of the set of MDP states visited in $h$.

E.g., *information gain* expressed as the decrease in entropy of the agent's belief of the MDP dynamics $\hat{p}(T)$, i.e., $H(\hat{p}(T|h_{t-1})) - H(\hat{p}(T|h_t))$ (Houthooft et al., 2016), can be viewed as a BAMPF for $\gamma = 1$ with $\phi(h) = -H(\hat{p}(T|h))$, i.e., the certainty of the posterior belief after updating on $h$, encouraging exploration towards states where the agent knows more about the environment. Due to the expressivity of $\phi$, it is straightforward to convert virtually any IM or reward shaping function to a BAMPF - take whatever measure of the desirability of the information and/or physical state that it is based on, and use that measure as $\phi$.

### 4.2 Bayes-Optimal RL Algorithms are Invariant to BAMPFs

We first consider the use of BAMPFs for guiding meta-RL systems to discover better RL algorithms more efficiently, without making them eventually converge to suboptimal "reward-hacking" algorithms. In this setting, the meta-learner generates RL algorithms $\bar{\pi}_\theta$, updating $\theta$ to maximize the expected shaped rewards it obtains while learning in MDPs sampled from task distribution $p(M)$. E.g., information gain pseudo-rewards could encourage the metalearner to generate $\bar{\pi}_\theta$ that take more information-gathering actions. But if the pseudo-reward doesn't preserve optimality, it could cause the meta-learner to converge on algorithms that explore badly with respect to the true rewards. We extend existing theory on PBSFs preserving optimal policies in MDPs, to prove BAMPFs preserve optimal RL algorithms in any BAMDPs, i.e., in meta RL problems.

#### 4.2.1 Main Results

We model the effect of pseudo-reward function $F(h_t)$ as producing *shaped BAMDP* $\bar{M}'$ with shaped reward $\bar{R}'(\bar{s}_t, a, \bar{s}_{t+1}) = \bar{R}(\bar{s}_t, a) + F(h_{t+1})$, while $\bar{\mathcal{S}}$ and $\bar{T}$ are unchanged, i.e., $h_t$ still only contains the underlying rewards. This reflects the fact that $F(h_t)$ is fully known from the start, so it

should not be treated as information or influence the posterior. The RL algorithm observes the underlying rewards in $h_t$, while only the meta-learner receives the pseudo-rewards in this setting. An optimal algorithm for $\bar{M}'$ maximizes the expected shaped return from $\bar{R}'$, i.e., $\bar{\pi}^{*\prime} = \arg\max_{\bar{\pi}} \mathbb{E}_{\bar{\pi}}[\bar{G}']$.

We now state our main theorem that BAMPFs always preserve Bayes-Optimality.

**Theorem 4.2** (BAMDP Potential-Based Shaping Theorem)**.** *For a pseudo-reward function to guarantee that the optimal algorithm for any shaped BAMDP is optimal for the original BAMDP, i.e., Bayes-optimal for the underlying RL problem, it is necessary and sufficient for it to be a potential-based shaping function on the BAMDP state.*

*Proof Sketch.* For sufficiency, we show that the $\phi$ form a telescoping sum, reducing to a constant. For necessity, we construct a BAMDP such that when $F - (\gamma\phi' - \phi)$ is nonzero, different actions maximize the shaped and extrinsic returns. The proof follows Ng et al. (1999) but rewards impact the BAMDP state, making it more complex than for regular MDPs; see A.1 for full proofs. □

Thus, if the meta-learner converges to an RL algorithm that learns optimally for the BAMPF-shaped rewards, this algorithm will also always explore optimally with respect to the true reward distribution. Meanwhile, if we use IM that is not a BAMPF, there will be settings where $\bar{\pi}^{*\prime}$ explores suboptimally for the underlying problem. We extend this result to prove that BAMPFS also preserve approximate optimality of RL algorithms in Appendix A.2.

#### 4.2.2 Shaping Meta-RL on Bernoulli Bandits

We demonstrate this in the Bernoulli Bandit meta-RL problem introduced by Wang et al. (2016). Every MDP in $p(M)$ has two arms, one with reward probability $0.1$ and the other $0.9$ (randomly assigned), and a budget of 10 pulls. At each step an RNN-based RL agent observes the last arm that was pulled, the reward that it produced, and how many pulls it has left, and chooses which arm to pull next. After 10 pulls, the episode ends and a new MDP is sampled from $p(M)$. The meta-learner (we used A2C (Mnih, 2016)) continually updates the RNN agent to maximize expected return in its 10-step lifetime, i.e., to find the RL algorithm that optimally balances exploration and exploitation with respect to $p(M)$. Fig. 3b shows how without shaping (the grey curve), the meta-learner gradually learns to generate RL agents that try fewer arms on average, i.e., avoiding over-exploration. This shows that the meta-learner initially over-estimates the VOI of trying more arms, so we could add a BAMPF to correct its prior. The *1st Winner Pulls BAMPF* sets $\phi(h)$ to the total pull count of the first arm that produced a reward, decreasing the relative perceived VOI of exploring the other arm. Fig. 3b (green curve) shows it helps A2C learn more exploitative RL agents more quickly, and Fig. 3a shows that these agents achieve lower regret more quickly, while it doesn't prevent eventual convergence to an optimal agent. In contrast, when this pull count is added directly as a pseudo-reward (purple curve), it causes the meta-learner to converge on an agent that exploits too heavily and never achieves the optimal regret, because if the $p = 0.1$ arm is ever the "first winner" then shaped return is maximized by continuing to pull it, even if it never yields a reward again. See appendix H for full experimental details.

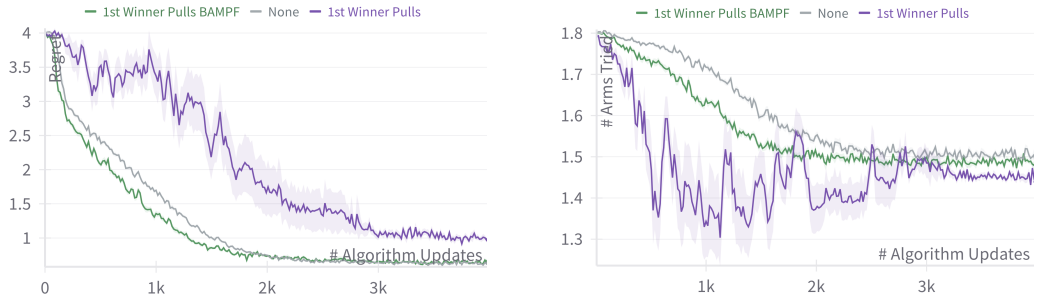
### 4.3 Bounded Monotone BAMPFs Preserve Approximate Optimality in MDPs

Now we turn our attention to the common RL setting, where an RL algorithm updates an MDP policy to maximize return. A certain natural type of BAMPF is also un-hackable at the MDP level, i.e., RL algorithms cannot converge on policies maximizing shaped rewards without also maximizing the true rewards. These are any BAMPFS based on $\phi$ that are bounded monotone functions over increasing experience (i.e., either $\phi(h_{t_1}) \leq \phi(h_{t_2})$ or $\phi(h_{t_1}) \geq \phi(h_{t_2})$ for all training steps $t_1 < t_2$).

**Theorem 4.3** (Bounded Monotonic BAMPF Theorem)**.** *If the pseudo-rewards added to an MDP can be expressed as a BAMPF with a bounded potential that is monotonic over time, it will eventually preserve approximate optimality in the MDP, i.e.,*

$$\forall \epsilon > 0 \quad \exists H : \forall t > H : \mathbb{E}_{\pi_t^{*\prime}}[G] > \mathbb{E}_{\pi^*}[G] - \epsilon, \tag{6}$$

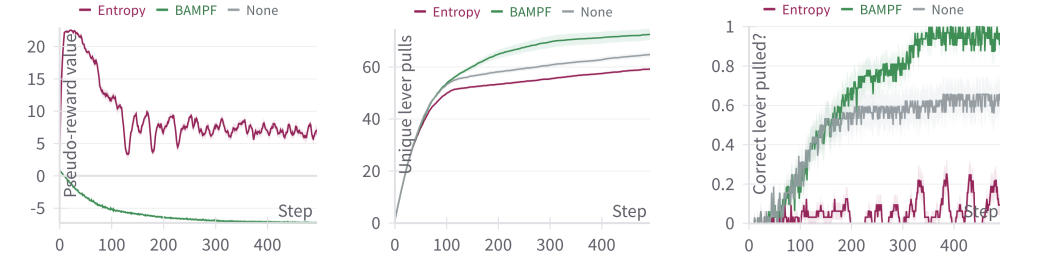
*Where $t$ is the training step, $\mathbb{E}_\pi[G]$ denotes the expected (unshaped) return of MDP policy $\pi$, $\pi_t^{*'}$ is a policy maximizing BAMPF-shaped return at step $t$, and $\pi^*$ is an optimal policy for the underlying MDP.*




(a) Average regret of the learnt RL agents as they are updated through meta-learning.

(b) Average number of arms tried by the learnt agents.

Figure 3: The effect of reward shaping on A2C meta-learning an RNN-based RL agent for Bernoulli Bandits with two arms, reward probabilities $(0.1, 0.9)$ and a budget of 10 pulls. The mean and standard error of 10 seeds are plotted for each condition. Without shaping, the meta-learner gradually learns to generate RL agents that try fewer arms on average, i.e., avoiding over-exploration (grey curve in 3b). The *1st Winner Pulls BAMPF* sets $\phi$ to the pull count of the first arm that yielded a reward, helping A2C learn to exploit and achieve lower regret more quickly, while still converging to the same optimal strategy. When this pull count is added directly as a pseudo-reward (*1st Winner Pulls*), it causes the meta-learner to converge on an agent that over-exploits.




