IASD M2 at Paris Dauphine

Deep Reinforcement Learning

21: Inverse Reinforcement Learning

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Acknowledgement

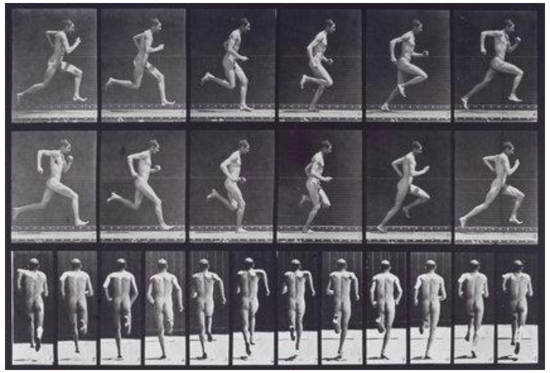
These materials are based on the seminal course of Sergey Levine CS285

Today's Lecture

1. So far: manually design reward function to define a task
2. What if we want to *learn* the reward function from observing an expert, and then use reinforcement learning?
3. Apply approximate optimality model from last time, but now learn the reward!

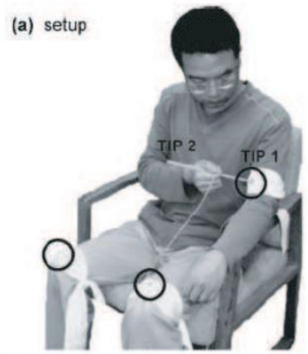
- Goals:
  - Understand the inverse reinforcement learning problem definition
  - Understand how probabilistic models of behavior can be used to derive inverse reinforcement learning algorithms
  - Understand a few practical inverse reinforcement learning algorithms we can use

Optimal Control as a Model of Human Behavior



Muybridge (c. 1870)

Mombaur et al. ‘09



Li & Todorov ‘06

Ziebart ‘08

$$\mathbf{a}_1, \ldots, \mathbf{a}_T = \arg \max_{\mathbf{a}_1, \ldots, \mathbf{a}_T} \sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t)$$

$$\mathbf{s}_{t+1} = f(\mathbf{s}_t, \mathbf{a}_t)$$

optimize this to explain the data

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

$$\mathbf{a}_t \sim \pi(\mathbf{a}_t|\mathbf{s}_t)$$

Why should we worry about learning rewards?

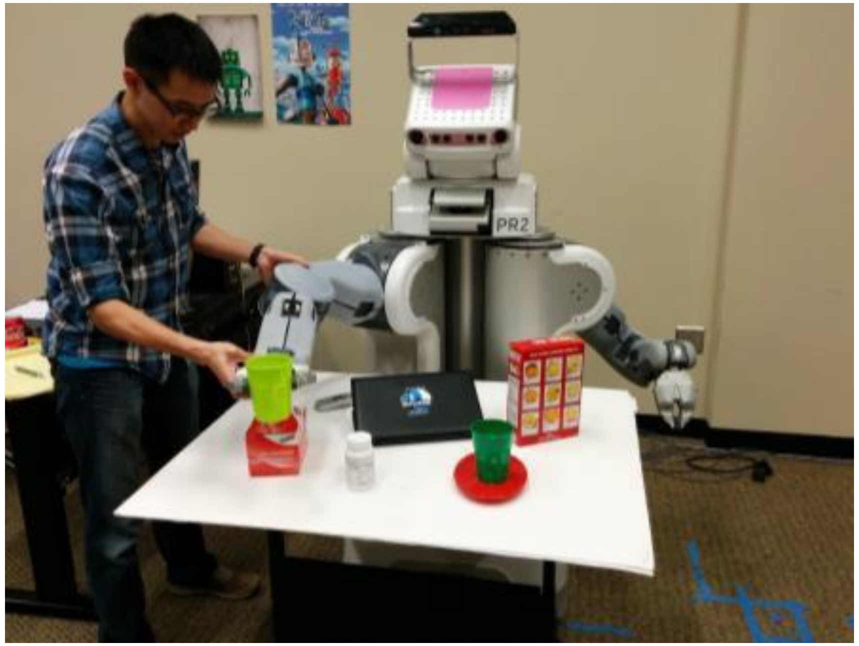
The imitation learning perspective

Standard imitation learning:

- copy the *actions* performed by the expert
- no reasoning about outcomes of actions

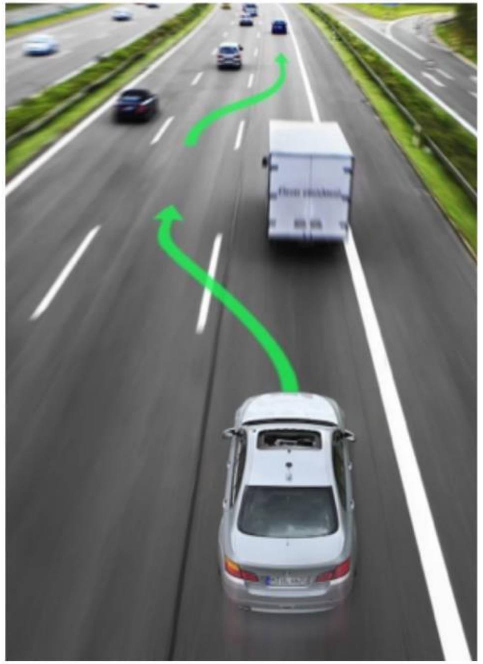
Human imitation learning:

- copy the *intent* of the expert
- might take very different actions!



Why should we worry about learning rewards?

