Lecture 7: Imitation Learning in Large State Spaces[2]

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CS234 Reinforcement Learning.

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[2] With slides from Katerina Fragkiadaki and Pieter Abbeel

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Recap: DQN (Mnih et al. Nature 2015)

$$r_t + \gamma \max_a Q(s_{t+1}, a) - Q \quad \swarrow w$$

- DQN uses experience replay and fixed Q-targets
- Store transition $(s_t, a_t, r_{t+1}, s_{t+1})$ in replay memory $\mathcal{D}$
- Sample random mini-batch of transitions (s, a, r, s') from $\mathcal{D}$
- Compute Q-learning targets w.r.t. old, fixed parameters $\boldsymbol{w}^-$
- Optimizes MSE between Q-network and Q-learning targets
- Uses stochastic gradient descent
- Achieved human-level performance on a number of Atari games

Recap: Deep Model-free RL, 3 of the Big Ideas

- Double DQN: (Deep Reinforcement Learning with Double Q-Learning, Van Hasselt et al, AAAI 2016)
- Prioritized Replay (Prioritized Experience Replay, Schaul et al, ICLR 2016)
- Dueling DQN (best paper ICML 2016) (Dueling Network Architectures for Deep Reinforcement Learning, Wang et al, ICML 2016)

Summary of Model Free Value Function Approximation with DNN

- DNN are very expressive function approximators
- Can use to represent the Q function and do MC or TD style methods
- Should be able to implement DQN (assignment 2)
- Be able to list a few extensions that help performance beyond DQN

We want RL Algorithms that Perform

- Optimization
- Delayed consequences
- Exploration
- Generalization
- And do it all statistically and computationally efficiently

Generalization and Efficiency

- We will discuss efficient exploration in more depth later in the class
- But exist hardness results that if learning in a generic MDP, can require large number of samples to learn a good policy
- This number is generally infeasible
- Alternate idea: use structure and additional knowledge to help constrain and speed reinforcement learning
- Today: Imitation learning
- Later:
  - Policy search (can encode domain knowledge in the form of the policy class used)
  - Strategic exploration
  - Incorporating human help (in the form of teaching, reward specification, action specification, ...)

Class Structure

- Last time: CNNs and Deep Reinforcement learning
- **This time: Imitation Learning with Large State Spaces**
- Next time: Policy Search

Consider Montezuma's revenge

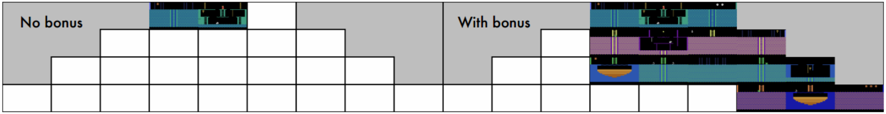
- 

Figure 3: "Known world" of a DQN agent trained for 50 million frames with (**right**) and without (**left**) count-based exploration bonuses, in MONTEZUMA'S REVENGE.

- Bellemare et al. "Unifying Count-Based Exploration and Intrinsic Motivation"
- Vs: https://www.youtube.com/watch?v=JR6wmLaYuu4

So Far in this Course

Reinforcement Learning: Learning policies guided by (often sparse) rewards (e.g. win the game or not)

- Good: simple, cheap form of supervision
- Bad: High sample complexity

Where is it successful? where RL might work well ?

- In simulation where data is cheap and parallelization is easy
- Not when:
  - Execution of actions is slow
  - Very expensive or not tolerable to fail helicopter
  - Want to be safe

Reward Shaping

Rewards that are **dense in time** closely guide the agent

How can we supply these rewards?