(a) Psuedo-reward values over time.

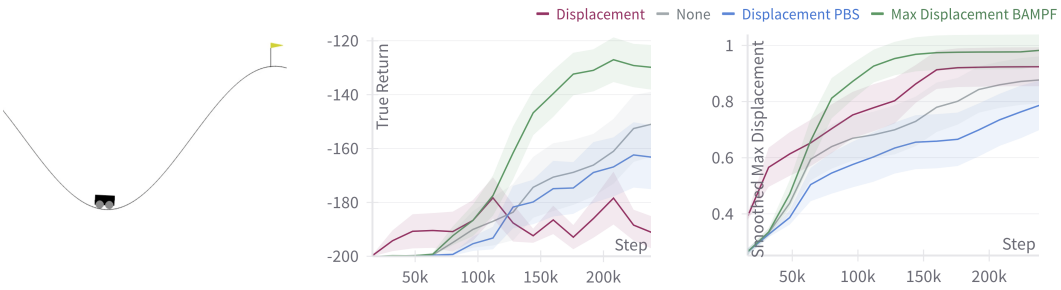
(b) Levers tried over time.

(c) Correct lever pull fraction over time.

Figure 4: The effect of a bounded monotone BAMPF and entropy bonus pseudo-rewards on DQN in a 1-state MDP, where 1 in 100 total levers gives reward 10 when pulled. *None* refers to DQN without any pseudo-rewards. The *BAMPF* potential is the count of unique levers tried, and the *Entropy* reward is 10x the entropy of the last 10 lever pulls. The setting is non-episodic with $\gamma = 0.9$. The mean and standard error of 32 seeds are plotted for each condition. See appendix G for full details.

*Proof Sketch.* Because $\phi$ is bounded and monotone, there must be a final point in training $H$ where it changes by at least $\epsilon$. The BAMPF rewards form a telescoping sum leaving a single policy-dependent $\phi$ term from the final step. Thus, after time $H$ the BAMPF can only modify the difference in any two policies' returns by at most $\epsilon$. Therefore the optimal policy in the shaped MDP can only be $\epsilon$ worse than the optimal policy in the true MDP. See appendix A.3 for the full proof. □

This class of BAMPF naturally includes intrinsic motivation terms that signal the total value of information gathered so far, e.g., count-based rewards (Bellemare et al., 2016) or information gain (Houthooft et al., 2016), and they are simple and intuitive to design. For example, take a single-state MDP with 100 levers only one of which yields a reward when pulled. A bounded monotone $\phi$ could be the number of unique levers tried so far, encoding the VOI from having explored more levers. Figure 4a shows how, when applied to DQN, the BAMPF reward converges to a constant as more levers are tried. Figure 4b shows how this BAMPF causes the agent to try more levers on average than without pseudo-rewards (which relies purely on $\epsilon-$greedy exploration). And yet, it doesn't prevent DQN from converging to the optimal policy, i.e., pulling the correct lever at every step (Fig. 4c). Meanwhile, entropy bonus (the entropy of the last 10 lever pulls, which isn't a BAMPF) makes the agent oscillate between pulling the correct lever to get the extrinsic reward, and pulling other levers to increase the entropy bonus, which achieves higher shaped rewards (but lower true rewards) than pulling the correct lever at every step.




(a) Visualization of the environment.

(b) Episodic extrinsic returns over training.

(c) Exponentially smoothed maximum displacement.

Figure 5: The effect of pseudo-rewards on PPO in *Mountain Car*; the mean and standard error of 10 seeds are plotted for each type of reward shaping. *Displacement* rewards the current displacement of the car, *Displacement PBS* is potential-based shaping with the current displacement as the MDP state potential $\phi(s)$, and *Max Displacement BAMPF* uses the exponentially smoothed maximum displacement over training (5c) as the BAMDP state potential $\phi(h)$. With *Displacement* the agent learns a reward-hacking policy that avoids the goal to collect more pseudo-rewards (see Fig. 7), while the BAMPF helps PPO learn to reach the goal more quickly while preserving optimality (5b).

#### 4.3.1 Shaping RL in Mountain Car

We now demonstrate the benefits of BAMPFs in a more realistic setting: with PPO (Schulman et al., 2017) in the Mountain Car environment (Brockman et al., 2016) which has a 2D continuous state comprising the car's position and velocity. The reward is -1 at each timestep; each episode lasts 200 steps or ends early if the car reaches the goal. The car starts in a valley, and to reach the goal (the flag post in Fig. 5a) it must build momentum by first moving up the *opposite* slope. Thus, displacement from the lowest point in the valley is an intuitive shaping reward to signal the VOO of being further uphill in either direction. We find this helps PPO reach greater displacements early in training (red curve in Fig. 5c), but eventually results in reward-hacking policies that collect more pseudo-rewards by avoiding the goal (Figures 5b and 7). Converting this to classic potential-based shaping by setting $\phi(s)$ to the displacement, we find it preserves optimality but doesn't help learning (blue curve in Fig. 5b), possibly because the further uphill the car gets, the more negative PBS rewards it soon receives when it rolls back. We can understand these failures as a result of the fact that displacement is too weak a signal for the true VOO in Mountain Car. Instead, we could signal VOI by rewarding the *maximum* displacement so far, which doesn't penalize temporary decreases in displacement. This value clearly depends on more than the current state, so isn't a valid MDP potential- but it *is* a valid BAMDP potential $\phi(h_t)$. It is bounded due to the finite width of the environment, and monotonically increases throughout training. It signals the VOI of the RL agent learning how to get further uphill; because it sometimes surpasses its maximum displacement by chance before learning how to consistently get so far, we apply exponential smoothing. Fig. 5c (green curve) shows the resulting BAMPF gets the agent to explore further more quickly, and Fig. 5b shows it learns to reach the goal and maximize true rewards sooner while avoiding reward-hacking. See Appendix I for full experimental details.

#### 4.3.2 Converting Pseudo-Rewards to Preserve Optimality in MDPs

Although virtually any pseudo-reward can be cast as a BAMPF, bounded monotone BAMPFs don't naturally include terms purely based on the latest behavior, e.g., prediction error (the predictability of the latest observations) or entropy bonus (the randomness of the latest policy). However, these terms would still preserve optimality if they could be converted to the sum of a bounded monotone BAMPF and a classic PBSF. E.g., Curiosity (Pathak et al., 2017) rewards the error of a learnt dynamics model in predicting the latest observations, to encourage continually seeking novel experiences while improving the dynamics model. To convert this, it could be split into a PBSF with $\phi(s)$ equal to the error of a *fixed model*'s prediction of features of $s$ (similar to RND (Burda et al., 2018)), plus a BAMPF with bounded monotone $\phi(h)$ equal to the minimum error of the dynamics model on a *fixed*

*set of transitions*[4]. The PBSF encourages visiting increasingly unfamiliar states, and the BAMPF encourages gathering experiences that make its world model increasingly accurate. This form of Curiosity would no longer be susceptible to the Noisy TV problem, since the dynamics model's error $\phi(h)$ would not keep decreasing while watching TV, and even if the fixed model's prediction error $\phi(s)$ were higher at the TV, Ng et al. (1999)'s result guarantees that a policy can't maximize its total shaped return by staying there. See Appendix D for a more detailed exposition.

## 5 Related Work

**Theory of Intrinsic Motivation** Oudeyer & Kaplan (2007) categorize IM as knowledge-based, competence-based or morphological, and evaluate them by their exploration (leading to exploratory and investigative behavior) and organization (leading to structured and organized behavior) potentials, which are similar to the effects of signalling $\bar{V}_O$ and $\bar{V}_I$. Singh et al. (2009) propose an evolutionary framework for rewards as maximizing expected fitness over a distribution of environments, concluding that optimal IM depends on regularities across the distribution and properties of the learning agent. Aubret et al. (2023) propose an information-theoretic taxonomy of IM, but this only captures IM terms signalling value of information, and they do not consider the prior distribution and so cannot explain how IM should be designed for a given domain.

**Extensions of Potential-Based Shaping** Devlin & Kudenko (2012) and Forbes et al. (2024) extend PBS theory to potential functions that vary over time, including functions of the history, showing that they also preserve the optimal MDP policy. However, Devlin & Kudenko (2012)'s proof omits finite-horizon episodes, and Forbes et al. (2024) modify the potential at the last step of each episode to cancel out all prior shaping rewards. This is inappropriate for potentials measuring the value of information, since observations from an episode do not lose all value once the episode ends. Eck et al. (2016) extend PBSFs to POMDP planning, defining potential functions over POMDP belief states and categorizing them as Domain-dependent and Domain-independent, which share similarities to $\bar{V}_O$ and $\bar{V}_I$. Kim et al. (2015) propose BAMDP potential-based shaping specifically for a model-based Bayesian RL method, although they do not prove that the PBS theorem still holds for BAMDPs (which is non-trivial, because rewards influence the BAMDP state) and do not consider the broader implications for developing IM for any RL algorithm.

See Appendix E for an extended discussion of related work.