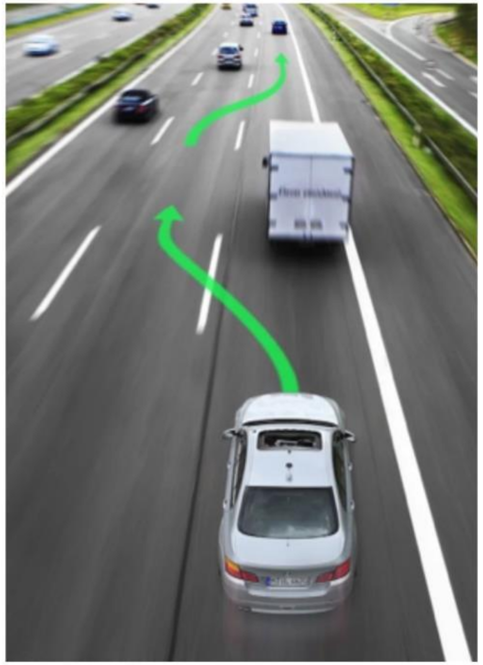
The reinforcement learning perspective



what is the reward?

Inverse reinforcement learning

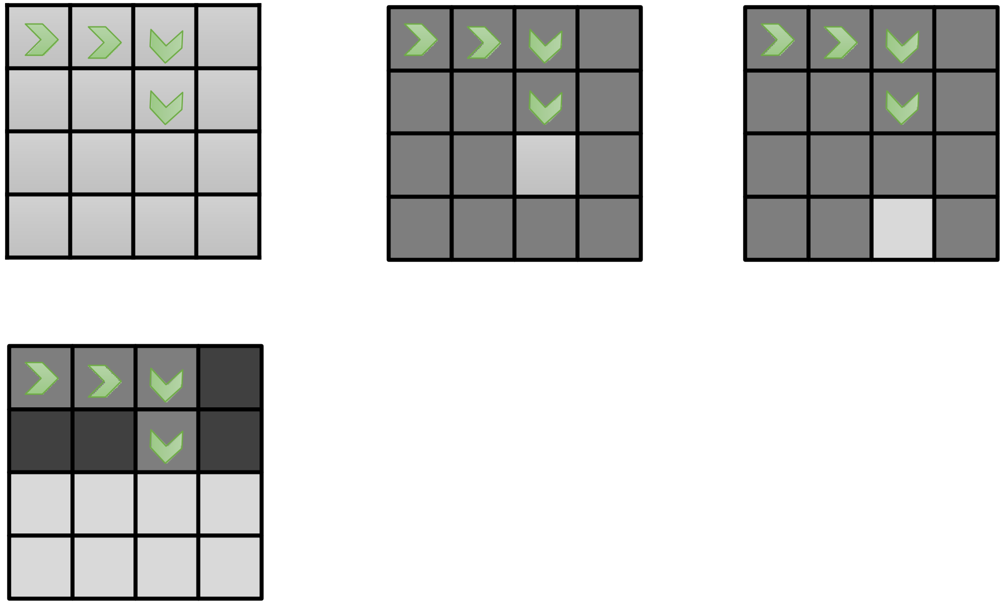
Infer reward functions from demonstrations



$$r(\mathbf{s}, \mathbf{a})$$

by itself, this is an **underspecified** problem

many reward functions can explain the **same** behavior



A bit more formally

"forward" reinforcement learning

given:

states $\mathbf{s} \in \mathcal{S}$, actions $\mathbf{a} \in \mathcal{A}$

(sometimes) transitions $p(\mathbf{s}'|\mathbf{s}, \mathbf{a})$

reward function $r(\mathbf{s}, \mathbf{a})$

learn $\pi^\star(\mathbf{a}|\mathbf{s})$

inverse reinforcement learning

given:

states $\mathbf{s} \in \mathcal{S}$, actions $\mathbf{a} \in \mathcal{A}$

(sometimes) transitions $p(\mathbf{s}'|\mathbf{s}, \mathbf{a})$

samples $\{\tau_i\}$ sampled from $\pi^\star(\tau)$

learn $r_\psi(\mathbf{s}, \mathbf{a})$

reward parameters

...and then use it to learn $\pi^\star(\mathbf{a}|\mathbf{s})$

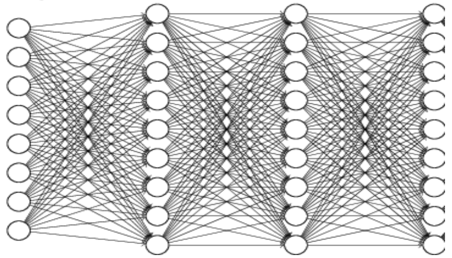
---

linear reward function:

$r_\psi(\mathbf{s}, \mathbf{a}) = \sum_i \psi_i f_i(\mathbf{s}, \mathbf{a}) = \psi^T \mathbf{f}(\mathbf{s}, \mathbf{a})$

neural net reward function:

$\mathbf{s}$
$\mathbf{a}$



$r_\psi(\mathbf{s}, \mathbf{a})$

parameters ψ

Feature matching IRL

linear reward function:

$$r_\psi(\mathbf{s},\mathbf{a}) = \sum_i \psi_i f_i(\mathbf{s},\mathbf{a}) = \psi^T \mathbf{f}(\mathbf{s},\mathbf{a})$$

if features $\mathbf{f}$ are important, what if we match their expectations?

let π^{r_ψ} be the optimal policy for r_ψ

pick ψ such that $E_{\pi^{r_\psi}}[\mathbf{f}(\mathbf{s},\mathbf{a})] = E_{\pi^\star}[\mathbf{f}(\mathbf{s},\mathbf{a})]$

still ambiguous!

state-action marginal under π^{r_ψ}

unknown optimal policy
approximate using expert samples

maximum margin principle:

$$\max_{\psi,m} m \qquad \text{such that } \psi^T E_{\pi^\star}[\mathbf{f}(\mathbf{s},\mathbf{a})] \geq \underbrace{\max_{\pi\in\Pi} \psi^T E_\pi[\mathbf{f}(\mathbf{s},\mathbf{a})] + m}$$

need to somehow "weight" by similarity between $\pi^\star$ and π

Feature matching IRL & maximum margin

remember the "SVM trick":

$$\max_{\psi,m} m \qquad \text{such that } \psi^T E_{\pi^\star}[\mathbf{f}(\mathbf{s},\mathbf{a})] \geq \max_{\pi\in\Pi} \psi^T E_\pi[\mathbf{f}(\mathbf{s},\mathbf{a})] + m$$

$$\Updownarrow$$

$$\min_{\psi} \frac{1}{2}\|\psi\|^2 \qquad \text{such that } \psi^T E_{\pi^\star}[\mathbf{f}(\mathbf{s},\mathbf{a})] \geq \max_{\pi\in\Pi} \psi^T E_\pi[\mathbf{f}(\mathbf{s},\mathbf{a})] + D(\pi,\pi^\star)$$

e.g., difference in feature expectations!

