Overview of Robot Decision Making

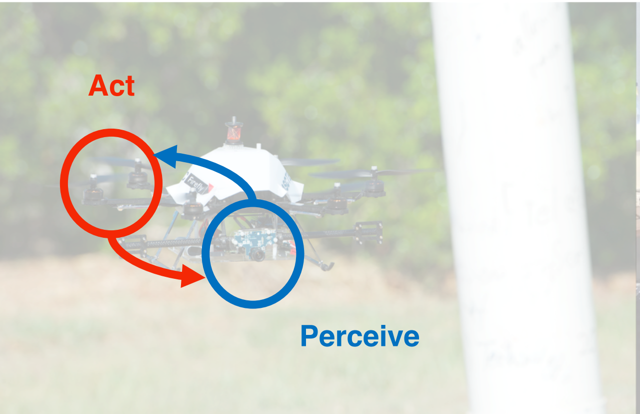
Prof. Yuke Zhu

Fall 2020

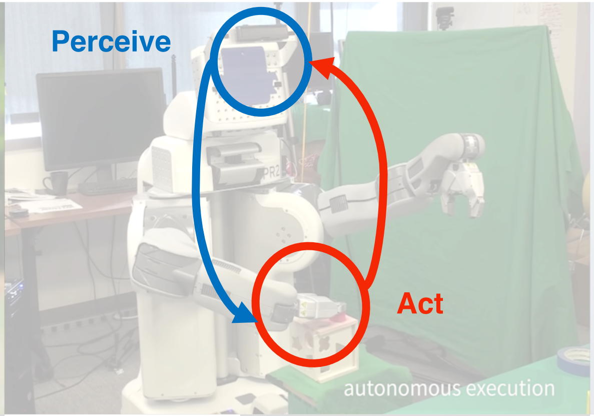
Today's Agenda

- What is Robot Decision Making?
- Mathematical Framework of Sequential Decision Making
- Learning for Decision Making
    - reinforcement learning (model-free vs. model-based)
    - imitation learning (behavior cloning, DAgger, IRL, and adversarial learning)
- Research Frontiers
    - compositionality, learning to learn, …

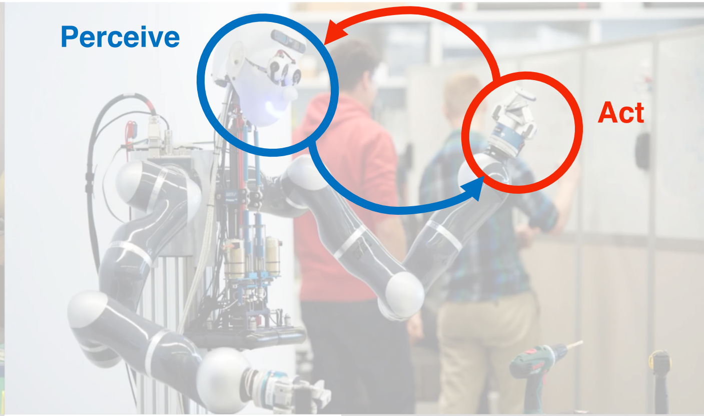
Robot Learning is to close the perception-**action** loop.



[Sa et al. IROS 2014]



[Levine et al. JMLR 2016]

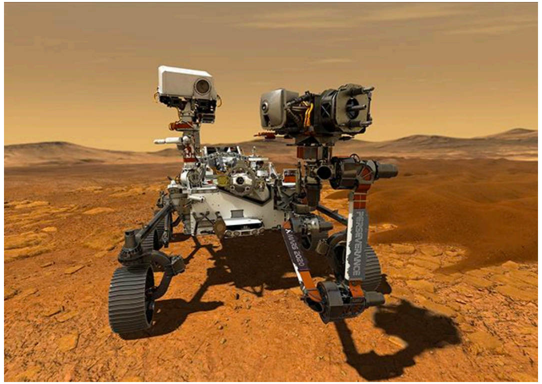


[Bohg et al. ICRA 2018]

What is Robot Decision Making?

Choosing the action a robot should perform in the physical world…

Assistive Robots (Companions)

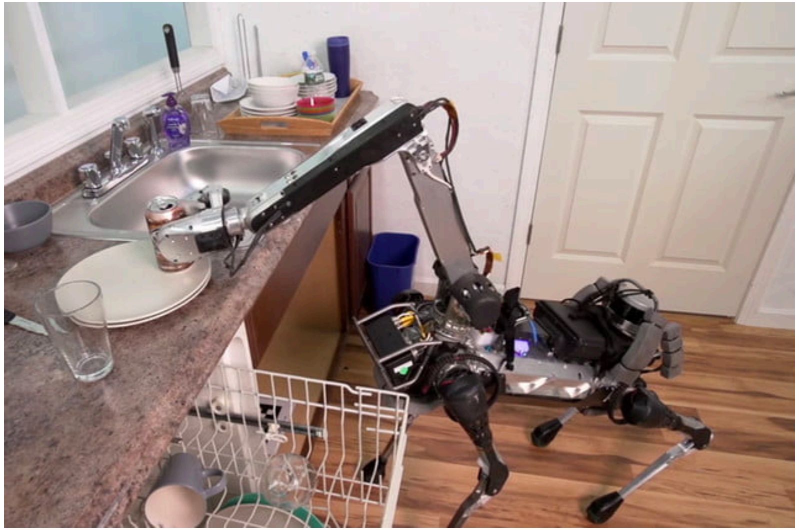


Outer Space (Explorers)

Autonomous Driving (Transporters)

What is Robot Decision Making?