## 6 Discussion

By formulating RL problems as BAMDPs, we formalize how intrinsic motivation and reward shaping guide exploration by signalling the value of BAMDP states, which we decompose into the value of information and the value of opportunity. This allows us to characterize the roles of existing pseudo-rewards, and explain failure modes where they introduce incentives that are misaligned with the actual value in the environments they're used in. We also extend potential-based shaping theory to prove that pseudo-rewards in the form of BAMDP potential-based shaping functions always preserve the optimality of RL algorithms. Thus, BAMPFs can guide meta-RL without risking the meta-learner converging to RL algorithms that explore optimally for the shaped rewards but are suboptimal for the underlying domain. We demonstrate this by designing a BAMPF for a Bernoulli Bandits domain, showing that it helps the meta-RL agent learn an optimal RL algorithm more quickly. Returning to the regular RL setting, we finally prove that BAMPFs based on bounded monotone potentials will eventually preserve the optimality of MDP policies. Thus, they also ensure RL algorithms cannot converge on reward-hacking policies that maximize shaped rewards to the detriment of real rewards. Although it is a manual process, it is straightforward to design and convert many existing pseudo-rewards into this form. We provide an empirical demonstration in the Mountain Car environment: we leverage the BAMDP value decomposition to inform the design of a BAMPF potential, and demonstrate that it improves learning efficiency and preserves optimality, whereas similar pseudo-rewards result in reward hacking.

[4]The fixed model and transition set could be refreshed regularly between batch updates– optimality is preserved as long as the RL algorithm's choice of policy doesn't affect them.

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# A Potential-Based Shaping Proofs

## A.1 Main Theorem

**Theorem 4.2** (BAMDP Potential-Based Shaping Theorem)**.** *For a pseudo-reward function to guarantee that the optimal algorithm for any shaped BAMDP is optimal for the original BAMDP, i.e., Bayes-optimal for the underlying RL problem, it is necessary and sufficient for it to be a potential-based shaping function on the BAMDP state.*

*Proof.* (Sufficiency) Denote the original BAMDP $\bar{M} = (\bar{\mathcal{S}}, \mathcal{A}, \bar{R}, \bar{T}, \bar{T}_0, \gamma)$ with optimal algorithm $\bar{\pi}^*$, and the shaped BAMDP as $\bar{M}' = (\bar{\mathcal{S}}, \mathcal{A}, \bar{R}', \bar{T}, \bar{T}_0, \gamma)$, i.e., it is identical to $\bar{M}$ except for its shaped reward function $\bar{R}'(\bar{s}_t, a, \bar{s}_{t+1}) = \bar{R}(\bar{s}_t, a) + F(\bar{s}_{t+1}) = \bar{R}(\bar{s}_t, a) + \gamma\phi(h_{t+1}) - \phi(h_t)$. So we model the pseudo-rewards as being added to the RL algorithm's reward signal internally, rather than entering through the history in the BAMDP state $\bar{s}_t$. We denote the optimal algorithm for $\bar{M}'$ by $\bar{\pi}^{*\prime}$.

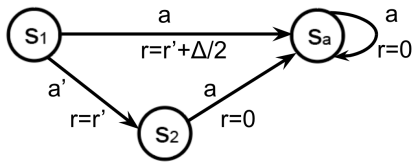


Figure 6: All edges have probability 1, and only action $a$ is applicable from $s_2$ and $s_a$.

Abbreviating $\phi(h_t)$ to $\phi_t$, we can now express the expected return of an algorithm in $\bar{M}'$ in terms of the underlying return it would achieve in $\bar{M}$:

$$\begin{aligned}
\mathbb{E}_{\bar{\pi}}[\bar{G}'] &= \mathbb{E}_{\bar{T},\bar{T}_0,\bar{\pi}}\left[\sum_t \gamma^t \bar{R}'\left(\bar{s}_t, a_t, \bar{s}_{t+1}\right)\right] \\
&= \mathbb{E}_{\bar{T},\bar{T}_0,\bar{\pi}}\left[\sum_t \gamma^t \left(\bar{R}\left(\bar{s}_t, a_t\right) + \gamma\phi_{t+1} - \phi_t\right)\right] \\
&= \mathbb{E}_{\bar{T},\bar{T}_0,\bar{\pi}}\left[\sum_{t=0}^{\infty} \gamma^t \bar{R}(\bar{s}_t, a_t)\right] + \mathbb{E}_{\bar{T},\bar{T}_0,\bar{\pi}}\left[-\phi_0 + \sum_{t=1}^{\infty} \gamma^t(\phi_t - \phi_t)\right] \\
&= \mathbb{E}_{\bar{\pi}}[\bar{G}] - \phi_0
\end{aligned} \tag{7}$$

Plugging this into the definitions of the Bayes-optimal algorithms for $\bar{M}'$ and $\bar{M}$:

$$\begin{aligned}
\bar{\pi}^{*\prime} &\in \arg\max_{\bar{\pi}} \mathbb{E}_{\bar{\pi}}[\bar{G}'] \\
&= \arg\max_{\bar{\pi}} \mathbb{E}_{\bar{\pi}}[\bar{G}] - \phi_0 \\
&= \arg\max_{\bar{\pi}} \mathbb{E}_{\bar{\pi}}[\bar{G}] = \bar{\pi}^*
\end{aligned} \tag{8}$$

□

We now prove that if pseudo-reward function $F(h)$ is not a BAMPF, then there exists BAMDP reward and transition functions such that no Bayes-optimal algorithm for the shaped BAMDP is Bayes-optimal in the original BAMDP.

*Proof.* (Necessity) Our proof follows Ng et al. (1999)'s proof of necessity, but is more complex because the BAMDP state contains the entire history. Assume $F$ is not a BAMPF. We need to show that we can construct $\bar{T}, \bar{R}$ such that no optimal algorithm in shaped BAMDP $\bar{M}'$ is also optimal in $\bar{M}$. We abbreviate a sub-sequence $h_{ij}$ of a history that repeats itself $n$ times by $(h_{ij})_n$. Define $\phi(h) = -\sum_{t=0}^{\infty} \gamma^t F(h(a0s_a)_{t+1})$ for all $h$ with $s_a \in \mathcal{S}, a \in \mathcal{A}$. By assumption of $F$ not being a BAMPF, there exists a valid transition between two BAMDP states $\langle s_1, h_1\rangle, \langle s_2, h_1 a' r' s_2\rangle \in \bar{\mathcal{S}}$ via some action $a' \in \mathcal{A}$ yielding reward $r'$ such that $\gamma\phi(h_1 a' r' s_2) - \phi(h_1) \neq F(h_1 a' r' s_2)$. Define $\Delta = F(h_1 a' r' s_2) - \gamma\phi(h_1 a' r' s_2) + \phi(h_1)$. We now construct $\bar{M}$ with no uncertainty over $R, T$, i.e., $p(M)$ is concentrated on a single MDP $M$, illustrated in Figure 6. In this $M$, we have $T(s_a|s_1, a) = T(s_2|s_1, a') = 1.0$, and from $s_2$ and $s_a$ the only applicable action $a$ leads to $s_a$ with probability 1. The initial MDP state is $s_1$, so for $s_1, h_1$ to be realizable in this environment $h_1$ is the length 1 sequence $s_1$. Let $R(s_1, a) = r' + \Delta/2, R(s_1, a') = r', R(\cdot, \cdot) = 0$ elsewhere. Then we have

$$
\begin{aligned}
\bar{Q}^*(\langle s_1, h_1\rangle, a) &= r' + \Delta/2 \\
\bar{Q}^*(\langle s_1, h_1\rangle, a') &= r' \\
\bar{Q}^{*\prime}(\langle s_1, h_1\rangle, a) &= r' + \Delta/2 + \sum_{t=0}^{\infty} \gamma^t F(h_1(a0s_a)_{t+1}) \\
&= r' + \Delta/2 - \phi(h_1) \\
&= r' + \Delta/2 + F(h_1 a' r' s_2) - \gamma\phi(h_1 a' r' s_2) - \Delta \\
&= r' + F(h_1 a' r' s_2) - \gamma\phi(h_1 a' r' s_2) - \Delta/2 \\
\bar{Q}^{*\prime}(\langle s_1, h_1\rangle, a') &= r' + F(h_1 a' r' s_2) + \gamma \sum_{t=0}^{\infty} \gamma^t F(h_1 a' r' s_2 (a0s_a)_{t+1}) \\
&= r' + F(h_1 a' r' s_2) - \gamma\phi(h_1 a' r' s_2).
\end{aligned}
$$

Hence

$$
\bar{\pi}^*(\langle s_1, h_1\rangle) = \begin{cases} a & \text{if } \Delta/2 > 0 \\ a' & \text{otherwise} \end{cases} \qquad \bar{\pi}^{*\prime}(\langle s_1, h_1\rangle) = \begin{cases} a' & \text{if } \Delta/2 > 0 \\ a & \text{otherwise} \end{cases} \tag{9}
$$

□

### A.2 Near Optimal Algorithms are Nearly Invariant to BAMPFs

We now extend our results to approximately optimal algorithms, first providing an overview of the results and proof sketches before diving into the full proofs.

**Corollary A.1.** *With BAMPF shaping, a near-optimal algorithm $\bar{\pi}^\epsilon$ for $\bar{M}'$ will also be near-optimal when applied to $\bar{M}$, i.e.,*

$$
\mathbb{E}_{\bar{\pi}^{*\prime}}[\bar{G}'] - \mathbb{E}^\epsilon_{\bar{\pi}}[\bar{G}'] < \epsilon \iff \mathbb{E}_{\bar{\pi}^*}[\bar{G}] - \mathbb{E}^\epsilon_{\bar{\pi}}[\bar{G}] < \epsilon. \tag{10}
$$

*Proof Sketch.* Because BAMPF shaping shifts BAMDP returns by a constant, lower shaped return $\mathbb{E}_{\bar{\pi}}[\bar{G}']$ corresponds directly to $\mathbb{E}_{\bar{\pi}}[\bar{G}]$ decreasing by the same amount. See A.2.1 for the full proof. □

Another form of approximate optimality is the maximization of return over a finite horizon $k$. We can also upper-bound the regret as a function of $k$.