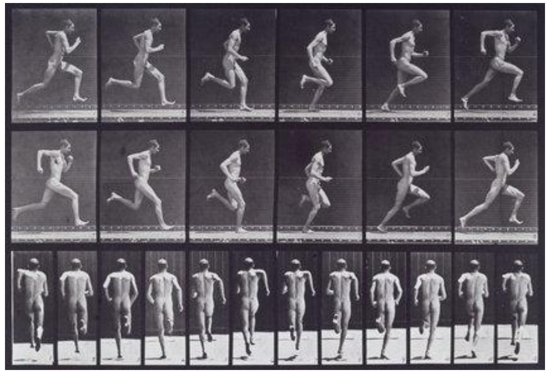
Issues:

- Maximizing the margin is a bit arbitrary
- No clear model of expert suboptimality (can add slack variables…)
- Messy constrained optimization problem – not great for deep learning!

Further reading:

- Abbeel & Ng: Apprenticeship learning via inverse reinforcement learning
- Ratliff et al: Maximum margin planning

Optimal Control as a Model of Human Behavior



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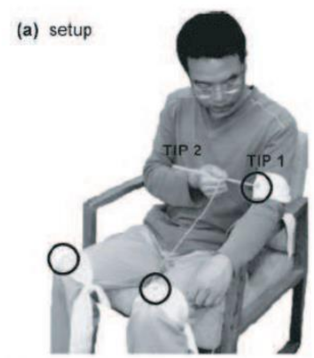
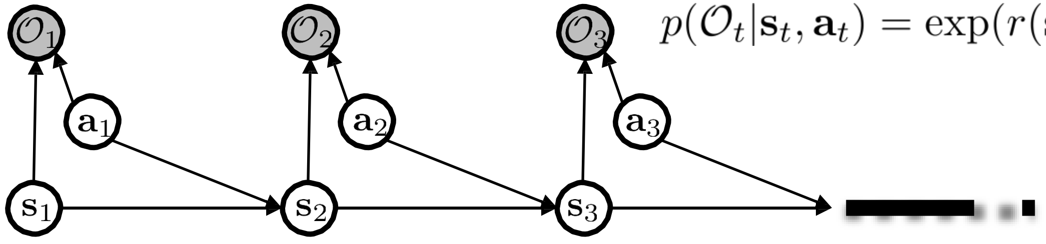


Li & Todorov '06

Ziebart '08

$$p(\mathbf{s}_{1:T}, \mathbf{a}_{1:T} | \mathcal{O}_{1:T})$$



$$p(\mathcal{O}_t | \mathbf{s}_t, \mathbf{a}_t) = \exp(r(\mathbf{s}_t, \mathbf{a}_t))$$

$$p(\mathbf{s}_1) \qquad p(\mathbf{s}_{t+1} | \mathbf{s}_t, \mathbf{a}_t)$$

A probabilistic graphical model of decision making

$$p(\underbrace{\mathbf{s}_{1:T}, \mathbf{a}_{1:T}}_{\tau}) = ??$$

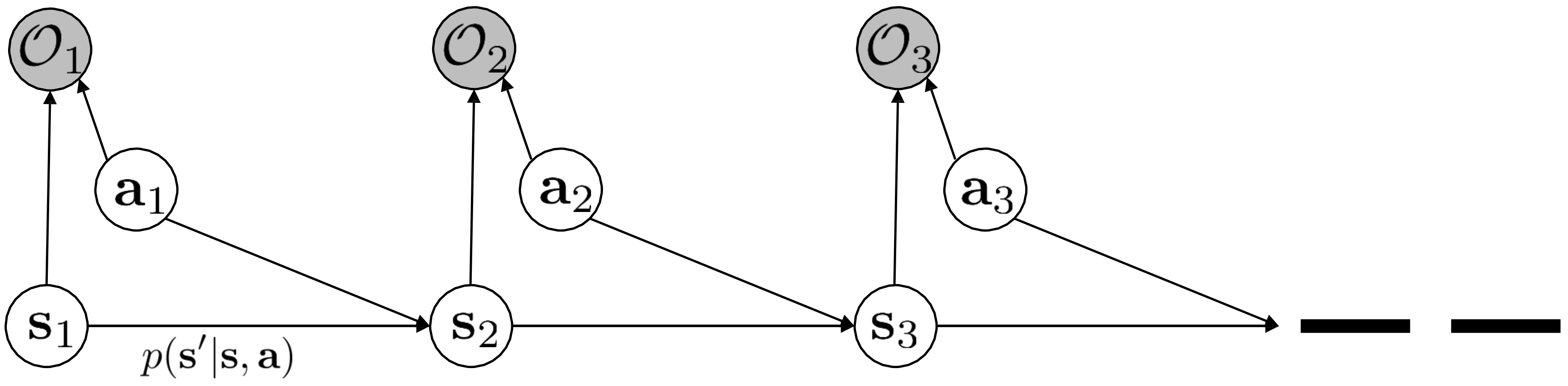
no assumption of optimal behavior!

$$p(\tau | \mathcal{O}_{1:T})$$

$$p(\mathcal{O}_t | \mathbf{s}_t, \mathbf{a}_t) = \exp(r(\mathbf{s}_t, \mathbf{a}_t))$$

$$p(\tau | \mathcal{O}_{1:T}) = \frac{p(\tau, \mathcal{O}_{1:T})}{p(\mathcal{O}_{1:T})}$$

$$\propto p(\tau) \prod_t \exp(r(\mathbf{s}_t, \mathbf{a}_t)) = p(\tau) \exp\left(\sum_t r(\mathbf{s}_t, \mathbf{a}_t)\right)$$