Choosing the action a robot should perform in the physical world…

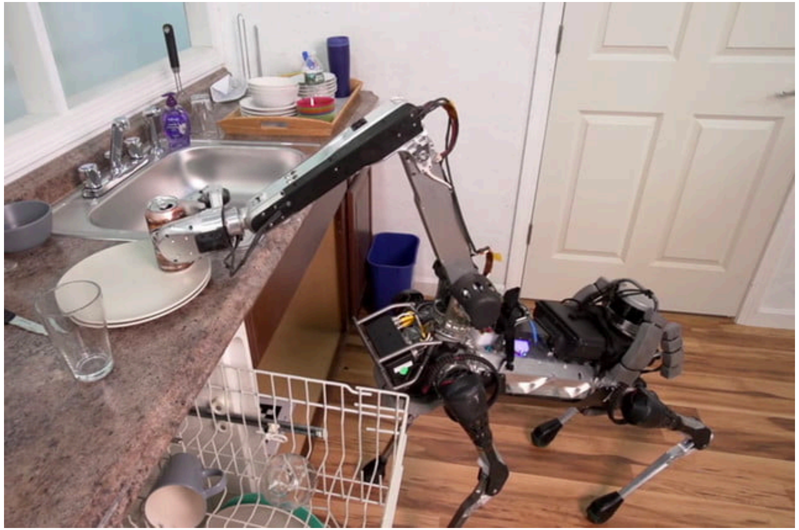


[Source: Boston Dynamics]

- Behaviors can't be easily programmed
- Imperfect sensing and actuation
- Safety and robustness under uncertainty

Robot Decision Making vs. Playing Games

Robot decision making is **embodied**, **active**, and **environmentally situated**.



[Source: Boston Dynamics]

[Source: DeepMind's AlphaGo]

Before We Dive In…

- This lecture is intended to provide a **high-level, bird-eye view** on (robot) decision making.
- The goal is not to go through all technical details:
  - We will re-visit them through paper reading in the following weeks.
  - Study the parts that you are less familiar with from online resources.
- Take related courses and read textbooks to learn this subject in depth (see the last slide).

Mathematical Framework: Markov Decision Processes

A **Markov Decision Process** is defined by a tuple $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$

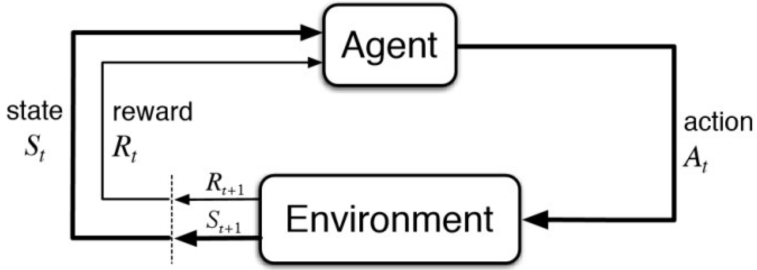
$\mathcal{S}$: state space $(s_t \in \mathcal{S})$

$\mathcal{A}$: action space $(a_t \in \mathcal{A})$

$\mathcal{P}$: transition probability $\mathcal{P}^a_{ss'} = \Pr[s_{t+1} \mid s_t, a_t]$

$\mathcal{R}$: reward function $r(s,a) = \mathbb{E}[r_{t+1} | s = s_t, a = a_t]$

γ : a discount factor $\gamma \in [0, 1]$



Mathematical Framework: Markov Decision Processes

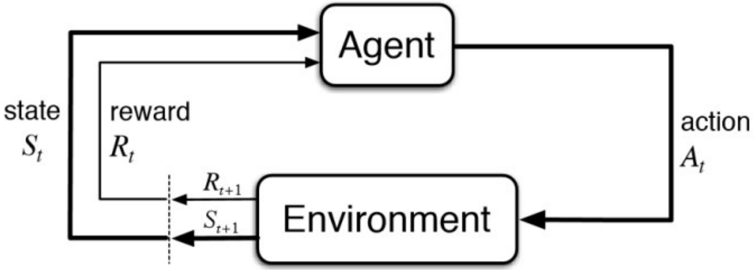
A **Markov Decision Process** is defined by a tuple $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$

A **policy** maps states to actions $\pi : \mathcal{S} \rightarrow \mathcal{A}$

Goal of (robot) decision making

Choose policy that maximizes cumulative reward

$$\pi^* = \arg\max_{\pi} \mathbb{E}[\sum_{t \geq 0} \gamma^t r(s_t, \pi(s_t))]$$



Mathematical Framework: Markov Decision Processes

We define two functions given a policy π

Pi*(a|s) = arg max_a Q*(s, a)

V*(s) = max_a Q*(s, a) → Pi*

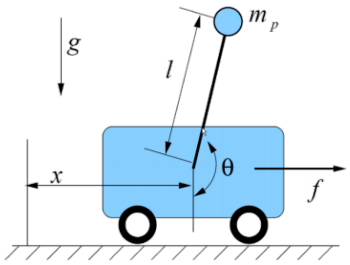
Value function: the expected cumulative discounted reward when acting according to the policy from a given state

$$V^\pi(s) = \mathbb{E}\left[\sum_{t=0} \gamma^t r(s_t, \pi(s_t)) \,|\, s_0 = s\right]$$

Q function: the expected cumulative discounted reward when acting according to the policy from a given state and taking a given action

$$Q^\pi(s,a) = r(s,a) + \gamma \sum_{s' \in \mathcal{S}} P(s'|s,a) V^\pi(s')$$

Solving MDPs with Known Models



When we know the model of the MDP $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$

