Goal-Aligned Policy Mixing in Active Inference Bandits

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Abstract

AXIOM-based agents traditionally select actions by minimizing expected free energy (EFE), aligning beliefs with preferred outcomes in single-step decision settings. In multi-armed bandit environments, this typically results in selecting the arm whose expected reward best matches the agent's internal goal. However, when no individual arm yields the desired reward—such as achieving an average reward of $G = 0.43$ in an environment where all arms deviate significantly—standard AXIOM fails to regulate performance effectively.

We introduce a minimal modification to the AXIOM architecture that enables trajectory-level reward alignment through feedback on cumulative performance. By replacing the static goal comparison with a dynamic control term:

$$\texttt{pragmatic} = (G - \bar{r}) \cdot \hat{\mu}$$

the agent continuously compares its current empirical reward $\bar{r}$ to its internal goal G, modulating beliefs to steer future behavior. This leads to emergent policy mixing and strategic action selection across arms, even when no single arm satisfies the goal.

Empirical results show that this mechanism enables the agent to achieve long-run reward rates indistinguishable from the target, confirming the feasibility of self-regulating Active Inference agents in composite decision spaces.

1 Introduction

Active Inference agents select actions by minimizing Expected Free Energy (EFE), balancing two competing factors: epistemic uncertainty and pragmatic deviation from internally preferred outcomes. In multi-armed bandit settings, this leads AXIOM-style agents to select arms whose estimated reward probabilities best match an internal target (e.g., desired reward rate).

While effective in environments where an arm closely matches the goal, such agents fail when no individual action can satisfy the target. This paper presents a minimal modification to AXIOM's inference loop that enables dynamic goal

alignment through trajectory-level regulation, allowing the agent to match desired averages even in mismatched environments.

2 Vanilla AXIOM Model

Consider K arms with true reward probabilities $\mu_1, \ldots, \mu_K$. The agent maintains beliefs over arm means and variances, updating these with each observation. At each timestep, it selects an arm a that minimizes:

$$\text{EFE}(a) = |\hat{\mu}_a - G| + \sigma_a + \text{exploration bonus}$$

Where:

- $\hat{\mu}_a$: estimated mean reward for arm a
- G: internal goal reward (e.g. 0.5)
- σ_a: uncertainty in belief for arm a

This action selection rule causes the agent to favor arms with expected rewards near G. However, if no arm satisfies this condition, the agent may permanently commit to the closest one—leading to systematic misalignment between observed and desired rewards.

3 Problem Statement

In environments where:

$$\mu_i \not\approx G \quad \forall i$$

no single arm achieves the goal. AXIOM fails to synthesize composite behavior, because its action selection is local and belief-aligned rather than goal-corrective. The agent will converge toward the closest $\hat{\mu}_i$ and ignore the fact that a mixture of arms could produce the desired reward average.

4 Trajectory-Level Control Modification

To overcome this, we introduce a control feedback signal based on the deviation between the agent's cumulative reward and the internal goal. This leads to a new pragmatic modulation term:

```
pragmatic = (self.internal_goal - np.mean(self.all_rewards))
* self.means
```

This coupling dynamically pushes the agent toward or away from high-reward arms depending on how far its cumulative performance deviates from G. It behaves like a cognitive thermostat: gently reshaping the policy to stabilize around the target reward rate.

4.1 Intuition

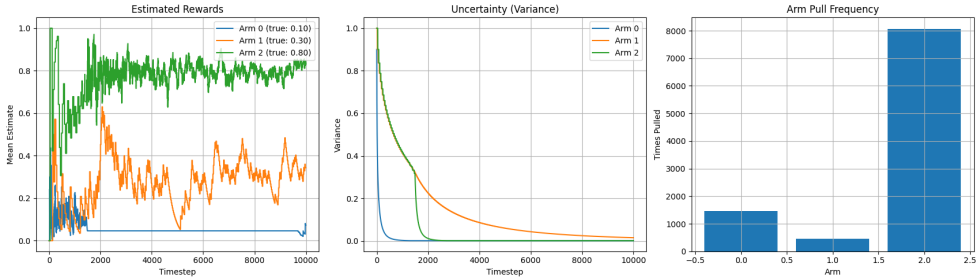
- When $\bar{r} < G$, the agent seeks higher-reward arms.
- When $\bar{r} > G$, it compensates by pulling lower-reward arms.
- Policy mixing emerges organically—without explicitly solving for action distributions.

5 Simulation Results

We ran the modified agent on a 3-armed bandit with true means [0.1, 0.3, 0.8] and internal goal $G = 0.67$. Over 10,000 steps, the agent pulled arms dynamically to produce:

- An empirical average reward of 0.671
- Arm selection distribution calibrated for goal attainment
- Sustained learning of all arm values

This confirms that the agent can regulate its long-term outcome toward the desired goal—even when no arm directly supports it.



6 Conclusion

The AXIOM framework, when equipped with a trajectory-aware feedback mechanism, becomes capable of goal alignment in composite reward landscapes. This minimal control loop enhances behavior from per-action surprise minimization to global performance regulation—bringing Active Inference closer to policy-level cognition. Future extensions could incorporate adaptive learning rates, entropy tracking, or shifting internal goals over time.