Learning the Reward Function

Learning the optimality variable

$$p(\mathcal{O}_t|\mathbf{s}_t,\mathbf{a}_t,\psi) = \exp(r_\psi(\mathbf{s}_t,\mathbf{a}_t))$$

reward parameters

given:

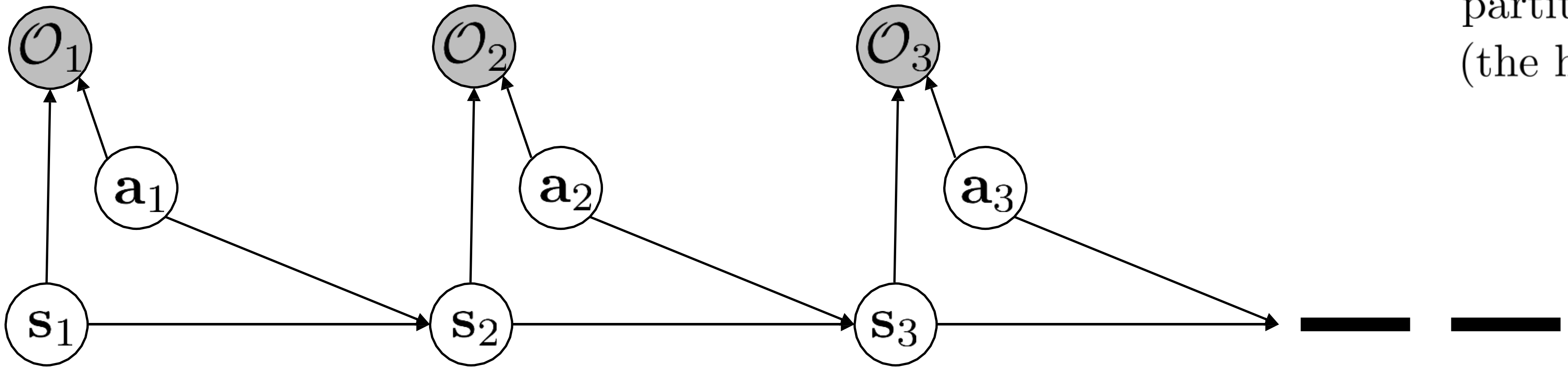
samples $\{\tau_i\}$ sampled from $\pi^\star(\tau)$

$$p(\tau|\mathcal{O}_{1:T},\psi) \propto \cancel{p(\tau)} \exp\left(\sum_t r_\psi(\mathbf{s}_t,\mathbf{a}_t)\right)$$

can ignore (independent of ψ)

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

partition function
(the hard part)



The IRL partition function

$$\max_{\psi} \frac{1}{N} \sum_{i=1}^{N} r_\psi(\tau_i) - \log Z \qquad Z = \int p(\tau) \exp(r_\psi(\tau)) d\tau$$

$$\nabla_\psi \mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \nabla_\psi r_\psi(\tau_i) - \underbrace{\frac{1}{Z} \int p(\tau) \exp(r_\psi(\tau))}_{p(\tau|\mathcal{O}_{1:T}, \psi)} \nabla_\psi r_\psi(\tau) d\tau$$

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

estimate with expert samples

soft optimal policy under current reward

Estimating the expectation

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

$$E_{\tau \sim p(\tau|\mathcal{O}_{1:T},\psi)}\left[\nabla_\psi \sum_{t=1}^{T} r_\psi(\mathbf{s}_t, \mathbf{a}_t)\right]$$

$$= \sum_{t=1}^{T} E_{(\mathbf{s}_t,\mathbf{a}_t) \sim p(\mathbf{s}_t,\mathbf{a}_t|\mathcal{O}_{1:T},\psi)}\left[\nabla_\psi r_\psi(\mathbf{s}_t, \mathbf{a}_t)\right]$$

$$p(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O}_{1:T}, \psi)p(\mathbf{s}_t|\mathcal{O}_{1:T}, \psi)$$

where have we seen this before?

$$= \frac{\beta(\mathbf{s}_t, \mathbf{a}_t)}{\beta(\mathbf{s}_t)} \qquad \propto \alpha(\mathbf{s}_t)\beta(\mathbf{s}_t)$$

$$p(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O}_{1:T}, \psi)p(\mathbf{s}_t|\mathcal{O}_{1:T}, \psi) \propto \beta(\mathbf{s}_t, \mathbf{a}_t)\alpha(\mathbf{s}_t)$$

backward message forward message

Estimating the expectation

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

let $\mu_t(\mathbf{s}_t, \mathbf{a}_t) \propto \beta(\mathbf{s}_t, \mathbf{a}_t)\alpha(\mathbf{s}_t)$

$$\sum_{t=1}^{T} \int \int \mu_t(\mathbf{s}_t, \mathbf{a}_t) \nabla_\psi r_\psi(\mathbf{s}_t, \mathbf{a}_t) d\mathbf{s}_t d\mathbf{a}_t$$

$$= \sum_{t=1}^{T} \vec{\mu}_t^T \nabla_\psi \vec{r}_\psi$$

state-action visitation probability for each $(\mathbf{s}_t, \mathbf{a}_t)$

The MaxEnt IRL algorithm

1. Given ψ, compute backward message $\beta(\mathbf{s}_t, \mathbf{a}_t)$ (see previous lecture)
2. Given ψ, compute forward message $\alpha(\mathbf{s}_t)$ (see previous lecture)
3. Compute $\mu_t(\mathbf{s}_t, \mathbf{a}_t) \propto \beta(\mathbf{s}_t, \mathbf{a}_t)\alpha(\mathbf{s}_t)$
4. Evaluate $\nabla_\psi \mathcal{L} = \frac{1}{N}\sum_{i=1}^N \sum_{t=1}^T \nabla_\psi r_\psi(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) - \sum_{t=1}^T \int\int \mu_t(\mathbf{s}_t, \mathbf{a}_t)\nabla_\psi r_\psi(\mathbf{s}_t, \mathbf{a}_t) d\mathbf{s}_t d\mathbf{a}_t$
5. $\psi \leftarrow \psi + \eta \nabla_\psi \mathcal{L}$