Use ideas from

Dynamic Programming

Value Iteration

1. Estimate optimal value function
2. Compute optimal policy from optimal value function

Initialize $V(s)$ to arbitrary values
Repeat
  For all $s \in S$
    For all $a \in \mathcal{A}$
      $Q(s,a) \leftarrow E[r|s,a] + \gamma \sum_{s' \in S} P(s'|s,a)V(s')$
    $V(s) \leftarrow \max_a Q(s,a)$
Until $V(s)$ converge

using model

Policy Iteration

1. Start with random policy
2. Iteratively improve it until convergence to optimal policy

Initialize a policy π' arbitrarily
Repeat
  $\pi \leftarrow \pi'$
  Compute the values using π by
    solving the linear equations
      $V^{\pi}(s) = E[r|s,\pi(s)] + \gamma \sum_{s' \in S} P(s'|s,\pi(s))V^{\pi}(s')$
  Improve the policy at each state
    $\pi'(s) \leftarrow \arg\max_a (E[r|s,a] + \gamma \sum_{s' \in S} P(s'|s,a)V^{\pi}(s'))$
Until $\pi = \pi'$

using model

Solving MDPs with Known Models

When we know the model of the MDP $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$

Optimal Control (LQR)

Assume **linear transitions** and **quadratic reward functions**

A special case: exact solution π^* is easily to solve

Linear transition $s_{t+1} = A_t s_t + B_t a_t$

Quadratic reward $r(s_t, a_t) = -s_t^\top U_t s_t - a_t^\top W_t a_t$

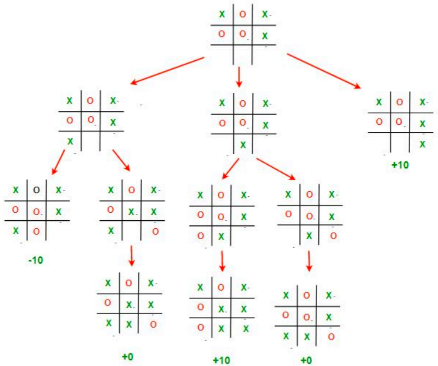
always negative

Extensions: LQG (Gaussian noise), iLQR (non-linear transition)

Sampling-based Planning

Evaluate outcomes of sampled actions with models

Choose the action that leads to the best (predicted) outcome



Monte-Carlo Tree Search (MCTS) for Tic-Tac-Toe

Solving MDPs with Learned Models

A key role of learning in model-based approaches

Model is known in restricted domains: **games**, **simulated robots**, **simple mechanics**

When model is not known, we can **learn the model from data**.

agent's experience → learned model → Use **planning** and **optimization** methods for known models (previous two slides)

$$\tau = \{(s_i, a_i, r_i) \,|\, i = 0, \ldots, H\}$$

$\hat{\mathcal{P}}$

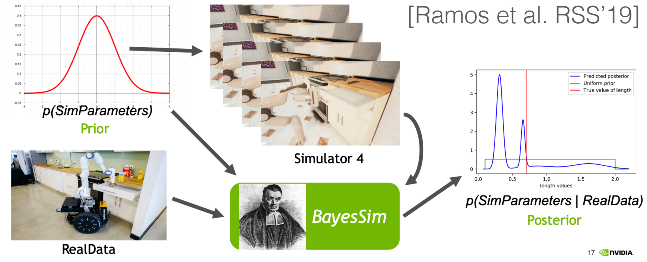
Can be represented by **Gaussian Processes**, **Neural Networks**, **GMMs**, etc.

model-based RL

Solving MDPs with Learned Models

System Identification

Week 12 Tue



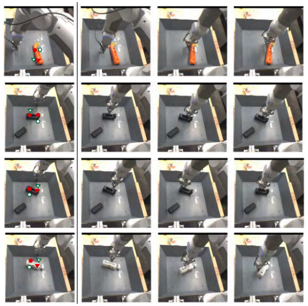
[Ramos et al. RSS'19]

Model structure is known (e.g., simulator). We tune some model parameters (e.g., mass and friction).

$$\Pr[\mu \mid \mathcal{D}]$$

Sensor-Space Model

Week 8 Tue



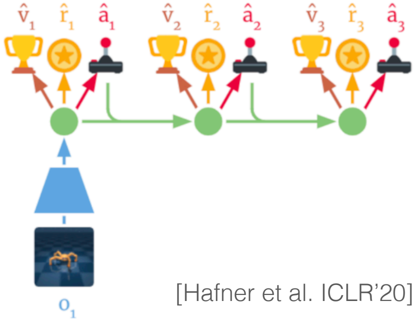
[Finn et al. ICRA'17]

Predicting future raw sensory data

$$f(s_{t+1} \mid s_t, a_t)$$

Latent-Space Model

Week 8 Tue



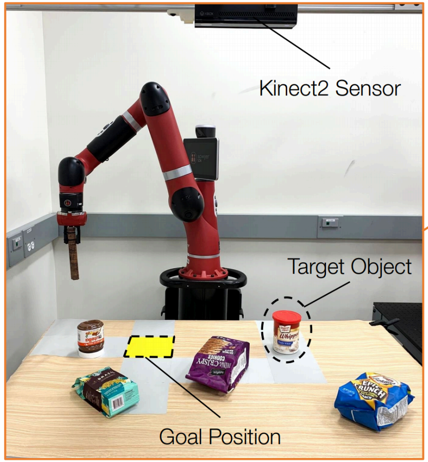
[Hafner et al. ICLR'20]

