ROIL: Robust Offline Imitation Learning

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Summary

Motivation

- Learning from data in a robust offline way is important in many fields, like health care, robotics or finance.

Limitations of existing methods

- Reliance on $\hat{u}_e$ leads to covariate shift for off-policy datasets.
- Inability to specify reliance on $\hat{u}_e$.
- No guarantees of policy convergence to u_e even when every state is visited.

Our contributions

- New algorithm for robust offline imitation learning.
- Guaranteed convergence to the optimal policy for tabular domains.
- Flexibility to define the reliance on $\hat{u}_e$.

Inverse Reinforcement Learning (IRL)

$$\rho(\pi, r) = \lim_{T\to\infty} \mathbb{E}^{\pi, p_0}\Big[\sum_{t=0}^{T} \gamma^t r(\tilde{s}_t, \pi(\tilde{s}_t))\Big]$$

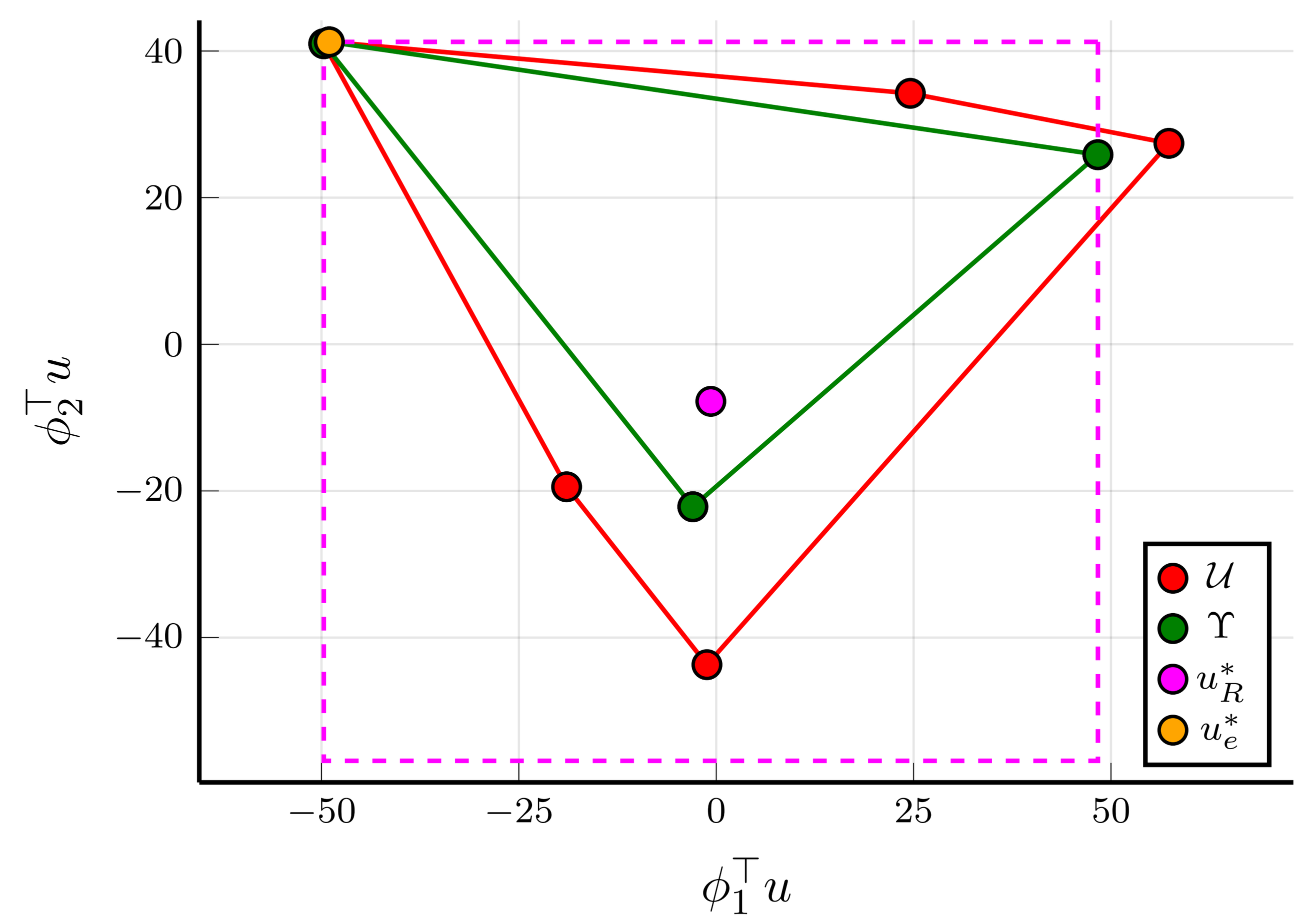
$$\pi^*_{IRL} = \arg\min_{\pi\in\Pi} \max_{r\in\mathcal{R}} \rho(\hat{\pi}_e, r) - \rho(\pi, r)$$