Why MaxEnt?

in the case where $r_\psi(\mathbf{s}_t, \mathbf{a}_t) = \psi^T \mathbf{f}(\mathbf{s}_t, \mathbf{a}_t)$, we can show that it optimizes

$$\max_\psi \mathcal{H}(\pi^{r_\psi}) \text{ such that } E_{\pi^{r_\psi}}[\mathbf{f}] = E_{\pi^\star}[\mathbf{f}]$$

optimal max-ent policy under r^ψ

unknown expert policy estimated with samples

as random as possible while matching features

Ziebart et al. 2008: Maximum Entropy Inverse Reinforcement Learning

Maximum Entropy Inverse Reinforcement Learning

Brian D. Ziebart, Andrew Maas, J.Andrew Bagnell, and Anind K. Dey
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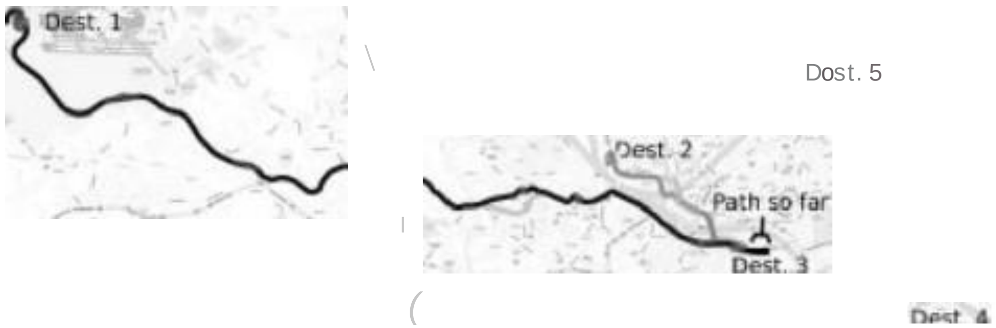
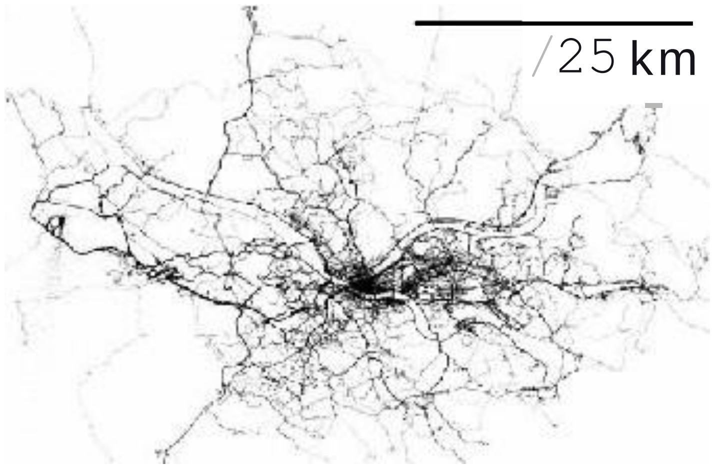
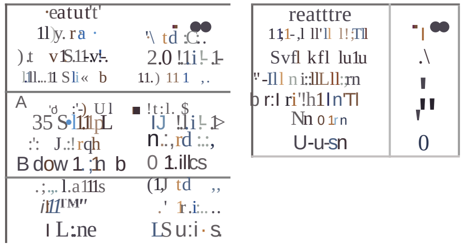






Approximations in High Dimensions

What's missing so far?

- MaxEnt IRL so far requires…
  - Solving for (soft) optimal policy in the inner loop
  - Enumerating all state-action tuples for visitation frequency and gradient

- To apply this in practical problem settings, we need to handle…
  - Large and continuous state and action spaces
  - States obtained via sampling only
  - Unknown dynamics

Unknown dynamics & large state/action spaces

Assume we don't know the dynamics, but we can sample, like in standard RL

recall:

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

estimate with expert samples

soft optimal policy under current reward

idea: learn $p(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O}_{1:T}, \psi)$ using any max-ent RL algorithm
then run this policy to sample $\{\tau_j\}$

$$J(\theta) = \sum_t E_{\pi(\mathbf{s}_t,\mathbf{a}_t)}[r_\psi(\mathbf{s}_t,\mathbf{a}_t)] + E_{\pi(\mathbf{s}_t)}[\mathcal{H}(\pi(\mathbf{a}|\mathbf{s}_t))]$$

$$\nabla_\psi \mathcal{L} \approx \frac{1}{N}\sum_{i=1}^{N} \nabla_\psi r_\psi(\tau_i) - \frac{1}{M}\sum_{j=1}^{M} \nabla_\psi r_\psi(\tau_j)$$

sum over expert samples

sum over policy samples

More efficient sample-based updates

$$\nabla_\psi \mathcal{L} \approx \frac{1}{N}\sum_{i=1}^{N} \nabla_\psi r_\psi(\tau_i) - \frac{1}{M}\sum_{j=1}^{M} \nabla_\psi r_\psi(\tau_j)$$

sum over expert samples   sum over policy samples

improve (a little) ~~learn~~ $p(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O}_{1:T}, \psi)$ using any max-ent RL algorithm

then run this policy to sample $\{\tau_j\}$

looks expensive! what if we use "lazy" policy optimization?

problem: estimator is now biased! wrong distribution!

solution 1: use importance sampling

$$\nabla_\psi \mathcal{L} \approx \frac{1}{N}\sum_{i=1}^{N} \nabla_\psi r_\psi(\tau_i) - \frac{1}{\sum_j w_j}\sum_{j=1}^{M} w_j \nabla_\psi r_\psi(\tau_j) \qquad w_j = \frac{p(\tau)\exp(r_\psi(\tau_j))}{\pi(\tau_j)}$$