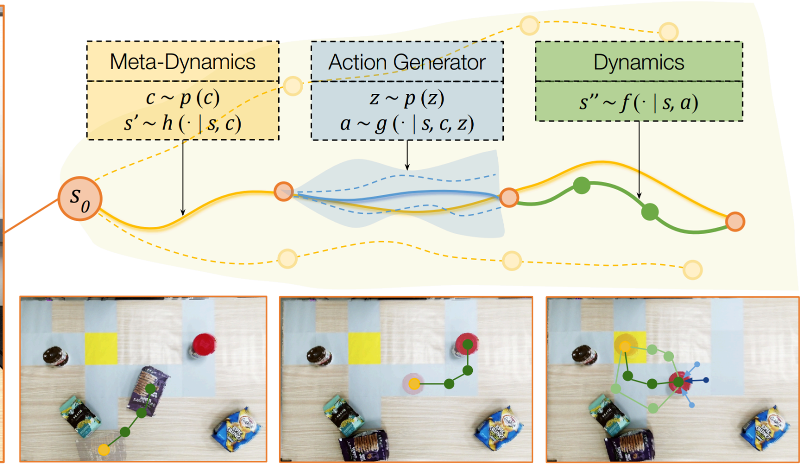
Learn behavior in imagination

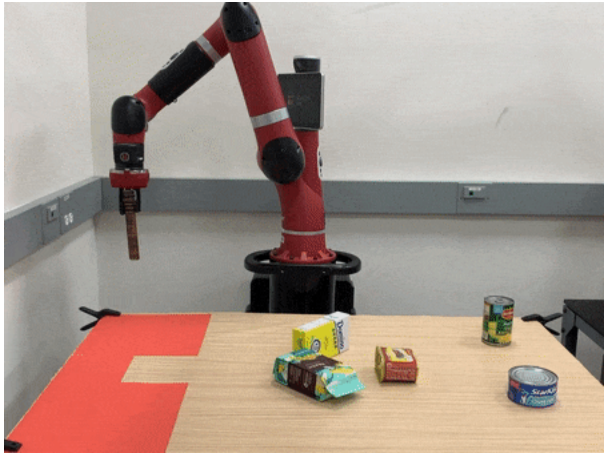
Predicting future latent state

$$h_t = g(s_t) \quad f(h_{t+1} \mid h_t, a_t)$$

Examples of Model-Based Reinforcement Learning







"Dynamics Learning with Cascaded Variational Inference for Multi-Step Manipulation." Fang, Zhu, Garg, Savarese, Fei-Fei, CoRL 2019

Solving MDPs without Models

When model is unknown and hard to estimate, we can **learn policy directly** from the agent's trajectories τ from interacting with an MDP.

agent's experience

$$\tau = \{(s_i, a_i, r_i) \mid i = 0, \dots, H\}$$

model-free RL

optimal policy

$$\pi^* = \arg\max_{\pi} \mathbb{E}[\sum_{t \geq 0} \gamma^t r(s_t, \pi(s_t))]$$

Solving MDPs without Models

Model-free

Value-based RL

Week 7 Thu

Optimality condition (Bellman equation)

$$Q^*(s,a) = r(s,a) + \gamma\, \mathbb{E}_{s'|s,a}[\max_{a'} Q^*(s',a')]$$

$$\pi^*(a|s) = \arg\max_{a'} Q^*(s,a')$$

Deep Q-Network (DQN):

Represent Q with neural networks

Q-learning rule (temporal different learning)

$$Q(s_t,a_t) \leftarrow (1-\alpha)\cdot \underbrace{Q(s_t,a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\Big(\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1},a)}_{\text{estimate of optimal future value}} \Big)}^{\text{learned value}}$$

Solving MDPs without Models

Model-free

Policy-Gradient RL

Week 7 Thu

policy parameterized by θ

Total reward of trajectory

Objective Function $J(\theta) = \mathbb{E}_{\tau \sim p(\tau|\theta)}[r(\tau)]$

trajectories under policy π_θ

policy gradient theorem

$$\nabla_\theta J(\theta) = \mathbb{E}_\pi [Q^\pi(s,a) \nabla_\theta \log \pi_\theta(a|s)]$$

Different ways of computing the Q values lead to different PG variants: Monte-Carlo estimates (REINFORCE), learning value functions (Actor-Critic)

Solving MDPs without Models

Model-free

Policy-Gradient RL

Week 7 Thu

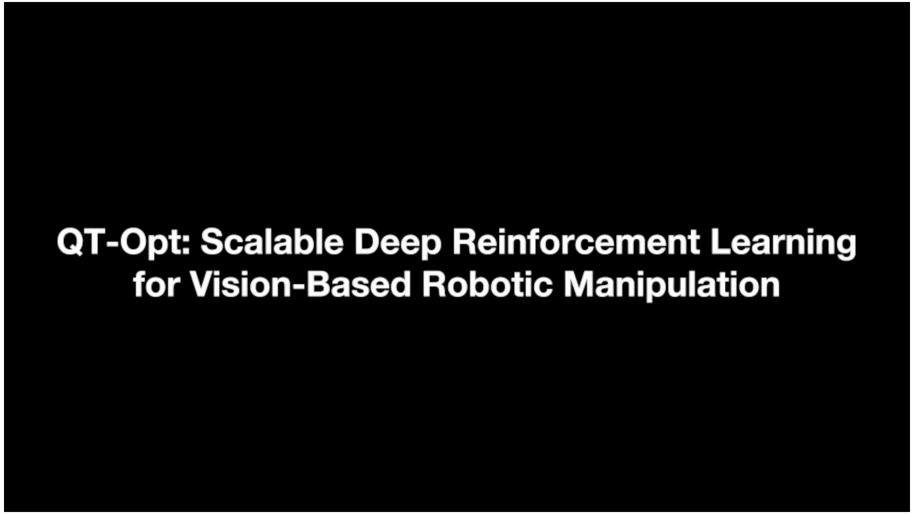
$$\nabla \mathbb{E}_\pi [r(\tau)] = \nabla \int \pi(\tau) r(\tau) d\tau$$