**Definition A.1** (k-Step learning-aware)**.** We define an RL algorithm as k-step learning-aware for a BAMDP if it maximizes the expected k-step return in it:

$$
\bar{\pi}^*_k \in \arg\max_{\bar{\pi}} \mathbb{E}_{\bar{T}_0, \bar{T}} \left[ \sum\nolimits_{t=0}^{k} \gamma^t \bar{R}(\bar{s}_t, \bar{\pi}(\bar{s}_t)) \right]. \tag{11}
$$

**Corollary A.2.** *If $F$ is a BAMPF with potential function of maximum magnitude $\phi_{\max}$, and the extrinsic reward has maximum magnitude $R_{\max}$, then the k-step learning-aware algorithm for the shaped BAMDP, $\bar{\pi}^{*\prime}_k$, has regret bounded by $2\gamma^k(\phi_{\max} + R_{\max}\frac{\gamma}{1-\gamma})$ in the underlying BAMDP, i.e.,*

$$
\mathbb{E}_{\bar{\pi}^*}[\bar{G}] - \mathbb{E}_{\bar{\pi}^{*\prime}_k}[\bar{G}] \leq 2\gamma^k \left( \phi_{\max} + R_{\max} \frac{\gamma}{1-\gamma} \right). \tag{12}
$$

*Proof Sketch.* The telescoping $\phi$ summed over horizon $k$ leaves a trailing term of $\gamma^k \phi_k$ from the last step, which allows us to bound $\bar{\pi}^{*\prime}_k$'s k-step regret compared to $\bar{\pi}^*_k$ in terms of $\phi_{\max}$. The regret of $\bar{\pi}^*_k$ compared to the fully Bayes-optimal algorithm $\bar{\pi}^*$ is bounded by the worst-case regret after step $k$, giving us a bound in terms of $R_{\max}$. See A.1 for the full proof. □

### A.2.1 Full Proofs of Approximate Optimality Corollaries

The result in Equation 7 tells us that a near-optimal algorithm for $\bar{M}'$ will also be near-optimal in $\bar{M}$ because the return is just shifted by a constant.

**Corollary A.1.** *With BAMPF shaping, a near-optimal algorithm $\bar{\pi}^\epsilon$ for $\bar{M}'$ will also be near-optimal when applied to $\bar{M}$, i.e.,*

$$\mathbb{E}_{\bar{\pi}^{*\prime}}[\bar{G}'] - \mathbb{E}^{\epsilon}_{\bar{\pi}}[\bar{G}'] < \epsilon \iff \mathbb{E}_{\bar{\pi}^{*}}[\bar{G}] - \mathbb{E}^{\epsilon}_{\bar{\pi}}[\bar{G}] < \epsilon. \tag{10}$$

*Proof.*

$$\begin{aligned}\mathbb{E}_{\bar{\pi}^{*\prime}}[\bar{G}'] - \mathbb{E}_{\bar{\pi}}[\bar{G}'] &= \mathbb{E}_{\bar{\pi}^{*\prime}}[\bar{G}] - \phi_0 - (\mathbb{E}_{\bar{\pi}}[\bar{G}] - \phi_0) \\ &= \mathbb{E}_{\bar{\pi}^{*\prime}}[\bar{G}] - \mathbb{E}_{\bar{\pi}}[\bar{G}] \\ &= \mathbb{E}_{\bar{\pi}^{*}}[\bar{G}] - \mathbb{E}_{\bar{\pi}}[\bar{G}]\end{aligned} \tag{13}$$

□

Now to prove Corollary A.2 we first introduce the following Lemma:

**Lemma A.1.** *If $F$ is a BAMPF with potential function of maximum magnitude $\phi_{\max}$, then the k-step learning-aware algorithm for the shaped BAMDP, $\bar{\pi}^{*\prime}_k$, has k-step regret bounded by $2\gamma^k\phi_{\max}$ in the true BAMDP:*

$$\max_{s,h}|\phi(h)| = \phi_{\max} \implies \mathbb{E}_{\bar{\pi}^{*}_k}[\bar{G}_k] - \mathbb{E}_{\bar{\pi}^{*\prime}_k}[\bar{G}_k] \leq 2\gamma^k\phi_{\max} \tag{14}$$

*Proof.* First, observe that when PBSF rewards are summed over a finite horizon, all but the potentials of the first and last timesteps cancel out:

$$\begin{aligned}\sum_{t\,=0}^{k}\gamma^t(\gamma\phi_{t+1} - \phi_t) &= -\phi_0 + \sum_{t=1}^{k-1}\gamma^t(\phi_t - \phi_t) + \gamma^k\phi_k \\ &= \gamma^k\phi_k - \phi_0\end{aligned} \tag{15}$$

Thus, following the same steps as Equation 7 we can express the k-step return of an algorithm in the shaped BAMDP as:

$$\mathbb{E}_{\bar{\pi}}[\bar{G}'_k] = \mathbb{E}_{\bar{\pi}}[\bar{G}_k] + \mathbb{E}_{\bar{T},\bar{\pi}}[\gamma^k\phi_k] - \phi_0. \tag{16}$$

And so the k-step optimal algorithm in the shaped BAMDP can be expressed as:

$$\bar{\pi}^{*\prime}_k = \arg\max_{\bar{\pi}} \mathbb{E}_{\bar{\pi}}[\bar{G}'_k] = \arg\max_{\bar{\pi}} \mathbb{E}_{\bar{\pi}}[\bar{G}_k] + \mathbb{E}_{\bar{T},\bar{\pi}}[\gamma^k\phi_k] \tag{17}$$

Evaluating this expression at $\bar{\pi}^{*\prime}_k$ and applying the bound on the potential function, we get:

$$\begin{aligned}\mathbb{E}_{\bar{\pi}^{*\prime}_k}[\bar{G}_k] + \mathbb{E}_{\bar{T},\bar{\pi}^{*\prime}_k}[\gamma^k\phi_k] &= \max_{\bar{\pi}} \mathbb{E}_{\bar{\pi}}[\bar{G}_k] + \mathbb{E}_{\bar{T},\bar{\pi}}[\gamma^k\phi_k] \\ &\geq \max_{\bar{\pi}} \mathbb{E}_{\bar{\pi}}[\bar{G}_k] - \gamma^k\phi_{\max} \\ &= \mathbb{E}_{\bar{\pi}^{*}_k}[\bar{G}_k] - \gamma^k\phi_{\max}\end{aligned} \tag{18}$$

Rearranging the above inequality and applying the bound once more we get:

$$\begin{aligned}\mathbb{E}_{\bar{\pi}^{*}_k}[\bar{G}_k] - \mathbb{E}_{\bar{\pi}^{*\prime}_k}[\bar{G}_k] &\leq \gamma^k\phi_{\max} + \mathbb{E}_{\bar{T},\bar{\pi}^{*\prime}_k}[\gamma^k\phi_k] \\ &\leq 2\gamma^k\phi_{\max}.\end{aligned} \tag{19}$$

□

**Corollary A.2.** *If $F$ is a BAMPF with potential function of maximum magnitude $\phi_{\max}$, and the extrinsic reward has maximum magnitude $R_{\max}$, then the k-step learning-aware algorithm for the shaped BAMDP, $\bar{\pi}_k^{*\prime}$, has regret bounded by $2\gamma^k(\phi_{\max} + R_{\max}\frac{\gamma}{1-\gamma})$ in the underlying BAMDP, i.e.,*

$$\mathbb{E}_{\bar{\pi}^*}[\bar{G}] - \mathbb{E}_{\bar{\pi}_k^{*\prime}}[\bar{G}] \leq 2\gamma^k \left(\phi_{\max} + R_{\max}\frac{\gamma}{1-\gamma}\right). \tag{12}$$

*Proof.* Since magnitude of the reward is bounded by $R_{\max}$, we can upper bound the expected return of $\bar{\pi}^*$ by the optimal k-step return $\mathbb{E}_{\bar{\pi}_k^*}[\bar{G}_k]$ plus the maximum return from step $k+1$ onwards:

$$\begin{aligned}\mathbb{E}_{\bar{\pi}^*}[\bar{G}] &\leq \mathbb{E}_{\bar{\pi}_k^*}[\bar{G}_k] + \gamma^{k+1}\frac{1}{1-\gamma}R_{\max} \\ &\leq \mathbb{E}_{\bar{\pi}_k^{*\prime}}[\bar{G}_k] + 2\gamma^k\phi_{\max} + \gamma^{k+1}\frac{1}{1-\gamma}R_{\max},\end{aligned} \tag{20}$$

where we applied Lemma A.1 to substitute $\mathbb{E}_{\bar{\pi}_k^*}[\bar{G}_k]$ at the second line. Meanwhile, the full expected return of $\bar{\pi}_k^{*\prime}$ can be lower bounded by its k-step return plus the minimum return from step $k+1$ onwards:

$$\begin{aligned}\mathbb{E}_{\bar{\pi}_k^{*\prime}}[\bar{G}] &\geq \mathbb{E}_{\bar{\pi}_k^{*\prime}}[\bar{G}_k] - \gamma^{k+1}\frac{1}{1-\gamma}R_{\max} \\ &\geq \mathbb{E}_{\bar{\pi}^*}[\bar{G}] - 2\gamma^k\phi_{\max} - 2\gamma^{k+1}\frac{1}{1-\gamma}R_{\max},\end{aligned} \tag{21}$$

where we substituted the $\mathbb{E}_{\bar{\pi}_k^{*\prime}}[\bar{G}_k]$ in the first line using the result in Equation 20. □

*Remark* A.2. For RL algorithms that have a minimum resolution at which they distinguish returns, BAMPF shaping ceases to affect their behavior once they are optimal over a long enough horizon. More precisely, we call an RL Algorithm that does not distinguish returns less than $d$ apart $d$-insensitive. For k high enough that $2\gamma^k\phi_{\max} < d$, all k-step optimal $d$-insensitive algorithms in a BAMPF-shaped BAMDP are behaviorally equivalent to their counterparts in the original BAMDP.