Importance sampling

$$\nabla_\psi \mathcal{L} \approx \frac{1}{N}\sum_{i=1}^{N} \nabla_\psi r_\psi(\tau_i) - \frac{1}{\sum_j w_j}\sum_{j=1}^{M} w_j \nabla_\psi r_\psi(\tau_j)$$

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

$$\frac{\cancel{p(\mathbf{s}_1)}\prod_t \cancel{p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)}\exp(r_\psi(\mathbf{s}_t,\mathbf{a}_t))}{\cancel{p(\mathbf{s}_1)}\prod_t \cancel{p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)}\pi(\mathbf{a}_t|\mathbf{s}_t)}$$

$$= \frac{\exp(\sum_t r_\psi(\mathbf{s}_t,\mathbf{a}_t))}{\prod_t \pi(\mathbf{a}_t|\mathbf{s}_t)}$$

each policy update w.r.t. r_ψ brings us closer to the target distribution!

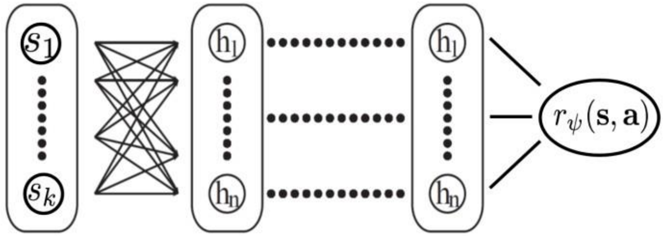
guided cost learning algorithm

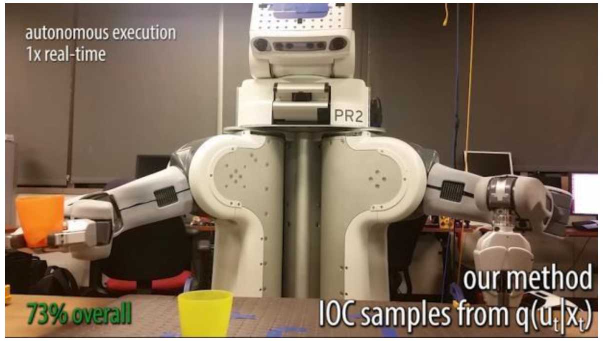
(Finn et al. ICML '16)

initial
policy π

human
demonstrations

generate policy
samples from π





Update reward using
samples & demos

$$w_j = \frac{\exp(r_\psi(\tau_j))}{\pi(\tau_j)}$$

update π w.r.t. reward

policy π

reward r

$$\nabla_\psi \mathcal{L} \approx \frac{1}{N} \sum_{i=1}^{N} \nabla_\psi r_\psi(\tau_i) - \frac{1}{\sum_j w_j} \sum_{j=1}^{M} w_j \nabla_\psi r_\psi(\tau_j)$$

IRL and GANs

It looks a bit like a game...

initial
policy π

samples from $\pi_\theta(\tau)$

human
demonstrations

samples from $\pi^\star(\tau)$

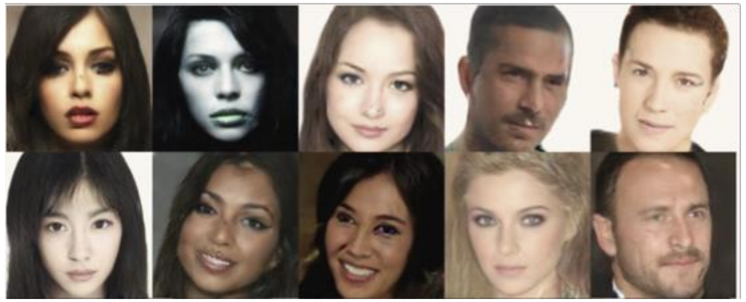
$$\nabla_\psi \mathcal{L} \approx \frac{1}{N}\sum_{i=1}^{N} \nabla_\psi r_\psi(\tau_i) - \frac{1}{\sum_j w_j}\sum_{j=1}^{M} w_j \nabla_\psi r_\psi(\tau_j)$$

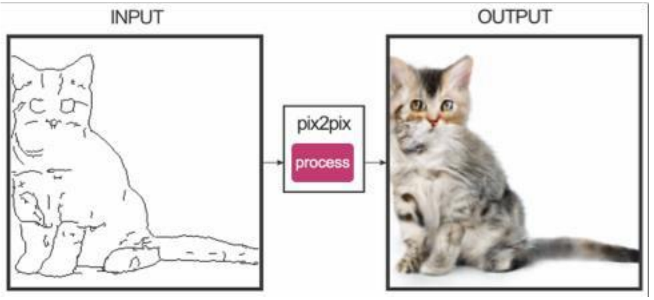
demos are made more likely, samples less likely

$$\nabla_\theta \mathcal{L} \approx \frac{1}{M}\sum_{j=1}^{M} \nabla_\theta \log \pi_\theta(\tau_j) r_\psi(\tau_j)$$

policy changed to make it *harder* to distinguish from demos

Generative Adversarial Networks



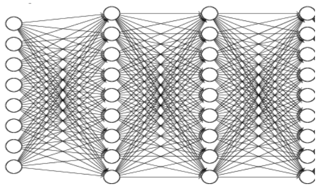


Zhu et al. '17

Arjovsky et al. '17

Isola et al. '17

"generator"

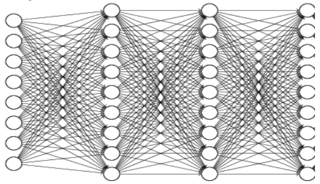
$\mathbf{z}$  $p_\theta(\mathbf{x}|\mathbf{z})$

samples from $p_\theta(\mathbf{x})$

data ("demonstrations")

samples from $\pi_\theta(\tau)$

$D(\mathbf{x}) = p_\psi(\text{real image}|\mathbf{x})$

$\mathbf{x}$ 

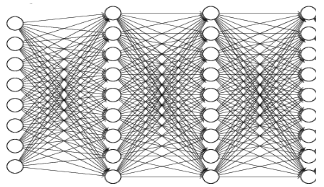
$$\psi = \arg\max_\psi \frac{1}{N} \sum_{\mathbf{x} \sim p^\star} \log D_\psi(\mathbf{x}) + \frac{1}{M} \sum_{\mathbf{x} \sim p_\theta} \log(1 - D_\psi(\mathbf{x}))$$

$$\theta \leftarrow \arg\max_\theta E_{\mathbf{x} \sim p_\theta} \log D_\psi(\mathbf{x})$$