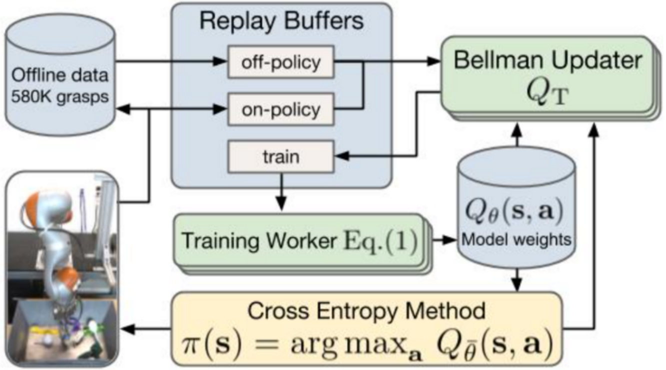
$$= \int \nabla \pi(\tau) r(\tau) d\tau$$

$$= \int \pi(\tau) \nabla \log \pi(\tau) r(\tau) d\tau$$

$$\nabla \mathbb{E}_\pi [r(\tau)] = \mathbb{E}_\pi [r(\tau) \nabla \log \pi(\tau)]$$

Examples of Model-Free Reinforcement Learning





"QT-Opt: Scalable Deep Reinforcement Learning for Vision-Based Robotic Manipulation." Kalashnikov et al. CoRL 2018

Week 13 Thu, Nov 19

Solving MDPs without Models

Model-free Value-based RL

- ✓ Can learn Q function from any interaction data, not just trajectories gathered using the current policy (“off-policy” algorithm)
- ✓ Relatively data-efficient (can reuse old interaction data)
- ✗ Need to optimize over actions: hard to apply to continuous action spaces
- ✗ Optimal Q function can be complicated, hard to learn

Model-free Policy-Gradient RL

- ✓ Learns policy directly – often more stable
- ✓ Works for continuous action spaces
- ✗ Needs data from current policy to compute policy gradient (“on-policy” algorithm) – data inefficient
- ✗ Gradient estimates can be very noisy

Mathematical Framework: Markov Decision Processes

Reinforcement learning optimizes policy by **trial and error** in an MDP.

Goal: To maximize the long-term rewards

$\mathcal{S}$: state space $(s_t \in \mathcal{S})$

$\mathcal{A}$: action space $(a_t \in \mathcal{A})$

$\mathcal{P}$: transition probability $\mathcal{P}^a_{ss'} = \Pr[s_{t+1} \mid s_t, a_t]$

$\mathcal{R}$: reward function $r(s,a) = \mathbb{E}[r_{t+1} | s = s_t, a = a_t]$

γ : a discount factor $\gamma \in [0, 1]$

Fundamental assumption of RL: **reward function**

Mathematical Framework: Markov Decision Processes

Imitation learning optimizes policy by **imitating the expert** in an MDP.

Goal: To match the behavioral distributions

$\mathcal{S}$: state space $(s_t \in \mathcal{S})$

$\mathcal{A}$: action space $(a_t \in \mathcal{A})$

$\mathcal{P}$: transition probability $\mathcal{P}^a_{ss'} = \Pr[s_{t+1} \mid s_t, a_t]$

~~$\mathcal{R}$: reward function $r(s, a) = \mathbb{E}[r_{t+1} | s = s_t, a = a_t]$~~

~~γ : a discount factor $\gamma \in [0, 1]$~~

$\mathcal{D}$: set of demonstrations drawn from the expert policy π_E

Mathematical Framework: Markov Decision Processes

Imitation learning optimizes policy by **imitating the expert** in an MDP.

Goal: To match the behavioral distributions

Two basic ideas

- Direct estimation of the expert policy from expert data (behavioral cloning)
- Reconstruct a reward function (inverse RL) and then learn a policy from the reward (RL)

Imitation as Supervised Learning

Idea 1: Direct estimation of the expert policy from expert data

Week 8 Thu

This can be cast as a **supervised learning** problem, called **behavioral cloning**

action from expert policy

$$\pi^* = \arg\min_{\pi} \sum_{s_t \in \mathcal{D}} L\Big(\pi(s_t), \pi_E(s_t)\Big)$$

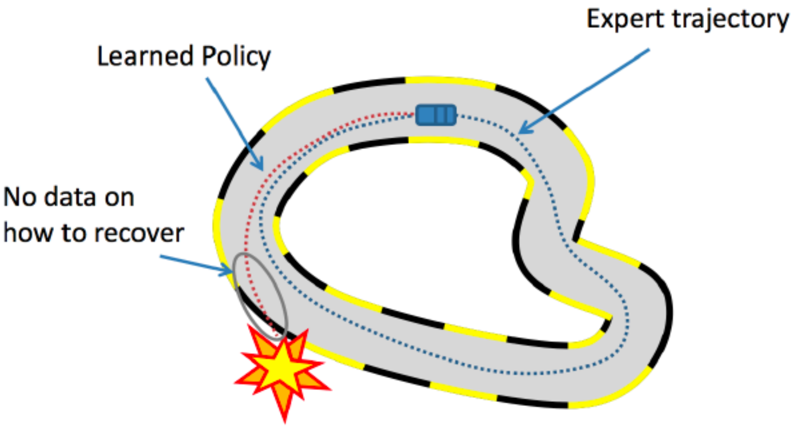
Distance metric that measures the discrepancy between the expert action and the policy action (e.g., KL-divergence)

Imitation as Supervised Learning

Idea 1: Direct estimation of the expert policy from expert data

Week 8 Thu

This can be cast as a **supervised learning** problem, called **behavioral cloning**

