ROIL: Robust Offline Imitation Learning

Gersi Doko[1], Guang Yang[2], Daniel S. Brown[2] Marek Petrik[1]

[1]University of New Hampshire, [2]University of Utah

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.

Our contributions

New algorithm for robust offline imitation learning.

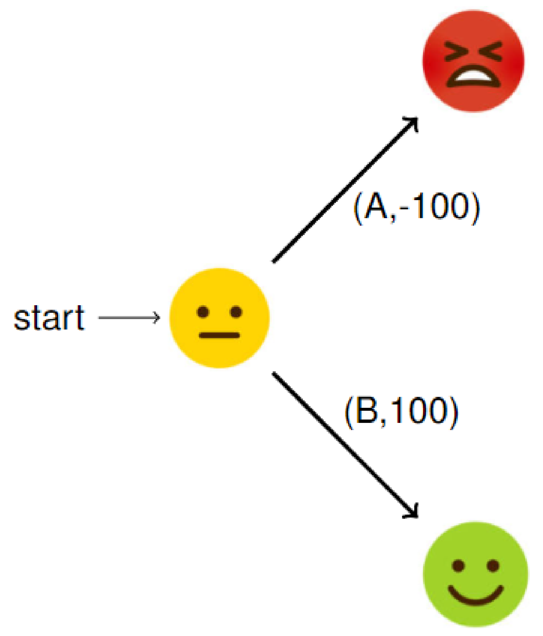
Guaranteed convergence to the optimal policy for tabular domains.

Flexibility to define the reliance on $\hat{u}_e$.

Markov Decision Process (MDP)

MDP : consists of a tuple $<\mathcal{S}, \mathcal{A}, p, r>$

- State space $\mathcal{S}$ = { mild, moderate, severe}
- Action space $\mathcal{A}$= {A, B}
- Transition probability p: p(, ,) = 1
- Reward function r : r(,) = **100**



Inverse Reinforcement Learning (IRL)

Given a dataset of expert demonstrations and an MDP model without a reward function, IRL aims to learn a policy π from a dataset of expert demonstrations $D_e = \{s_i, a_i, r_i\}_{i=0}^N$.