$$\pi^*_{ROIL} = \arg\min_{\pi\in\Pi} \max_{\pi_e\in\Pi} \max_{r\in\mathcal{R}} \rho(\pi_e, r) - \rho(\pi, r)$$

Previous Work

- **LPAL**
- **MILO**
- **GAIL**
- **BROIL**

Visual Representation of ROIL



ROIL LP

$$\begin{aligned}
&\min_{t\in\mathbb{R}, u\in\mathbb{R}^{S\times A}} && t \\
&\text{s.t.} && t \geq -u^\top \Phi w + \max_{v\in\Upsilon} v^\top \Phi w, \quad \forall\, w \in ext(\mathcal{W}), \\
& && u \in \Upsilon,
\end{aligned}$$

Gridworld Results

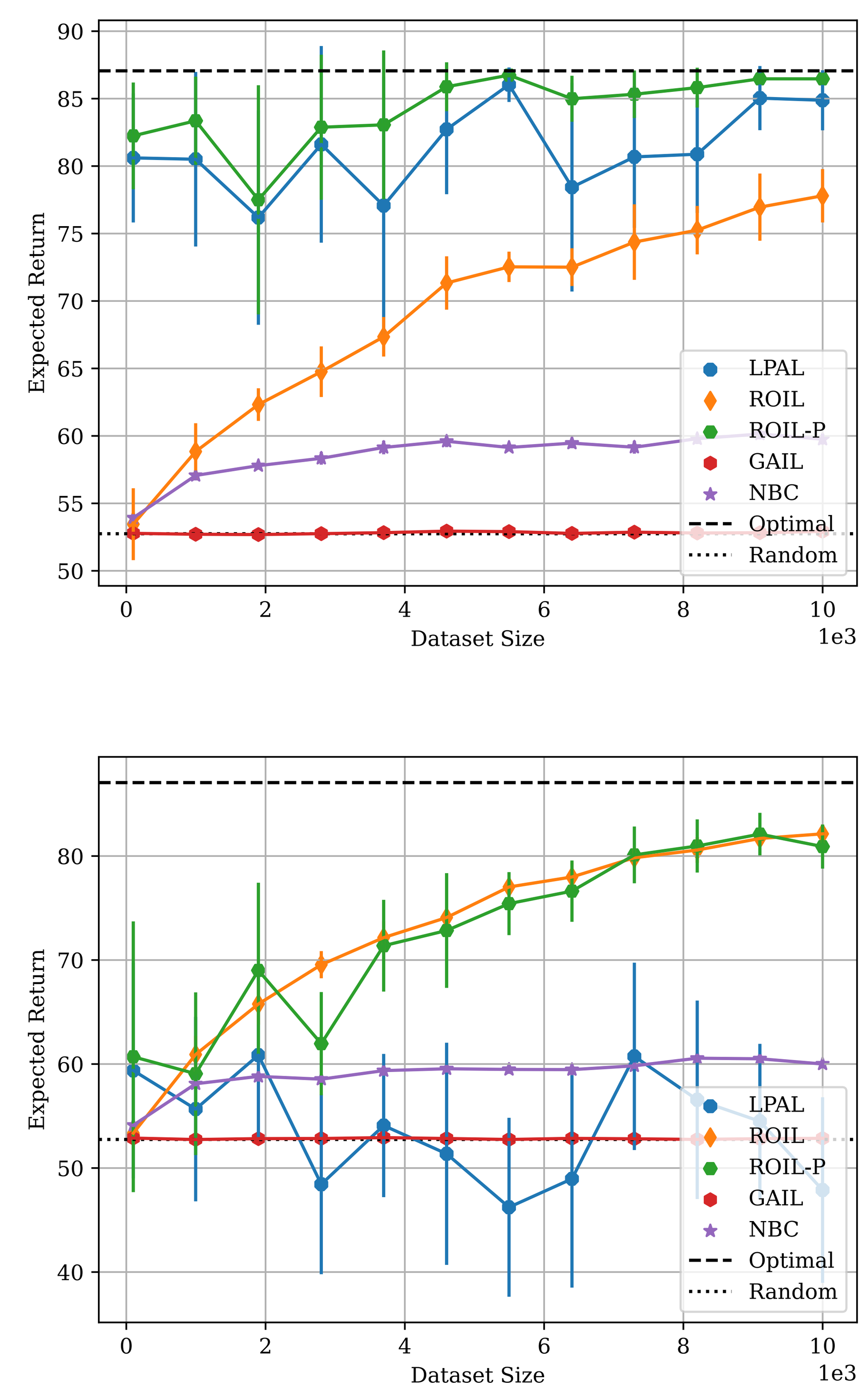


Figure: On-policy and off-policy returns (respectively) for 40x40 Gridworld.

Regret Results

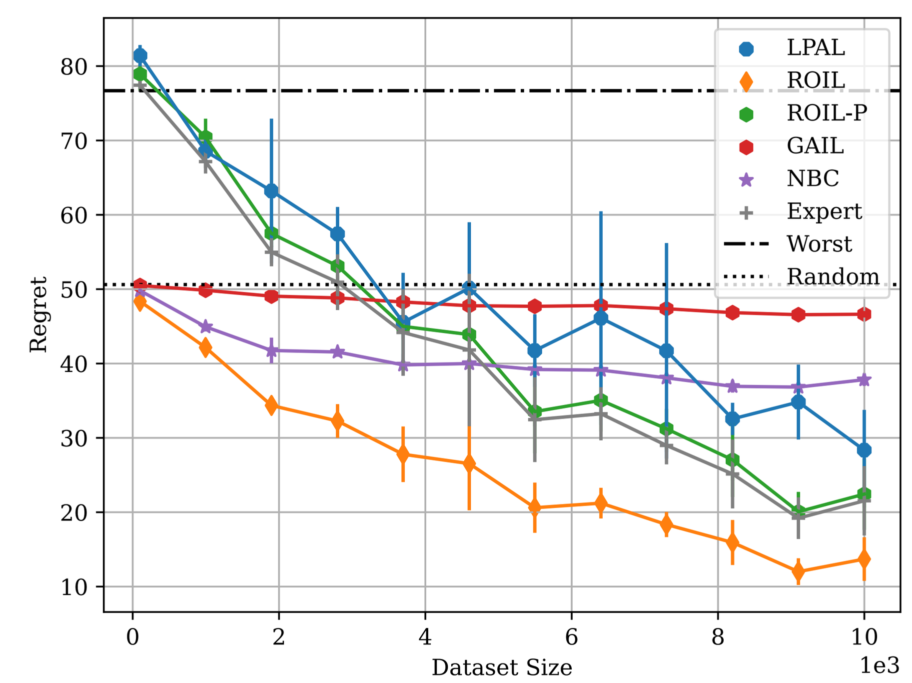


Figure: On-policy regret for 40x40 Gridworld.