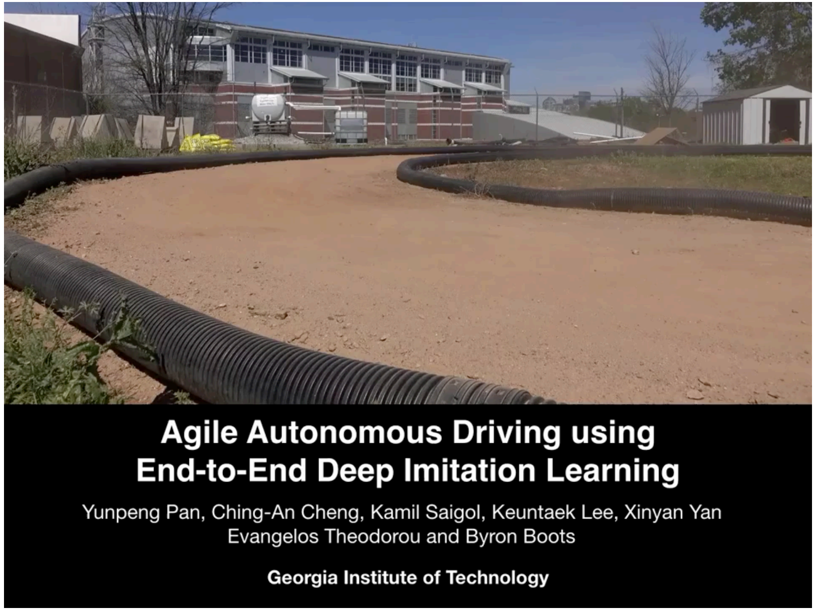


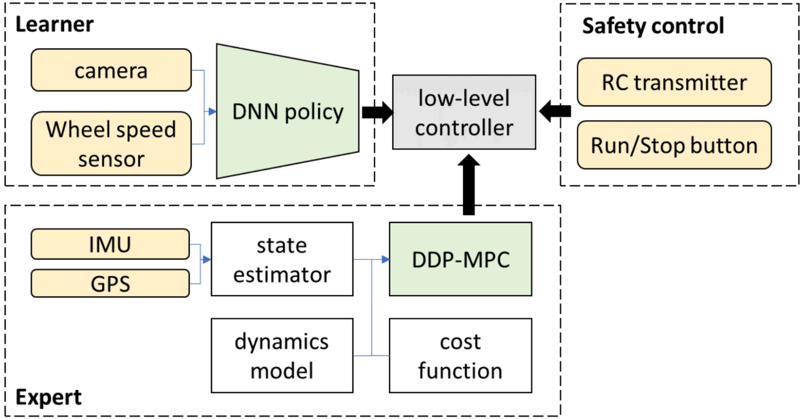
What can go wrong?

compounding errors

How to fix: Asking expert for more data (DAgger)

Examples of Supervised Imitation Learning





"Agile Autonomous Driving using End-to-End Deep Imitation Learning"
Pan, Cheng, Saigol, Lee, Yan, Theodorou, Boots. RSS 2018

Inverse Reinforcement Learning

Idea 2: Reconstruct a reward function and then learn a policy from the reward

Solving full-fledged RL in the inner loop

- Collect expert demonstrations: $D = \{\tau_1, \tau_2, \ldots, \tau_m\}$
- In a loop:
  - Learn reward function: $r_\theta(s_t, a_t)$
  - Given the reward function r_θ, learn π policy using RL
  - Compare π with π^* (expert's policy)
  - STOP if π is satisfactory

To solve efficiently, IRL methods often assume:

- Known dynamics (for comparing π and π^* efficiently)
- Linear reward function $r(s,a) = w^\top \phi(s)$

Problem: IRL is generally ill-posed – many reward functions under which the expert policy is optimal.

How can we address it?

Examples of Inverse Reinforcement Learning

The International Journal of Robotics Research OnlineFirst, published on June 23, 2010 as doi:10.1177/0278364910371999

ijrr

The International Journal of
Robotics Research
000(00) 1–31

DOI: 10.1177/0278364910371999
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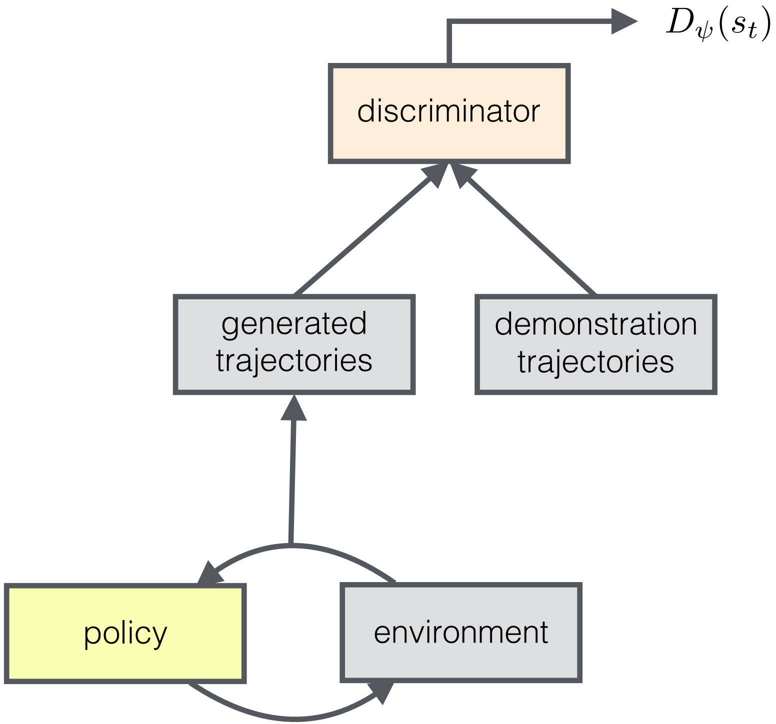
Autonomous Helicopter Aerobatics through Apprenticeship Learning