### A.3 MDP Optimality

**Theorem 4.3** (Bounded Monotonic BAMPF Theorem)**.** *If the pseudo-rewards added to an MDP can be expressed as a BAMPF with a bounded potential that is monotonic over time, it will eventually preserve approximate optimality in the MDP, i.e.,*

$$\forall\epsilon > 0 \quad \exists H : \forall t > H : \mathbb{E}_{\pi_t^{*\prime}}[G] > \mathbb{E}_{\pi^*}[G] - \epsilon, \tag{6}$$

*Where $t$ is the training step, $\mathbb{E}_\pi[G]$ denotes the expected (unshaped) return of MDP policy $\pi$, $\pi_t^{*'}$ is a policy maximizing BAMPF-shaped return at step $t$, and $\pi^*$ is an optimal policy for the underlying MDP.*

*Proof.* We first introduce a lemma to bound the maximum change in the potential function:

**Lemma A.2.** *If $\phi$ is bounded and monotonic, then for any finite $\epsilon > 0$ we have some point in time $H$ at which $\phi$ has changed by $\epsilon$ or more for the last time, and thus all future values of $\phi(h_t)$ must be within $\epsilon$ of each other, i.e.:*

$$\forall\epsilon > 0 \quad \exists H : \forall t > H, \Delta t \geq 0 : |\phi(h_{t+\Delta t}) - \phi(h_t)| < \epsilon \tag{22}$$

*Proof.* Proof by contradiction: if this does not hold, because $\phi$ is monotonic we could keep stepping $\phi$ in the same direction by fixed amount $\epsilon$ an infinite number of times, and thus $\phi$ would not be bounded. □

Now we can express the expected return of a policy $\pi$ shaped by the BAMPF at training step $t$, $\mathbb{E}_\pi[G'_t]$, in terms of the unshaped return $\mathbb{E}_\pi[G]$ and the episode length $N$:

$$\begin{aligned}\mathbb{E}_\pi[G'_t] &= \mathbb{E}_\pi[G + \gamma\phi(h_{t+1}) - \phi(h_t) + \gamma^2\phi(h_{t+2}) - \gamma\phi(h_{t+1}) ... + \gamma^N\phi(h_{t+N})] \\ &= \mathbb{E}_\pi[G] - \phi(h_t) + \gamma^N\mathbb{E}_\pi[\phi(h_{t+N})]\end{aligned} \tag{23}$$

We use this to express the difference in shaped return between two policies $\pi_1, \pi_2$ in terms of the difference in their unshaped returns:

$$\begin{aligned}\mathbb{E}_{\pi_1}[G'_t] - \mathbb{E}_{\pi_1}[G'_t] &= \mathbb{E}_{\pi_1}[G] - \phi(h_t) + \gamma^N\mathbb{E}_{\pi_1}[\phi(h_{t+N})] - \mathbb{E}_{\pi_2}[G] + \phi(h_t) - \gamma^N\mathbb{E}_{\pi_2}[\phi(h_{t+N})] \\ &= \mathbb{E}_{\pi_1}[G] - \mathbb{E}_{\pi_2}[G] + \gamma^N(\mathbb{E}_{\pi_1}[\phi(h_{t+N})] - \mathbb{E}_{\pi_2}[\phi(h_{t+N})])\end{aligned} \tag{24}$$

If the left hand side is positive, the right hand side must also be positive:

$$\mathbb{E}_{\pi_1}[G'_t] - \mathbb{E}_{\pi_1}[G'_t] > 0 \iff \mathbb{E}_{\pi_1}[G] - \mathbb{E}_{\pi_2}[G] + \gamma^N(\mathbb{E}_{\pi_1}[\phi(h_{t+N})] - \mathbb{E}_{\pi_2}[\phi(h_{t+N})]) > 0 \tag{25}$$

Rearranging the inequalities, and then applying Lemma A.2 and using the fact that $\gamma < 1$:

$$\begin{aligned}\mathbb{E}_{\pi_1}[G'_t] \geq \mathbb{E}_{\pi_1}[G'_t] \iff \mathbb{E}_{\pi_1}[G] &\geq \mathbb{E}_{\pi_2}[G] - \gamma^N(\mathbb{E}_{\pi_1}[\phi(h_{t+N})] - \mathbb{E}_{\pi_2}[\phi(h_{t+N})]) \\ &> \mathbb{E}_{\pi_2}[G] - \epsilon\end{aligned} \tag{26}$$

Thus, if $\pi_t^{*'}$ maximizes return shaped by a bounded monotonic BAMPF at time $t > H$, i.e.,

$$\forall\pi : \mathbb{E}_{\pi_t^{*'}}[G'_t] \geq \mathbb{E}_\pi[G'_t], \tag{27}$$

then it must also approximately maximize return in the underlying MDP:

$$\forall\pi : \mathbb{E}_{\pi_t^{*'}}[G] > \mathbb{E}_\pi[G] - \epsilon. \tag{28}$$

Specifically, we can plug in the actual optimal policy for the original MDP $\pi^*$ in the right hand side, and we get our result:

$$\mathbb{E}_{\pi_t^{*'}}[G] > \mathbb{E}_{\pi^*}[G] - \epsilon. \tag{29}$$

□

# B Examples of Pseudo-reward Value Signalling

## B.1 Pure $\bar{V}_O^*$ Signal

These pseudo-rewards help when $\bar{V}_O^*$ has a large influence on $\bar{Q}^*$ but the RL algorithm's (implicit or explicit) value estimate is misaligned with it. This often happens when there is significant prior information of the relative values of reaching states in $M$, which the algorithm is not initialized with. Thus $F$ is often very problem-specific, to correct the perceived value of certain states according to the actual distribution of the problem.

### B.1.1 Attractive $\bar{V}_O^*$ Signal

These terms help where the RL agent *underestimates* the value of getting to certain states, by rewarding it for reaching them. A common example is *goal proximity*-based reward shaping (Ng et al., 1999; Ghosh et al., 2018; Lee et al., 2021; Ma et al., 2022); which rewards each step of progress towards a goal in problems where the true reward is only at the goal itself. The goal location varies across MDPs in $p(M)$ but is fully observable from the initial state, therefore going towards it yields no information and thus does not increase $\bar{V}_I^*$, but is Bayes-optimal because it maximizes $\bar{V}_O^*$. An RL algorithm that is not initialized with this prior information would not prioritize going towards the goal over any other state, and would have to discover the sparse reward there through blind trial and error. Shaping rewards compensate for this, incentivizing behavior that approaches the goal.

Another common example with the same underlying mechanism is rewarding points scored in points-based-victory games like Pong. But if winning is not purely points-based, this is not necessarily good signal for $\bar{V}_O^*$; e.g., Clark & Amodei (2016) found an agent learned to crash itself to maximize points, when the true goal was to place first in the race.

### B.1.2 REPULSIVE $\bar{V}_O^*$ SIGNAL

Psuedo-rewards based on repulsive $\bar{V}_O^*$ signal help in RL problems where the agent would take suboptimal actions because it overestimates the Value of Opportunity, again due to missing prior knowledge, by penalizing behavior that goes to states with lower $\bar{V}_O^*$. Prime examples are *negative surprise* or *information-cost*-based IM (Berseth et al., 2019; Eysenbach et al., 2021) which give negative rewards based on the unpredictability of the states and transitions experienced. This is beneficial, assuming:

1. Unpredictable situations are undesirable in the MDPs in prior $p(M)$, e.g. for driverless cars where it is dangerous to drive near other erratic vehicles, or robotic surgery, where it is dangerous to use unreliable surgical techniques with highly variable outcomes.
2. The RL algorithm does not a priori expect danger in unpredictable states and thus overestimates the $\bar{V}_O$ of exploring them; it could learn to avoid them by getting into accidents and receiving negative task rewards, but that would be incredibly costly in the real world.

These rewards decrease the Bayesian regret of RL algorithms by decreasing their estimates of the value of going to these dangerous states, better aligning them with the optimal $p(M)$-aware $\bar{Q}^*$, so they return to safety *before* getting into accidents.

More formally, negative surprise works under the assumption that *on the distribution of trajectories the agent actually experiences*, surprise almost always correlates well with negative outcomes. An example where this assumption wouldn't hold is if Times Square were a popular and safe destination for the driverless taxi, but the unpredictability of all the adverts were included in the surprise penalty. This measure of surprise correlates poorly with negative outcomes in trajectories through Times Square, so it would increase regret by making the agent unnecessarily reroute around it. In this problem, the signal for $\bar{V}_O^*$ must be more specific- only penalizing surprise with respect to things that could cause accidents, such as the positions of other vehicles.

