Inverse Reinforcement Learning in robotics

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Why worry about learning rewards in RL?

What could be an optimal control?

$$\pi = \arg\max_{\pi} E_{\mathbf{x}_{t+1} \sim p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t), \mathbf{u}_{t+1} \sim \pi(\mathbf{u}_t|\mathbf{x}_t)} [r(\mathbf{x}_t, \mathbf{u}_t)] \tag{1}$$

Better to optimize $r(\mathbf{x}_t, \mathbf{u}_t)$ to explain the data better.

Why worry about learning rewards in RL?

Imitation learning perspective:

- Simply copying actions of expert has no reasoning
- We want to infer the **intent**

RL perspective:

- Inferring reward is **underspecified** problem
- Many rewards can explain the same behaviour equally-well

IRL vs RL formally

"Forward" reinforcement learning:

- states $\mathbf{x} \in \mathbf{X}$
- controls $\mathbf{u} \in \mathbf{U}$
- (sometimes) dynamics $f(\mathbf{x}^+|\mathbf{x}, \mathbf{u})$
- reward $r(\mathbf{x}, \mathbf{u})$

Learn policy $\pi^*(\mathbf{u}|\mathbf{x})$

Inverse reinforcement learning:

- states $\mathbf{x} \in \mathbf{X}$
- controls $\mathbf{u} \in \mathbf{U}$
- (sometimes) dynamics $f(\mathbf{x}^+|\mathbf{x}, \mathbf{u})$
- samples τ_i from $\pi^*(\tau)$

Learn $r_\psi(\mathbf{x}, \mathbf{u})$ to later learn policy $\pi^*(\mathbf{u}|\mathbf{x})$

Reward function parameterization

Linear reward function:

$$r_\psi(\mathbf{x}, \mathbf{u}) = \sum_i \psi_i f_i(\mathbf{x}, \mathbf{u}) = \psi^T \mathbf{f}(\mathbf{x}, \mathbf{u}) \tag{2}$$

In more complex case the reward could be a separate neural net mapping from $\mathbf{x}$ and $\mathbf{u}$ to $r_\psi(\mathbf{x}, \mathbf{u})$

Learning the reward

Same as learning the optimality variable.

$$p(\mathcal{O}|\mathbf{x}_t, \mathbf{u}_t, \psi) = exp(r_\psi(\mathbf{x}_t, \mathbf{u}_t)) \tag{3}$$

$$p(\tau|\mathcal{O}, \psi) \propto p(\tau)\ exp(\sum_t r_\psi(\mathbf{x}_t, \mathbf{u}_t)) \tag{4}$$

Note that $p(\tau)$ is not dependent on ψ.
The whole thing becomes maximum likelihood learning:

$$\max_\psi \frac{1}{N}\sum_{i=1}^{N} log\ p(\tau_i|\mathcal{O}_{1:T}, \psi) = \max_\psi \frac{1}{N}\sum_{i=1}^{N} r_\psi(\tau_i) - log\ Z \tag{5}$$

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Partition function

Normalizer (partition) function could be defined as:

$$Z = \int p(\tau)\ exp(r_\psi(\tau))\ d\tau \tag{6}$$

Just compute gradient and optimize:

$$\nabla_\psi \mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} \nabla_\psi\ r_\psi(\tau_i) - \frac{1}{Z}\int p(\tau)\ exp(r_\psi(\tau))\ \nabla_\psi\ r_\psi(\tau)\ d\tau \tag{7}$$

Partition function

But second term can be considered as expected value and equation becomes:

$$\nabla_\psi \mathcal{L} = E_{\tau \sim \pi^\star(\tau)} \left[\nabla_\psi r_\psi \left(\tau_i\right)\right] - E_{\tau \sim p(\tau | \mathcal{O}_{1:T}, \psi)} \left[\nabla_\psi r_\psi(\tau)\right] \tag{8}$$

- First item is estimation over expert samples
- Second item is soft optimal policy under current reward

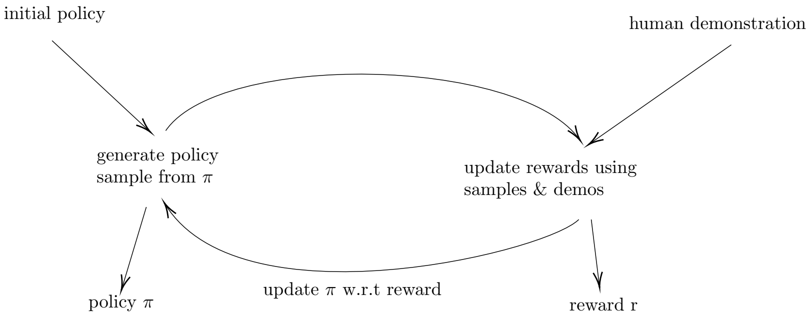
MaxEnt IRL algorithm [1]

- compute probability of control given state being optimal for reward (backward message)
- compute probability of state begin optimal for reward (forward message)
- compute state-action visitation probability for pairs $(\mathbf{x}_t, \mathbf{u}_t)$
- evaluate gradient
- update

Guided cost learning algorithm [2]

As summation over policy samples is quite costly, we can use weights:

$$w_j = \frac{p(\tau)\ exp(r_\psi(\tau_j))}{\pi(\tau_j)} \tag{9}$$



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IRL and GANs

- Policy tries to fool the reward that it is a human demo
- Reward tries to distinguish between human demo and artificial one

Correspondence:

- trajectory τ
- policy $\pi \sim q(\tau)$
- reward **r**

- sample **x**
- generator **G**
- discriminator **D**

OPIRL: Sample Efficient Off-Policy Inverse Reinforcement Learning via Distribution Matching [3]

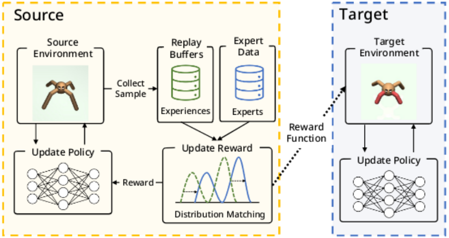

Fig. 1: **Overview of OPIRL framework:** OPIRL (1) achieves high sample efficiency and (2) recovers a robust reward function that can be transferred and generalize across different environments by applying off-policy training in distribution matching.