Pieter Abbeel[1], Adam Coates[2] and Andrew Y. Ng[2]

Abstract
Autonomous helicopter flight is widely regarded to be a highly challenging control problem. Despite this fact, human experts can reliably fly helicopters through a wide range of maneuvers, including aerobatic maneuvers at the edge of the helicopter's capabilities. We present apprenticeship learning algorithms, which leverage expert demonstrations to efficiently learn good controllers for tasks being demonstrated by an expert. These apprenticeship learning algorithms have enabled us to significantly extend the state of the art in autonomous helicopter aerobatics. Our experimental results include the first autonomous execution of a wide range of maneuvers, including but not limited to in-place flips, in-place rolls, loops and hurricanes, and even auto-rotation landings, chaos and tic-tocs, which only exceptional human pilots can perform. Our results also include complete airshows, which require autonomous transitions between many of these maneuvers. Our controllers perform as well as, and often even better than, our expert pilot.

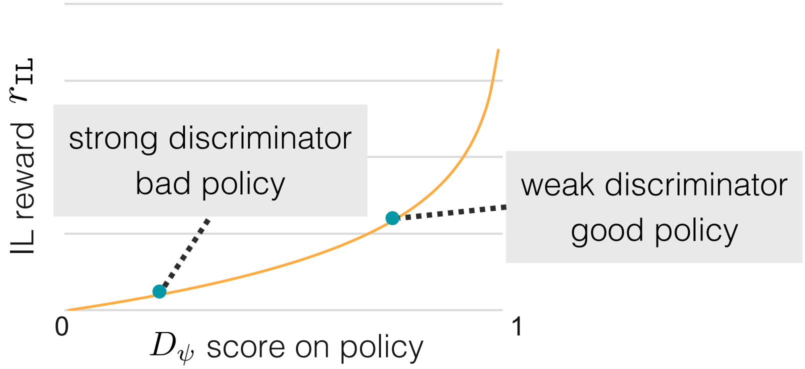
Adversarial Imitation Learning



discriminator objective

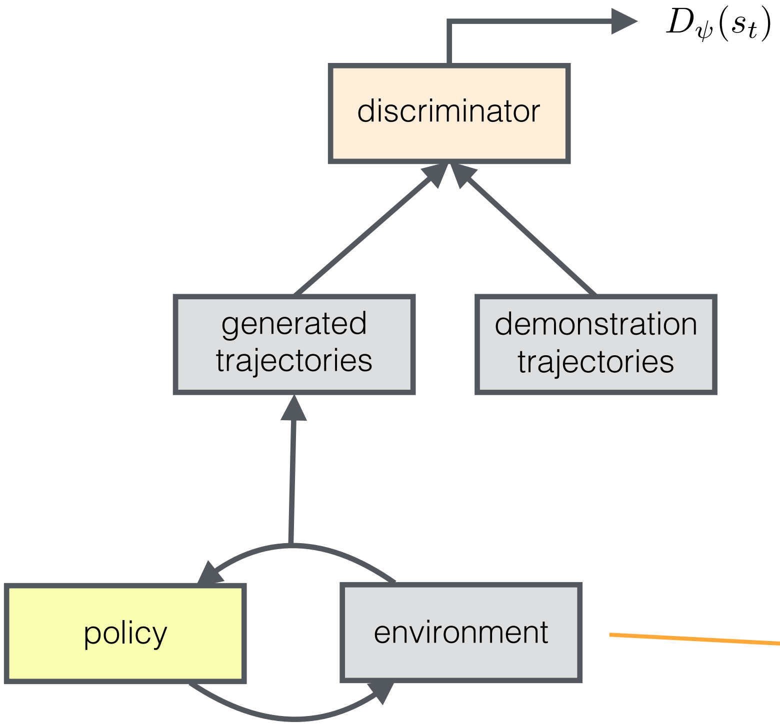
D_ψ predicts **0** if policy and **1** if demo

IL reward: $r_{\text{IL}}(s_t, a_t) = -\log(1 - D_\psi(s_t))$



[Goodfellow et al. 2014; Ho & Ermon, 2016]

Adversarial Imitation Learning



discriminator objective

D_ψ predicts **0** if policy and **1** if demo

IL reward: $r_{\text{IL}}(s_t, a_t) = -\log(1 - D_\psi(s_t))$

- Represent **complex reward function** by neural networks
- More **iterative approaches** to update reward and policy (no need to run full RL before updating the reward function)
- We don't know the dynamics but have access to a **simulator** to compare with π and π^*.

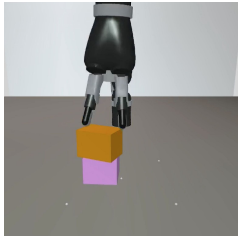
[Goodfellow et al. 2014; Ho & Ermon, 2016]