## B.2 ATTRACTIVE $\bar{V}_I^*$ SIGNAL

Many intrinsic motivation terms are intended to reward behavior that gains valuable experience. These are helpful for RL algorithms which ignore the value of gaining information (e.g., see section C), in problems containing significantly valuable information that is not immediately rewarding to gather. These IM terms aim to reward the agent for reaching states with more valuable information in $h_t$, to incentivize information-gathering behavior. Note that different types of information are valuable in different types of problems, i.e., for different $p(M)$, and this determines which form of IM provides the most helpful signal for $\bar{V}_I^*$.

- *Prediction Error*-based IM (Schmidhuber, 1991; Pathak et al., 2017) rewards experiences that are predicted poorly by models trained on $h_t$. This helps when unpredictability given $h_t$ is good signal for the Value of Information gained from the observation- thus, for $F$ based on dynamics models there must be *minimal stochasticity* (stochastic transitions are always unpredictable but yield no information) and in general *most information must be task-relevant* (so the information gained has value).
- *Count-based* IM (Bellemare et al., 2016; Burda et al., 2018; Lobel et al., 2023) provide a reward bonus for visiting states that have been visited less frequently, or in the case of large continuous state spaces pseudo-counts are used to group similar states into the same bucket. For example, Burda et al. (2018) observed dynamics prediction error failing in the 'noisy TV' problem, where a TV that changes channels randomly maximizes $F$ despite providing no information. This motivated their design of ***RND***, which only predicts features of the current state as an estimate for how many times that state, or similar states, had already been visited. However, these types of IM can be counterproductive when the novelty of a state is a poor signal for how valuable it is to explore it, e.g. an "infinite TV problem" where the TV has infinite unique channels that provide useless information.
- *Entropy bonus* IM is proportional to the entropy of the MDP policy's action distribution (Szepesvári, 2010; Mnih, 2016; Haarnoja et al., 2017). This increases the estimated return of more stochastic $\pi$, so it can be understood as adding in the value of exploring a wider range of actions. This helps when RL algorithms get stuck in local maxima, but breaks

down if the scale of the intrinsic rewards is too high, because overly random behavior is unlikely to reach interesting states, or could even be dangerous, e.g., if the increase in entropy when the robot overextends its joints outweighed the negative extrinsic rewards from the damage that does, it could encourage the robot to destroy itself. Therefore it must be carefully balanced with the scale and frequency of the extrinsic rewards (Hafner et al., 2023).

- *Mutual Information-based skill discovery* (Sharma et al., 2019; Warde-Farley et al., 2018; Eysenbach et al., 2018) rewards the agent based on the mutual information between the skills (temporally correlated sequences of actions) it learns and the resulting states. The higher this mutual information, the more diverse and controllable the skill set. It's a good signal for $\bar{V}_I^*$ in RL problems where this is a good measure for how useful the set of skills is for maximizing return, which also depends on the choice of representation used for the skills and states.
- *Information Gain* is a measure of the amount of information gained about the environment (Lindley, 1956). Info gain-based IM has led to successful exploration in RL (Sekar et al., 2020; Houthooft et al., 2016; Shyam et al., 2019); it is a good signal for $\bar{V}_I^*$ in problems where all information about the MDP is useful for maximizing return. But it could be a distraction in environments with many irrelevant dynamics to learn about, since the quantity of information gained would not always align with the value of that information.

### B.3 Composite Signal

Finally, we can analyze more complex pseudo-rewards that signal a combination of both $\bar{V}_I^*$ and $\bar{V}_O^*$.

#### B.3.1 Attractive VOI, Repulsive VOO

The *Empowerment* of an agent is typically measured as the mutual information $I(s'; a|s)$ between its actions and their effect on the environment (Klyubin et al., 2005; Salge et al., 2014a; Gregor et al., 2016). In prior work, this was generally understood as motivating agents to move to the states of "maximum influence" (Salge et al., 2014b; Mohamed & Jimenez Rezende, 2015), e.g., the center of the room, or the junction of intersecting hallways. However, this does not always explain the full story. Mohamed & Jimenez Rezende (2015) found that in problems with predators chasing or lava flowing toward the agent, Empowerment motivates it to barricade itself from the lava or avoid the predators- even when this requires holing up in a tiny corner of the room. We can understand this by decomposing Empowerment into the sum of attractive $\bar{V}_I$ and repulsive $\bar{V}_O$ signals:

$$I(s'; a|s) = H(a|s) - H(a|s, s'), \tag{30}$$

where we can view $H(a|s)$ as adding attractive signal for $\bar{V}_I^*$, similar to Entropy Regularization, encouraging the exploration of different actions such as the barricade-placing action. Meanwhile $-H(a|s, s')$ adds repulsive signal for $\bar{V}_O^*$, similar to Negative Surprise, signalling that states where the agent is caught or engulfed (which results in the agent's actions ceasing to have any predictable effect on the environment) have low value, and thus should be avoided. Empowerment intrinsic motivation has mostly been tested in small finite environments, but this decomposition suggests its potential for lifelong learning in open-ended worlds, where it can encourage the exploration of a wide range of possibilities while staying out of danger.

Similar to Empowerment is Information Capture (Rhinehart et al., 2021) where the intrinsic reward is based on the expected entropy of the belief distribution (encouraging exploration) minus the entropy of the latent state visitation distribution (which is low when the agent has "stabilized" the environment by controlling it and creating a niche for itself).

#### B.3.2 Attractive VOI and Attractive VOO

Another example of a composite value signal is pseudo-rewards based on the principle of *optimism* in the face of uncertainty, e.g. Sorg et al. (2012); Qian et al. (2019), rather than just rewarding novel experiences, aim to reward actions where there is a high upper confidence bound on the possible value they could lead to. Thus, these types of pseudo-rewards encourage gaining information about

the value of states and actions (signalling VOI), and/or reaching more valuable states (signalling VOO).

Reward bonuses for completing necessary subtasks for the first time, e.g. the first time successfully chopping wood as used in Crafter (Hafner, 2021), is one more example of a composite value signal. It adds both the value of discovering how to complete the subtask (because more wood will be needed) and the value of being one step closer to the ultimate objective of mining the diamond (one less woodblock needed to build a pick-axe). This adds the prior knowledge that in all worlds under $p(M)$, wood is a prerequisite for diamonds, and that it is valuable to learn how to gather new types of resources.

# C Certainty-Equivalent RL Algorithms Underestimate the Value of Information

Section 3.2 showed how we can understand many IM terms as encouraging and directing exploration through encoding the value of the resulting information. This type of IM is so popular because many commonly used RL algorithms under-estimate the value of information; we now introduce a model of these algorithms to formalize this within the BAMDP framework. Many RL algorithms, from policy-based methods like policy gradient (Sutton et al., 1999; Schulman et al., 2017) to value-based methods like Q-Learning (Watkins, 1989; Mnih et al., 2015), avoid the intractability of belief-space planning by acting as if beliefs are fixed. We formalize this objective with the Certainty-Equivalent[5] RL algorithm $\bar{\pi}^c$.

**Definition C.1** (Certainty-Equivalent RL Algorithm)**.** At each step, the Certainty-Equivalent Algorithm $\bar{\pi}^c$ follows the MDP policy maximizing its estimated expected return under current beliefs:[6]

$$\bar{\pi}^c(\langle s_t, h_t\rangle) \in \arg\max_\pi \mathbb{E}_{b^c(h_t)}[V^\pi(s_t)], \tag{31}$$

where $b^c(\cdot)$ denotes how $\bar{\pi}^c$ interprets its experience, which could be anything from a distribution over world models maintained by updating a prior, to a point estimate of $Q^*$ maintained by training a randomly initialized neural net on batches sampled from $h_t$ (Mnih et al., 2015). For ease of notation we use $\pi_t$ and $a_t$ interchangeably, since $\pi_t$ is only used at step $t$ to output $a_t$.

For example, policy gradient algorithms like Reinforce sample actions from an MDP policy $\pi_\theta$, i.e., $\bar{\pi}^{\text{Reinforce}}(\langle s_t, h_t\rangle) = \pi_\theta(s_t)$, where $\pi_\theta$ is learnt by gradient updates towards maximizing the expected returns $\mathcal{R}(\tau)$ of the trajectories $\tau$ that it generates, i.e. $J(\theta) = E_{\tau\sim\pi_\theta}[\mathcal{R}(\tau)]$. The algorithm estimates $J(\theta)$ from environment interactions so far, i.e. $h_t$, so $\hat{J}(\theta) = \mathbb{E}_{b^c(h_t)}[E_{\tau\sim\pi_\theta}[\mathcal{R}(\tau)]]$ where $b^c(h_t)$ is concentrated on a point estimate of $J(\theta)$. If, as a model, we assume that policy gradient were to maximize $J(\theta)$ between each interaction, then we find that it matches the behavior of $\bar{\pi}^c$:

$$\arg\max_\theta \hat{J}(\theta) = \arg\max_\theta \mathbb{E}_{b^c(h_t)}[E_{\tau\sim\pi_\theta}[\mathcal{R}(\tau)]] = \arg\max_\pi \mathbb{E}_{b^c(h_t)}[V^\pi(s)]. \tag{32}$$

The Certainty-Equivalent algorithm effectively estimates the Q value as:

$$\hat{\bar{Q}}(\bar{s}_t, a) = \max_\pi \mathbb{E}_{b^c(h_t)}[R(s_t, a) + \gamma V^\pi(s_{t+1})]. \tag{33}$$

Comparing this to the optimal value $\bar{Q}^*(\bar{s}_t, a) = \mathbb{E}_{p(M|h_t)}[R(s_t, a) + \gamma \bar{V}^*(\langle s_{t+1}, h_{t+1}\rangle)]$, we see that, even assuming accurate beliefs $b^c(h_t) = p(M|h_t)$, the Certainty-Equivalent algorithm still misses value from the ability to learn from the information in $h$, because with $V^\pi(s_{t+1})$ it assumes it would still follow the same $\pi$ from step $t+1$, when in reality it would have updated it with the latest observation. E.g., if $s_b$ in Fig. 2 was observed to be empty, $\bar{\pi}^c$ would update $\pi$ to return to $s_w$ forever, resulting in higher return than if it kept following the same $\pi$ back to $s_b$ (see section J.2 for the calculations). Thus, adding pseudo-rewards signalling VOI can compensate for this underestimation, causing the algorithm to predict higher value for behavior leading to valuable information.