Goodfellow et al. '14

Inverse RL as a GAN

$D(\mathbf{x}) = p_\psi(\text{real image}|\mathbf{x})$

$\mathbf{x}$ 

which discriminator is best?

$$D^\star(\mathbf{x}) = \frac{p^\star(\mathbf{x})}{p_\theta(\mathbf{x}) + p^\star(\mathbf{x})}$$

for IRL, optimal policy approaches $\pi_\theta(\tau) \propto p(\tau)\exp(r_\psi(\tau))$

choose this parameterization for discriminator:

optimize Z w.r.t. same objective as ψ!

$$D_\psi(\tau) = \frac{p(\tau)\frac{1}{Z}\exp(r(\tau))}{p_\theta(\tau) + p(\tau)\frac{1}{Z}\exp(r(\tau))} = \frac{\cancel{p(\tau)}\frac{1}{Z}\exp(r(\tau))}{\cancel{p(\tau)}\prod_t \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) + \cancel{p(\tau)}\frac{1}{Z}\exp(r(\tau))} = \frac{\frac{1}{Z}\exp(r(\tau))}{\prod_t \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) + \frac{1}{Z}\exp(r(\tau))}$$

optimize this w.r.t. ψ

$$\psi \leftarrow \arg\max_\psi E_{\tau\sim p^\star}[\log D_\psi(\tau)] + E_{\tau\sim\pi_\theta}[\log(1 - D_\psi(\tau))]$$

we don't need importance weights anymore – they are subsumed into Z

Finn*, Christiano* et al. "A Connection Between Generative Adversarial Networks, Inverse Reinforcement Learning, and Energy-Based Models."

Inverse RL as a GAN

generator/policy

$\pi_\theta(\tau)$

samples from $\pi_\theta(\tau)$

data/demonstrations

samples from $p^\star(\tau)$

$$\psi \leftarrow \arg\max_\psi E_{\tau\sim p^\star}[\log D_\psi(\tau)] + E_{\tau\sim\pi_\theta}[\log(1 - D_\psi(\tau))]$$

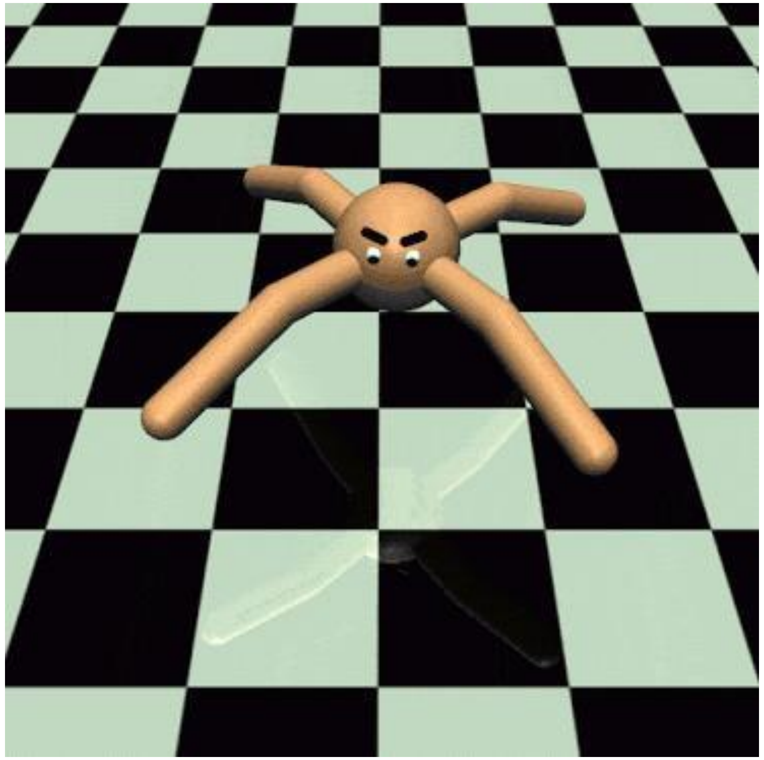
$$D_\psi(\tau) = \frac{\frac{1}{Z}\exp(r(\tau))}{\prod_t \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) + \frac{1}{Z}\exp(r(\tau))}$$

$$\nabla_\theta \mathcal{L} \approx \frac{1}{M}\sum_{j=1}^{M} \nabla_\theta \log \pi_\theta(\tau_j) r_\psi(\tau_j)$$

policy changed to make it *harder* to distinguish from demos

Finn*, Christiano* et al. "A Connection Between Generative Adversarial Networks, Inverse Reinforcement Learning, and Energy-Based Models."

