# Learning robust rewards with adversarial inverse reinforcement learning (J. Fu, K. Luo, S. Levine)

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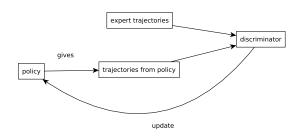
June 20, 2018

## Inverse Reinforcement Learning (IRL)

- Infer an expert's reward function from demonstrations
- Alternative: imitation learning, which does not recover reward
- Advantage: re-optimize reward in novel environment, analyze agent's intentions

# Adversarial learning

- Two agents working against each other
- GANs try to mimic an input data set
- Here: discriminator tries to classify expert data from policy samples, policy tries to confuse the discriminator
- Advantage: policy (generator) does not see the data set directly, better generalization



## Disentangled rewards

- Learned reward function can only depent on current state s
- Or else reward not robust to changes in dynamics
- Reward transformation:  $\hat{r}(s, a, s') = r(s, a, s') + \gamma \phi(s') \phi(s)$
- $D_{\theta,\phi} = \frac{\exp\{f_{\theta,\phi}(s,a,s')\}}{\exp\{f_{\theta,\phi}(s,a,s')\}+\pi(a|s)}$
- $f_{\theta,\phi}(s,a,s') = g_{\theta}(s,a) + \gamma h_{\phi}(s') h_{\phi}(s)$
- ullet With reward approximator  $g_{ heta}$  and shaping term  $h_{\phi}$

#### Code

$$D_{\theta,\phi} = \frac{\exp\{f_{\theta,\phi}(s,a,s')\}}{\exp\{f_{\theta,\phi}(s,a,s')\} + \pi(a|s)} = \exp\left(f_{\theta,\phi} - \log(\exp(f_{\theta,\phi}) + \pi(a|s))\right)$$

$$f_{\theta,\phi}(s,a,s') = g_{\theta}(s,a) + \gamma h_{\phi}(s') - h_{\phi}(s)$$
From sixt state we

### From airl\_state.py:

```
self.reward = reward\_arch (rew\_input , dout=1, **reward\_arch\_args) \\ \# value function shaping \\ fitted\_value\_fn\_n = value\_fn\_arch (self.nobs\_t , dout=1) \\ self.value\_fn = fitted\_value\_fn = value\_fn\_arch (self.obs\_t , dout=1) \\ \# Define log p\_tau(a|s) = r + gamma * V(s') - V(s) \\ self.value\_fn = self.reward + self.gamma*fitted\_value\_fn\_n \\ log\_p\_tau = self.reward + self.gamma*fitted\_value\_fn\_n - fitted\_value\_fn \\ log\_q\_tau = self.lprobs \\ log\_p\_q = tf.reduce\_logsumexp([log\_p\_tau , log\_q\_tau], axis=0) \\ self.discrim\_output = tf.exp(log\_p\_tau\_log\_pq) \\ self.loss = -tf.reduce\_mean(self.labels*(log\_p\_tau\_log\_pq)) \\ + (1-self.labels)*(log\_q\_tau\_log\_pq))
```

# Algorithm: Adversarial inverse reinforcement learning

```
Obtain expert trajectories \tau_i^E Initialize policy \pi and discriminator D_{\theta,\phi}. for step t in \{1,...,N\} do Collect trajectories \tau_i = (s_0, a_0,...,s_T,a_T) by executing \pi. Train D_{\theta,\phi} via binary logistic regression to classify expert data \tau_i^E from samples \tau_i. Update reward r_{\theta,\phi}(s,a,s') \leftarrow \log D_{\theta,\phi}(s,a,s') - \log(1-D_{\theta,\phi}(s,a,s')) Update \pi with respect to r_{\theta,\phi} using any policy optimization method. end for
```

#### Code

#### From irl\_batch\_polopt.py:

```
#itr is the iteration parameter
paths = self.obtain_samples(itr)
paths = self.compute_irl(paths, itr=itr)
samples_data = self.process_samples(itr, paths)
self.optimize_policy(itr, samples_data)
```

# Experiments: Ant

- observation space of 111, action space of 8
- reward = forward\_reward ctrl\_cost contact\_cost + flipped\_rew
- linear function approximator for the reward term g and a 2-layer
   ReLU network for the shaping term h
- policy: two-layer (32 units) ReLU gaussian policy

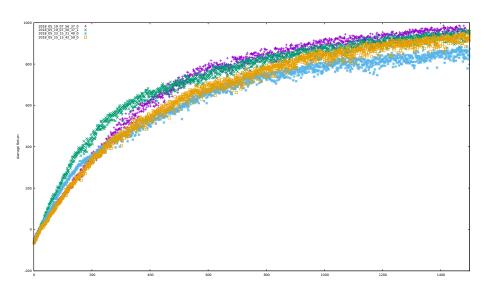
Table 1: Results on transfer learning tasks. Mean scores (higher is better) are reported over 5 runs. We also include results for TRPO optimizing the ground truth reward, and the performance of a policy learned via GAIL on the training environment.

	State-Only?	Pointmass-Maze	Ant-Disabled
GAN-GCL	No	-40.2	-44.8
GAN-GCL	Yes	-41.8	-43.4
AIRL (ours)	No	-31.2	-41.4
AIRL (ours)	Yes	-8.82	130.3
GAIL, policy transfer	N/A	-29.9	-58.8
TRPO, ground truth	N/A	-8.45	315.5

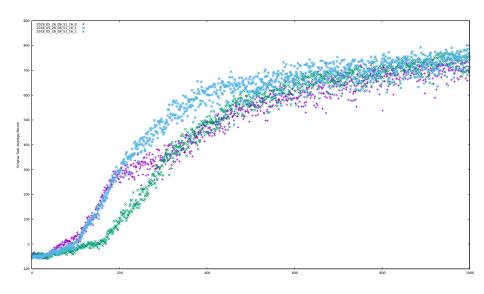
Table 2: Results on imitation learning benchmark tasks. Mean scores (higher is better) are reported across 5 runs.

	Pendulum	Ant	Swimmer	Half-Cheetah
GAN-GCL	-261.5	460.6	-10.6	-670.7
GAIL	-226.0	1358.7	140.2	1642.8
AIRL (ours)	-204.7	1238.6	139.1	1839.8
Expert (TRPO)	-179.6	1537.9	141.1	1811.2
Random	-634.5	-108.1	-11.5	-988.4

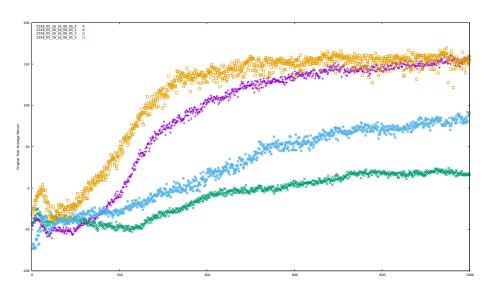
# ant\_data\_collect



## ant\_state\_irl



## ant\_transfer



#### Source and links

- https://sites.google.com/view/adversarial-irl
- https://github.com/mvieth/inverse\_rl
- https://arxiv.org/abs/1710.11248