[5]The idea of *certainty equivalent* solutions goes back to Simon (1956) and was also described by Duff (2002) as the *best reactive policy* with respect to $\bar{\pi}^c$'s beliefs

[6]Note that this is focused on exploitation- other than IM, ad-hoc methods such as epsilon-greedy or Boltzmann exploration may also be used to encourage exploration (Kaelbling et al., 1996).

## D CURIOSITY CASE STUDY

Curiosity (Pathak et al., 2017) rewards the error in predicting a feature encoding $e(s)$ of the state:

$$r_t^i = ||\hat{e}(s_{t+1}) - e(s_{t+1})||_2^2, \tag{34}$$

where $\hat{e}$ is predicted with dynamics model $d$, which is continually trained to minimize this same error on the past experiences $h_t$ of the agent, i.e.:

$$\hat{e}(s_{t+1}; h_t) = d(e(s_t), a_t; h_t). \tag{35}$$

The feature encoding $e(s_{t+1}|h_t)$ is also continually trained to minimize the error of a learnt inverse dynamics model $i$ that predicts the action from the encoded state transition:

$$\hat{a}_t = i(e(s_t), e(s_{t+1}); h_t). \tag{36}$$

The encoder, inverse dynamics model and predictor are all trained on the history, so this can also be converted to a BAMPF by directly using the error as the potential function $\phi(h_t) = ||\hat{e}(s_{t+1}) - e(s_{t+1})||_2^2$. However, this potential is not monotonic. For example in the Noisy TV problem, the prediction error always increases when the agent watches TV and decreases when it looks away, because the prediction error of the next image on the TV screen is higher than the prediction error for the next part of the maze.

Burda et al. (2018) mitigate this issue with Random Network Distillation (RND) by predicting features of the current state rather than the next state. This would not get distracted by noisy transitions such as the TV flipping randomly between a few images, but it would get trapped forever in front of a TV that incremented through an infinite set of novel images. It would also under-explore parts of the environment with *novel dynamics*, if the states themselves did not look very novel.

We could try to capture the same type of dynamics prediction-based IM of Curiosity by noting that it is designed to get the agent to simultaneously improve its dynamics model and reach novel parts of the environment. Specifically, it assumes that high prediction-error observations will improve the dynamics model, decreasing the error and thus the reward, so that the agent moves on to new parts of the environment. With the Noisy TV, the dynamics model can't learn anything from the TV and the error never decreases. We can split the novelty-seeking and dynamics model improvement into two components:

*Novelty Seeking:* A PBSF with $\phi(s)$ equal to the error of a *fixed model* $\hat{f}$'s prediction of fixed features $f$ of $s$ (similar to RND):

$$\phi_1(s_t) = ||\hat{f}(s_t) - f(s_t)||_2^2 \tag{37}$$

*Model improvement:* a bounded monotone BAMPF with $\phi(h)$ equal to the maximum accuracy of the learnt dynamics model on a *fixed set of transitions* $(s, a, s') \in \mathcal{T}$:

$$\phi_2(h_{t+1}) = \max\left(\phi(h_t), \quad -\sum\nolimits_{(s,a,s')\in\mathcal{T}} ||\hat{e}(s'; h_{t+1}) - e(s'; h_{t+1})||_2^2\right) \tag{38}$$

The total intrinsic reward would be:

$$\gamma(\phi_1(s_{t+1}) + \phi_2(h_{t+1})) - \phi_1(s_t) - \phi_2(h_t). \tag{39}$$

The PBSF encourages going to parts of the environment with novel states, while the BAMPF encourages going to areas with unfamiliar dynamics that will improve its world model.

This form of Curiosity would no longer be susceptible to the Noisy TV problem, since even if TV-watching transitions were in set $\mathcal{T}$, the dynamics model's accuracy over $\mathcal{T}$ would not increase indefinitely while watching it. And even if the fixed model's prediction error $\phi_1(s)$ were higher at the TV, Ng et al. (1999)'s result guarantees that a policy can't maximize its total shaped return by staying there because $\phi_1$ is a function of only the current MDP state.

To prevent stagnation, every few batches we could update $\hat{f}$ (e.g., by training it to minimize prediction error over the last batches of visited states), and we could refresh the set of transitions in

$\mathcal{T}$ (e.g., with more recently observed transitions, or transitions that $\hat{f}$ predicted the most poorly). What matters for avoiding reward hacking is that the RL algorithm's choice of policy $\pi$ for the next episode can't affect $\hat{f}$ *within the episode* (so $\phi_1$ remains a function of only the current MDP state), and we give the algorithm enough episodes with a fixed $\mathcal{T}$ for $\phi_2$ to converge.

# E More Related Work

Henaff et al. (2023) study exploration bonuses in contextual MDPs, where the dynamics are sampled from a distribution at the start of *every episode,* and the goal is to learn *one* policy that performs well across all contexts. We instead study the setting where the RL algorithm learns a different policy for each MDP, and the goal is to design an algorithm that can learn effectively across a distribution of MDPs. Our goal is to be good at learning in general, their goal is to learn one policy well. They find that global novelty bonuses work when the contexts are more similar, and episodic novelty bonuses work when the contexts are more different. We can explain this in the BAMDP framework by thinking of a CMDP as a lifelong infinite-sized MDP where the end of an episode corresponds to transitioning to a new part of the state space and resetting the episodic novelty counter. The more similar the contexts, the lower the $\bar{V}_I$ of an experience that already happened in a previous context, and thus the better signal a global novelty bonus will provide over episodic.

**Value of Information** The classical notion of the value of information originates in decision theory (Howard, 1966). Early work in metareasoning for tree search considers the utility of the information resulting from a computation (Russell & Wefald, 1989; 1991). Dearden et al. (1998) first applied the concept to RL, computing an approximation to the value of information to help select the Bayes-optimal action. They upper bound the "myopic value of information" for exploring action $a$ by the expected Value of Perfect Information, i.e. the expected gain in return due to learning the true value of the underlying MDP's $Q^*(s, a)$ given prior beliefs. Chalkiadakis & Boutilier (2003) described BAMDP Q values as including the value of information—defined as the value of the change in beliefs quantified by its impact on future decisions—but they do not derive an expression for it. Ryzhov & Powell (2011) define value of information of pulling a bandit arm as the expected resulting increase in the believed mean reward of the best arm, and derive an exact expression for bandits with exponentially distributed rewards. This value, which they also call the Knowledge Gradient, is related but clearly not equal to the expected return due to the knowledge.

**Reward Shaping and Meta-RL** Meta-Learning has been used to learn intrinsic motivation and reward shaping functions for RL (Zou et al., 2019; Alet et al., 2020; Li et al., 2021; Zou et al., 2021), but few existing works use reward shaping or intrinsic motivation *to guide the meta-learner itself* (Zhang et al., 2021).

**Learning Awareness** The idea of planning through learning has appeared across RL such as in Bayesian RL and meta-RL (Thrun & Pratt, 1998; Duan et al., 2016; Finn et al., 2017; Mikulik et al., 2020; Jackson et al., 2024) and multi-agent RL (Foerster et al., 2017; Cooijmans et al., 2023).

# F Settling BAMPFs

We refer to a BAMPF where the potential eventually stops changing over time as a *settling BAMPF*. First we formally define settling for BAMPFs.

**Definition F.1** (Settling)**.** For a given BAMPF and RL algorithm $\bar{\pi}$, we say that the BAMPF settles on the algorithm's trajectory if the potential function $\phi$ eventually stops changing over time, becoming a function of only the current MDP state for the rest of time, i.e.,

$$SETTLES(\phi, \bar{\pi}) \quad := \quad \exists H, \phi' : \forall t > H : \phi(h_t) = \phi'(s_t). \tag{40}$$

It is simple to verify if a BAMPF has settled while training an RL algorithm, by inspecting its values over time.

**Corollary F.1.** *If a BAMPF settles for an RL algorithm $\bar{\pi}$, it will eventually preserve the ordering of policies $\pi_t$ tried by that algorithm, i.e., for any policies $\pi_t, \pi'_t$ tried at time $t, t' > H$ after settling,*

$$SETTLES(\phi, \bar{\pi}) \quad \Rightarrow \quad \mathbb{E}_{\pi_t}[G'] > \mathbb{E}_{\pi'_{t'}}[G'] \iff \mathbb{E}_{\pi_t}[G] > \mathbb{E}_{\pi'_{t'}}[G] \tag{41}$$

*Proof.* Once a BAMPF settles, it can be expressed as a PBSF based on potential $\phi'$ on the subset of all MDP states visited from $t'$ onwards. We can construct an MDP from that subset where actions

from the original MDP that aren't taken have no effect, in which we can apply Ng et al. (1999) to prove that the ordering of policies is preserved. □

## G LEVER BAMPF DETAILS

We used the DQN implementation from Allen et al. (2021), with the default hyperparameters except for `n_steps_init=20` and `decay_period=100` due to the shorter time horizon used. This agent uses epsilon-greedy exploration, with $\epsilon = 1$ for the first 20 steps, decaying linearly to $0.05$ over the next $100$ steps (according to the schedule $1 - 0.95 * \min(0.01(t - 20), 1.0)$). The *None* condition with no pseudo-rewards relied purely on this epsilon-greedy behavior for exploration. In this lifelong setting, the network is updated at every step with a batch of transitions from the full trajectory so far. The value of $\gamma$ used by both DQN and to define the BAMPF was $0.9$. The Entropy Bonus intrinsic reward was calculated as $-10H(A)$ where $H(A)$ is the entropy of the categorical distribution of the last 10 lever pulls.