OPIRL: Sample Efficient Off-Policy Inverse Reinforcement Learning via Distribution Matching [3]

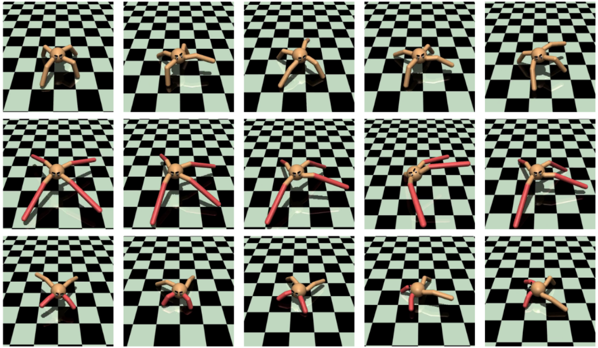

Fig. 9: **Top row:** The original quadrupedal ant moving from left to right. **Middle row:** BigAnt with successfully learning the policy with transferred reward function from the original quadrupedal ant. **Bottom row:** AmputatedAnt moving from left to right. Due to the amputated legs, it cannot move like the other environments, instead it turns backward to move in the right direction.

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DriveIRL: Drive in Real Life with Inverse Reinforcement Learning [4]

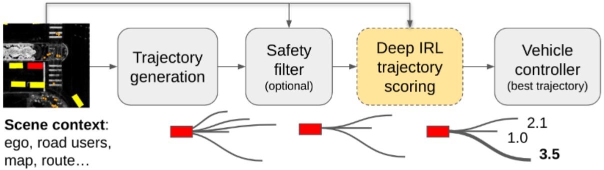
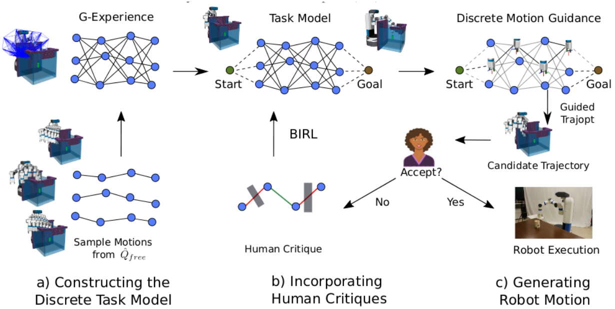
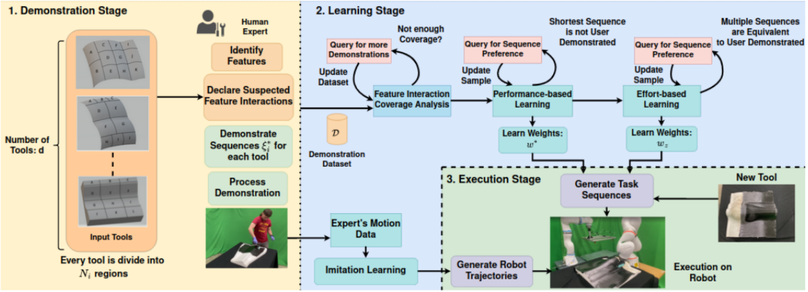


Fig. 1. DriveIRL architecture. The learned scoring component is indicated with a dotted boundary.

Human-Guided Motion Planning in Partially Observable Environments [5]



Inverse Reinforcement Learning Framework for Transferring Task Sequencing Policies from Humans to Robots in Manufacturing Applications [6]



Online Prediction of Lane Change with a Hierarchical Learning-Based Approach [7]

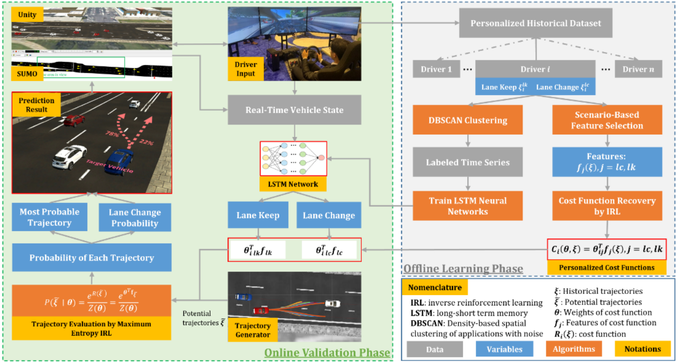


Fig. 1. System workflow of the hierarchical learning-based approach for lane-change prediction with an offline learning phase (in grey) and an online validation phase (in green).

Personalized Car Following for Autonomous Driving with Inverse Reinforcement Learning [8]

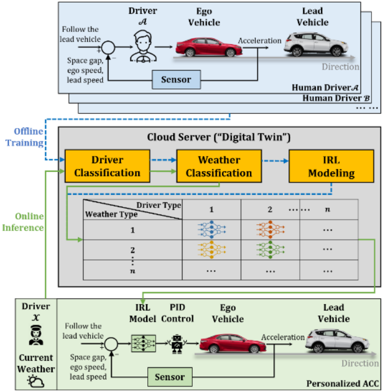


Fig. 1. System architecture of the proposed personalized adaptive cruise control (P-ACC) system.

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