Examples of Adversarial Imitation Learning

3D motion controller

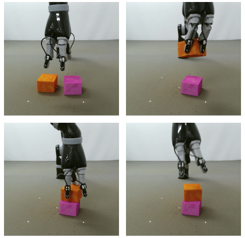
imitation

physics engine



sim2real

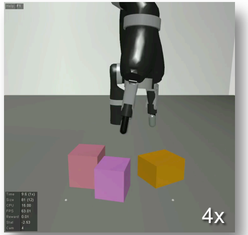
real environment

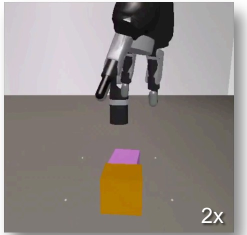


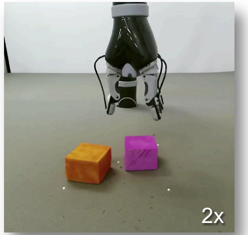
Collecting human demonstrations

Training in simulation

Running on real robot

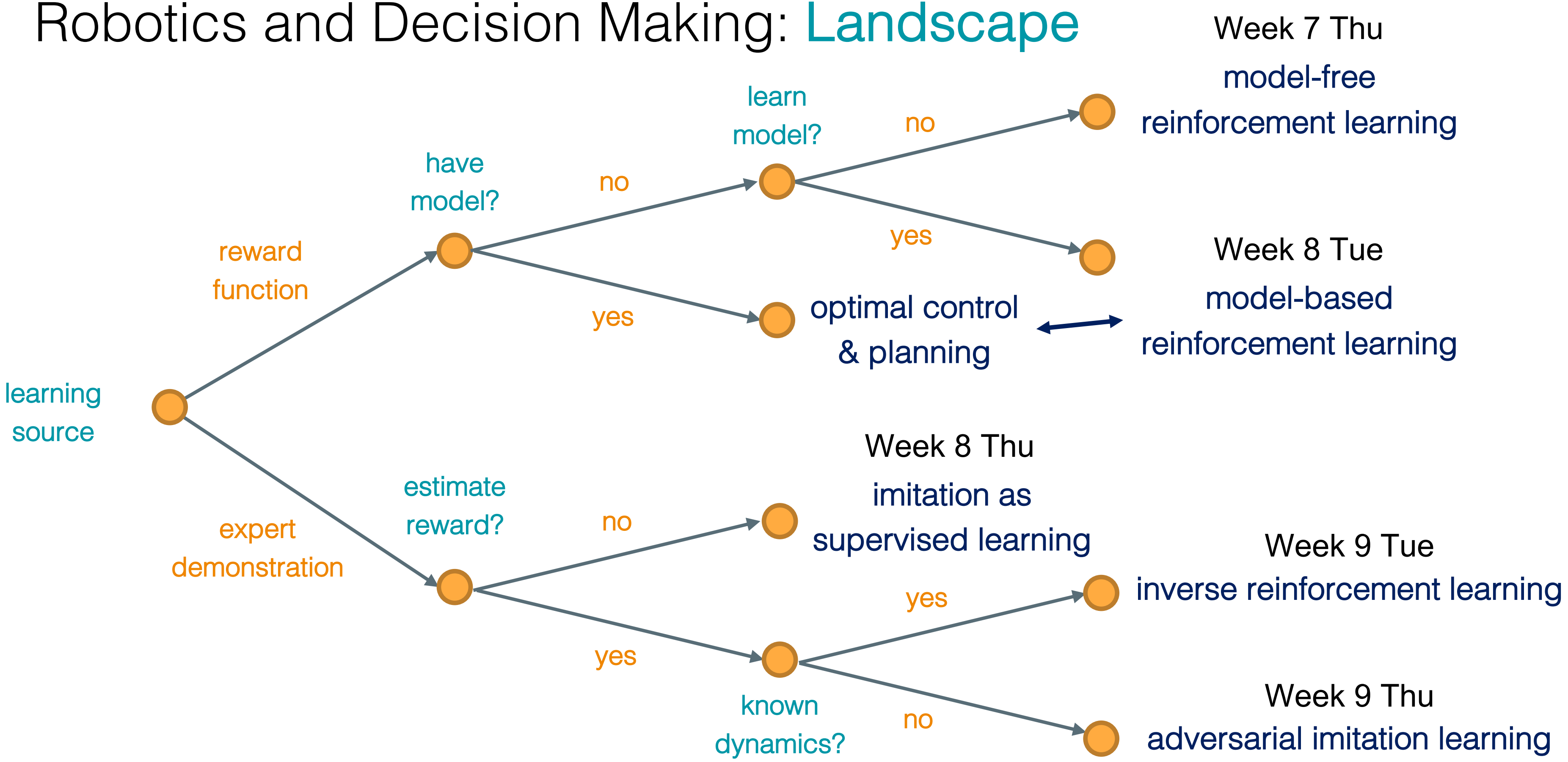




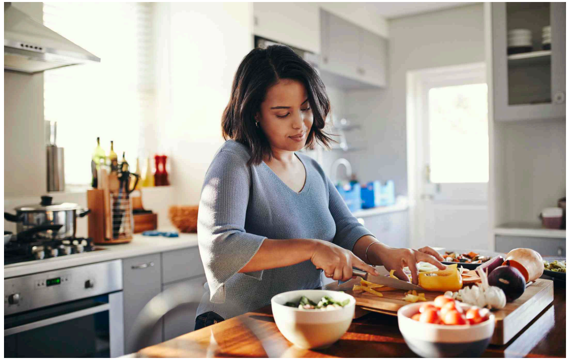


"Reinforcement and Imitation Learning for Diverse Visuomotor Skills." Zhu et al. RSS 2018

Robotics and Decision Making: Landscape



Robotics and Decision Making: Frontiers



Learning from rich data sources

Language, preferences, instruction videos. Suboptimal demonstrations. Object variations and long-horizon tasks.

Week 11 (Tue, Thu): Compositionality

Efficient learning of new tasks

Fast learning from limited experience. Representing and transferring past knowledge.

Week 10 (Tue, Thu): Learning to Learn

Safety and robustness

Probabilistic and formal guarantees of the robot behaviors during learning and inference

Resources

Related courses at UTCS

- CS342: Neural Networks
- CS394R: Reinforcement Learning: Theory and Practice

Other Course Materials and Textbooks

- UCL Course on RL by David Silver
- Berkeley CS 294: Deep Reinforcement Learning
- Reinforcement Learning: An Introduction, Sutton and Barto
- Reinforcement Learning and Optimal Control, Bertsekas