## H BERNOULLI BANDITS META-RL DETAILS

We run the Bernoulli Bandits environment and A2C implementation in Gymnax (Lange, 2022a), keeping all the default hyperparameter values except for changing the number of pulls in an episode to 10. The discount factor used for the BAMPF is $0.8$, matching the discount factor used by A2C.

Following Wang et al. (2016), we define the regret of an RL algorithm as $\sum_{t=1}^{T} \mu^* - \mu_{a_t} = \sum_{t=1}^{10} 0.9 - \mu_{a_t}$, where $\mu^*$ is the expected reward of the optimal arm and $\mu_{a_t}$ is the expected reward of the arm chosen at time $t$, so always pulling the optimal arm yields regret 0, and only pulling it half of the time (performance at random chance) has regret 4.

No rescaling was performed on either the BAMPF or the non-BAMPF pseudo-reward functions, since they were already of the same order of magnitude as the extrinsic rewards.

To handle the finite time horizon, we followed the approach of Grzes (2017) and set $\phi(h_{10}) = 0$ at the final (10th) step of each RL algorithm's trajectory, which ensures that the $\phi$ still sum to a constant over the trajectory to preserve optimality, and intuitively represents the fact that the final BAMDP state has no value, since the agent cannot collect any more rewards from it.

## I MOUNTAINCAR DETAILS

We run MountainCar implemented in Gymnax (Lange, 2022a) using the PPO implementation from (Lange, 2022b), keeping all the default hyperparameter settings. The MountainCar environment itself has discount factor 1 so the reported return is simply the sum of the rewards in each episode, but the PPO algorithm uses discount factor $\gamma = 0.99$ so this was the discount used for both the potential-based shaping and the BAMPF. To handle the finite episode lengths, we again follow the approach of Grzes (2017) for the potential-based shaping, setting $\phi(s_t) = 0$ when $s_t$ is the last step in an episode, ensuring that it preserves optimality within each episode. For the BAMPF, at the last step in each episode we multiply $\phi(h_t)$ by $\gamma^{200-t_e}$ (where $t_e$ is the within-episode time-step and the maximum episode length is 200). This corresponds to adding up all the remaining BAMPF rewards that would have been added between that time-step and the final step if the episode hadn't been truncated. This does not preserve optimality in general, but we prove with Theorem 4.3 that if $\phi$ is bounded and monotonic then it will eventually preserve approximate optimality, which holds for the maximum displacement $\phi$ that we used. Our formula for exponential smoothing ($\alpha = 0.5$) on the maximum displacement is:

$$M_t = 0.5 \max(M_{t-1}, |-0.5 - s_{xt}|) + 0.5 M_{t-1}, \tag{42}$$

where $M_t$ denotes the exponentially smoothed maximum displacement at training step $t$, $s_{xt}$ is the x position of the car at time $t$ and $-0.5$ is the x position of the lowest point between the two hills.

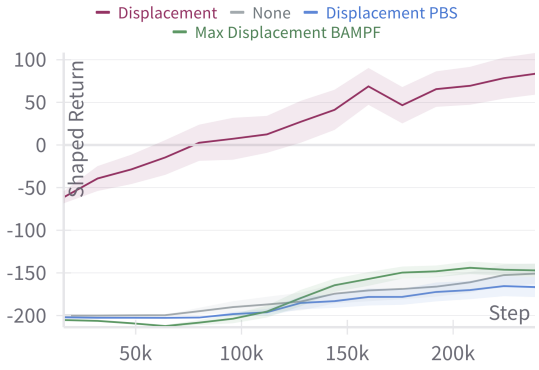


Figure 7: The (undiscounted) shaped episodic return for PPO trained with each type of pseudo-reward (mean and standard error of 10 seeds).

This PPO implementation runs 16 copies of the environment in parallel; we maintain a separate $M_t$ for each copy (whenever an episode ends, $M_t$ is carried over to the next episode in that environment copy) and plotted the mean over the 16 values of $M_t$ in Fig. 5c.

For each form of pseudo-reward, we scale it by a constant to be on the same order of magnitude as the environment rewards. For the BAMPF and PBS, we scaled it by 10, and for Displacement (non-PBS version) we scaled it by 4. Note that whether Displacement preserves optimality is sensitive to this scaling factor, but the BAMPF version preserves optimality no matter the scale.

# J Caterpillar Problem Analysis

## J.1 Bayes-Optimal Policy Values

In section 2.3 we describe the behavior for the Bayes-optimal algorithm: for large enough $\gamma$, $\bar{\pi}^*$ should check $s_b$ first, then stay there forever if it's alive, otherwise return to $s_w$ forever. Let's look at the $\bar{Q}^*$ values in this case, with $\gamma = 0.95$. First, the value of going to $s_b$:

$$\bar{Q}^*(\bar{s}_0, go) = -5 + \gamma \mathbb{E}[\bar{V}^*(\langle s_b, h_1^b \rangle)], \tag{43}$$

where the first term is the energy cost of travelling. Now the value from $h_1^b$ is the weighted sum of the values in the presence and absence of food at $s_b$:

$$\mathbb{E}[\bar{V}^*(\langle s_b, h_1^b \rangle)] = 0.1\frac{150}{1-\gamma} + 0.9(-5\gamma + \frac{21\gamma^2}{1-\gamma}) = 637, \tag{44}$$

where the first term is the return from eating at $s_b$ forever, and the second is from going back to eat at $s_w$ forever. Plugging this in, we get $\bar{Q}^*(\bar{s}_0, go) = 600$.

Now, the Q value for eating at $s_w$:

$$\bar{Q}^*(\bar{s}_0, eat) = 21 + \gamma \mathbb{E}[\bar{V}^*(\langle s_w, h_1^w \rangle)]. \tag{45}$$

Since $h_1^w$ contains no more information than $h_0$, $\bar{\pi}^*(\langle s_w, h_1^w \rangle)$ would make the same choice as $\bar{\pi}^*(\bar{s}_0)$ i.e. to check $s_b$, so $E_{p(M)}[V^*(\langle s_w, h_1^w \rangle)] = \bar{Q}^*(\bar{s}_0, go) = 600$. This gives us:

$$\bar{Q}^*(\bar{s}_0, eat) = 21 + 600\gamma = 591 < \bar{Q}^*(\bar{s}_0, go), \tag{46}$$

and thus $\bar{\pi}^*$ would first go to $s_b$.

## J.2 Certainty-Equivalent Algorithm Value Calculations

In section C we describe how the Certainty-Equivalent RL algorithm would act in the caterpillar MDP example. Here we go through the full calculations.

Algorithm $\bar{\pi}^c$, assuming it had the correct prior $p(M)$, would estimate the values of following various $\pi$ as follows:

- $\pi_b$ goes to the bush and stays there: $E_{p(M)}[V^{\pi_b}(s_w)] = -5 + 0.1 \times 150\frac{\gamma}{1-\gamma} = 280$
- $\pi_{alt}$ alternates between the plants: $E_{p(M)}[V^{\pi_{alt}}(s_w)] = -5\frac{1}{1-\gamma} = -100$
- $\pi_w$ eats at the weed forever: $E_{p(M)}[V^{\pi_w}(s_w)] = 21\frac{1}{1-\gamma} = 420$; and it would go from $s_b$ so $E_{p(M)}[V^{\pi_w}(s_b)] = -5 + \gamma 420 = 394$
- $\pi_{eat}$ always eats wherever it is, so $E_{p(M)}[V^{\pi_{eat}}(s_w)] = 21\frac{1}{1-\gamma} = 420$ and $E_{p(M)}[V^{\pi_{eat}}(s_b)] = 0.1 \times 150\frac{1}{1-\gamma} = 300$

Because $\pi_w$ gets the highest estimated value, $\bar{\pi}^c$ would choose to follow it, thus never learning about the bush and staying at the weed forever.

As an example of $\bar{\pi}^c$ underestimating its own value, take its estimate of its value of eating from $\langle s_b, h_0 \rangle$, i.e. if $s_0$ was actually at the bush. It assumes it would follow the best MDP policy under current information at the next step no matter what it found at $s_b$, which is still $\pi_w$, giving estimate:

$$\hat{\bar{Q}}^c(\langle s_b, h_0 \rangle, eat) = E_{p(M)}[R(s_w, eat) + \gamma V^{\pi_w}(s_b)] = 0.1 \times 150 + 394\gamma = 369 \tag{47}$$

However, this is very wrong. If $\bar{\pi}^c$ ate at $s_b$ and found no food, it would update to $\pi_w$ to go and eat at $s_w$, and if it did find food it would update to a $\pi$ that continues eating at $s_b$. This behavior corresponds to this much higher true value:

$$\bar{Q}^c(\langle s_b, h_0 \rangle, eat) = 0.1\frac{150}{1-\gamma} + 0.9(-5\gamma + \frac{21\gamma^2}{1-\gamma})) = 637 \tag{48}$$