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

Optimal policy π^*

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

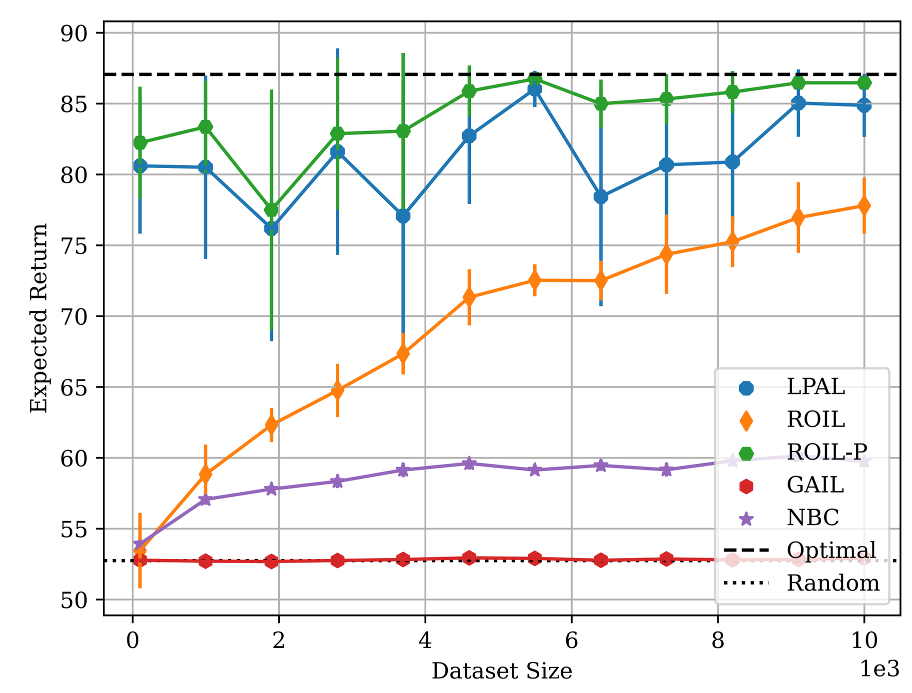
Previous Work

LPAL
MILO
GAIL
BROIL

ROIL LP

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

Gridworld Results



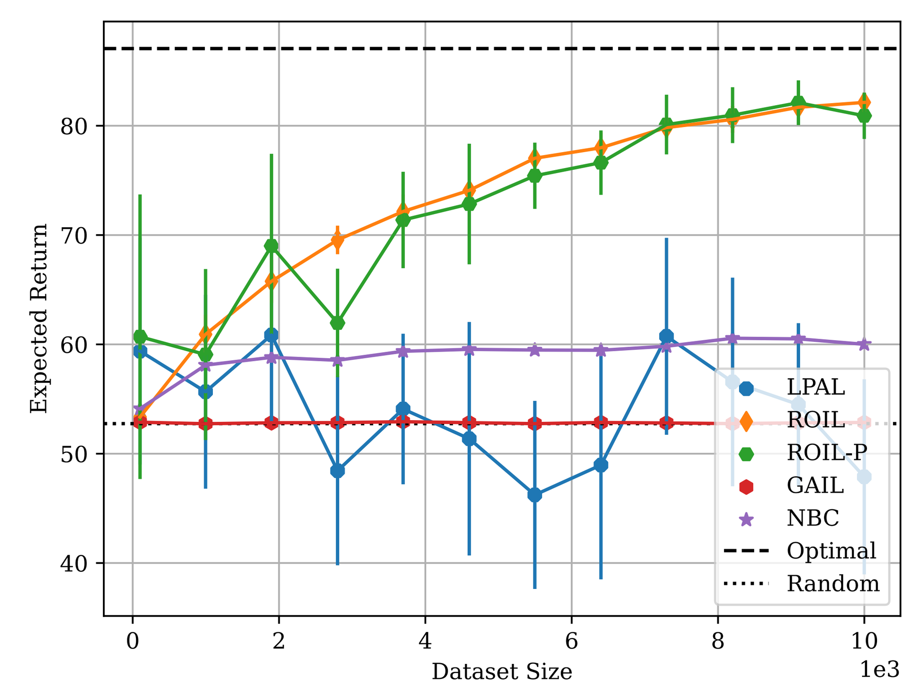


Figure: On-policy and off-policy returns (respectively) for 40x40 Gridworld.

Regret Results

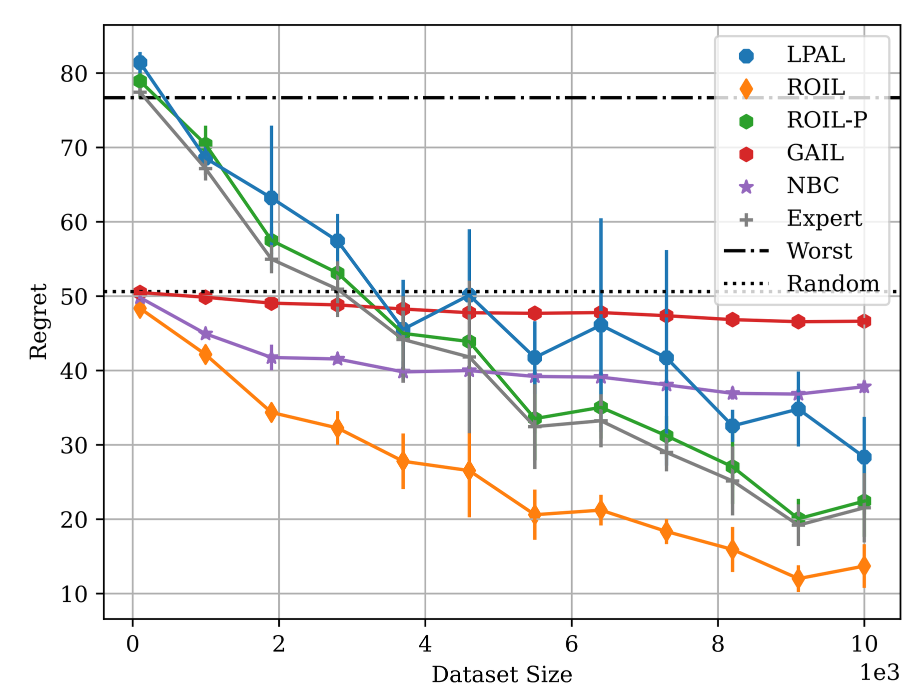


Figure: On-policy regret for 40x40 Gridworld.