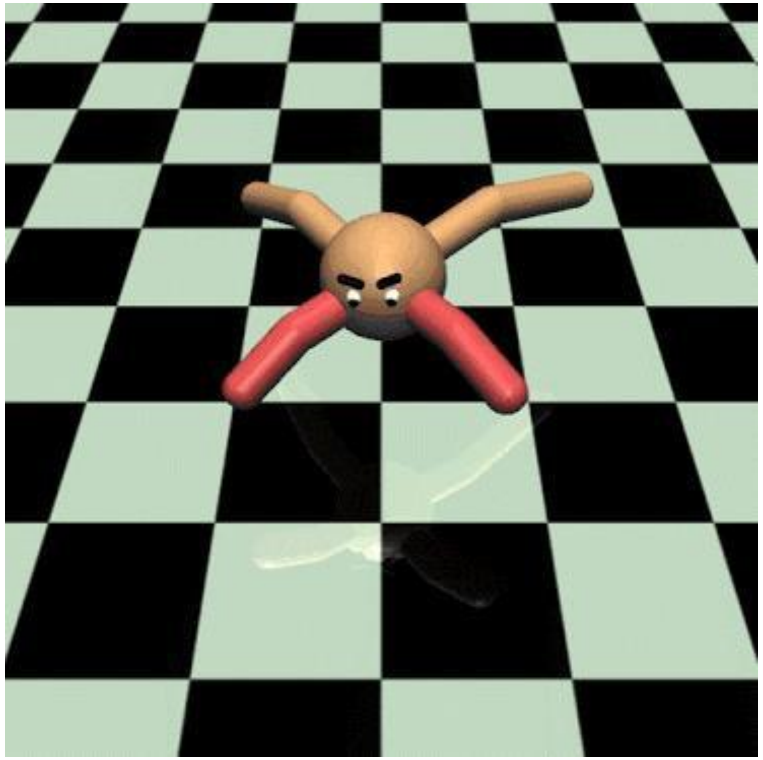
Generalization via inverse RL



what can we learn from the demonstration to enable better **transfer**?

need to decouple the **goal** from the **dynamics**!

policy = **reward** + **dynamics**



demonstration

reproduce behavior under different conditions

Fu et al. Learning Robust Rewards with Adversarial Inverse Reinforcement Learning

Can we just use a regular discriminator?

generator/policy

$\pi_\theta(\tau)$

samples from $\pi_\theta(\tau)$

data/demonstrations

samples from $p^\star(\tau)$

$$\psi \leftarrow \arg\max_\psi E_{\tau\sim p^\star}[\log D_\psi(\tau)] + E_{\tau\sim\pi_\theta}[\log(1 - D_\psi(\tau))]$$

$D_\psi(\tau) =$ standard binary neural net classifier

$$\nabla_\theta \mathcal{L} \approx \frac{1}{M}\sum_{j=1}^{M} \nabla_\theta \log \pi_\theta(\tau_j) \log D_\psi(\tau_j)$$

policy changed to make it *harder* to distinguish from demos

Pros & cons:

+ often simpler to set up optimization, fewer moving parts

- discriminator knows *nothing* at convergence

- generally cannot reoptimize the "reward"

Ho & Ermon. Generative adversarial imitation learning.

IRL as adversarial optimization

Guided Cost Learning

Finn et al., ICML 2016

minimized maximized

reward function

robot attempt

human demonstrations

learns distribution $p(\tau)$ such that demos have max likelihood

$p(\tau) \propto \exp(r(\tau))$ (MaxEnt model)

$$D(\tau) = \frac{\frac{1}{Z}\exp(r(\tau))}{\frac{1}{Z}\exp(r(\tau)) + \pi(\tau)}$$

actually the same thing!

Generative Adversarial Imitation Learning

Ho & Ermon, NIPS 2016

False True

classifier

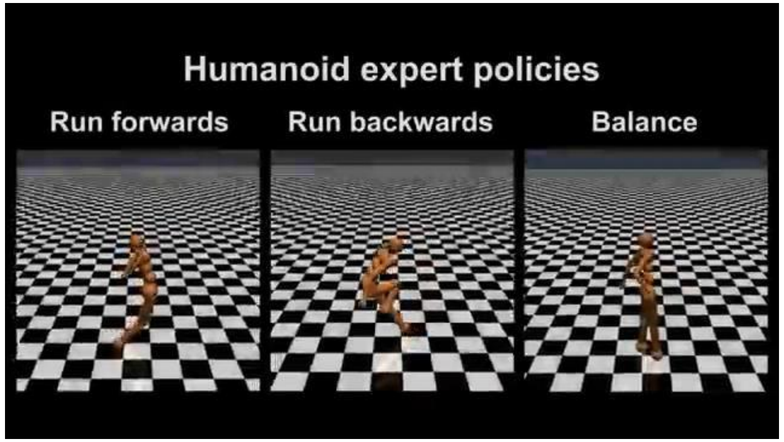
robot attempt

human demonstrations

$D(\tau) = \text{probability } \tau \text{ is a demo}$

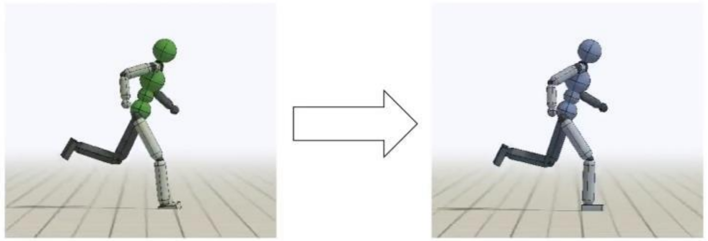
use $\log D(\tau)$ as "reward"

$D(\tau) = \text{some classifier}$



Hausman, Chebotar, Schaal, Sukhatme, Lim

Motion Imitation



Reference Motion (Mocap)

Learned Policy (Simulation)

the goal is to train a simulated character to imitate the motion.

Peng, Kanazawa, Toyer, Abbeel, Levine

Suggested Reading on Inverse RL

Classic Papers:
Abbeel & Ng ICML '04. *Apprenticeship Learning via Inverse Reinforcement Learning.* Good introduction to inverse reinforcement learning
Ziebart et al. AAAI '08. *Maximum Entropy Inverse Reinforcement Learning*. Introduction to probabilistic method for inverse reinforcement learning

Modern Papers:
Finn et al. ICML '16. *Guided Cost Learning*. Sampling based method for MaxEnt IRL that handles unknown dynamics and deep reward functions
Wulfmeier et al. arXiv '16. *Deep Maximum Entropy Inverse Reinforcement Learning.* MaxEnt inverse RL using deep reward functions
Ho & Ermon NIPS '16. *Generative Adversarial Imitation Learning*. Inverse RL method using generative adversarial networks
Fu, Luo, Levine ICLR '18. Learning Robust Rewards with Adversarial Inverse Reinforcement Learning