- **Manually design them**: often brittle
- **Implicitly specify them through demonstrations**

Learning from Demonstration for Autonomous Navigation in Complex Unstructured Terrain, Silver et al. 2010

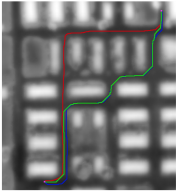
Examples

Simulated highway driving

- Abbeel and Ng, ICML 2004
- Syed and Schapire, NIPS 2007
- Majumdar et al., RSS 2017

Aerial imagery-based navigation

- Ratliff, Bagnell, and Zinkevich, ICML 2006



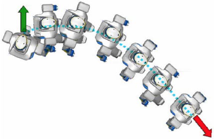
Parking lot navigation

- Abbeel, Dolgov, Ng, and Thrun, IROS 2008

Examples

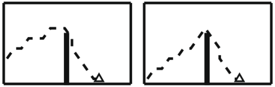
Human path planning

- Mombaur, Truong, and Laumond, AURO 2009



Human goal inference

- Baker, Saxe, and Tenenbaum, Cognition 2009



Quadruped locomotion

- Ratliff, Bradley, Bagnell, and Chestnutt, NIPS 2007
- Kolter, Abbeel, and Ng, NIPS 2008

Learning from Demonstrations

Inverse RL
Imitation learning

- Expert provides a set of **demonstration trajectories**: sequences of states and actions
- Imitation learning is useful when it is easier for the expert to demonstrate the desired behavior rather than:
  - Specifying a reward that would generate such behavior,
  - Specifying the desired policy directly

Problem Setup

- Input:
  - State space, action space
  - Transition model $P(s' \mid s, a)$
  - No reward function R
  - Set of one or more teacher's demonstrations $(s_0, a_0, s_1, s_0, \ldots)$ (actions drawn from teacher's policy π^*)
- Behavioral Cloning: $\hat{\pi}^*$
  - Can we directly learn the teacher's policy using supervised learning?
- Inverse RL:
  - Can we recover R? once we have the reward function, then we can us it to compute a policy.
- Apprenticeship learning via Inverse RL:
  - Can we use R to generate a good policy? Inverse RL + RL

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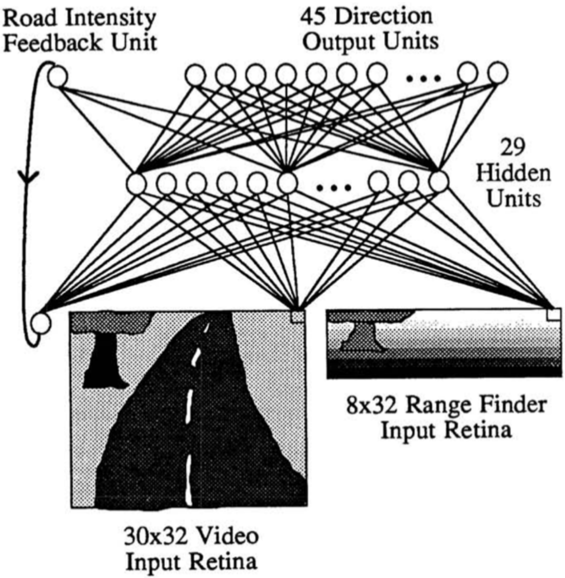
Behavioral Cloning

- Formulate problem as a standard machine learning problem:
  - Fix a policy class (e.g. neural network, decision tree, etc.)
  - Estimate a policy from training examples $(s_0, a_0), (s_1, a_1), (s_2, a_2), \ldots$

$s \rightarrow a$

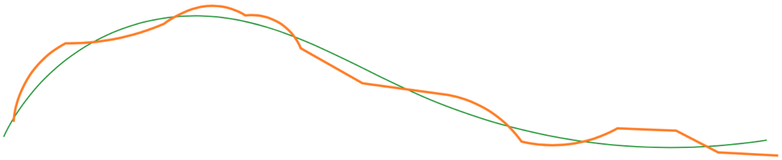
- Two notable success stories:
  - Pomerleau, NIPS 1989: ALVINN
  - Summut et al., ICML 1992: Learning to fly in flight simulator

ALVINN


Road Intensity
Feedback Unit
45 Direction
Output Units
29
Hidden
Units
8x32 Range Finder
Input Retina
30x32 Video
Input Retina

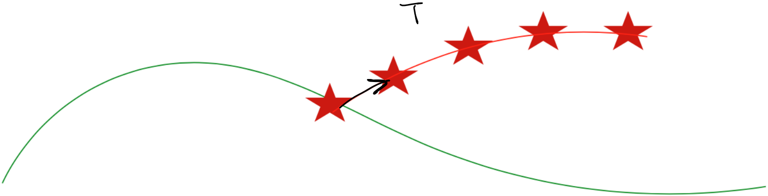
Problem: Compounding Errors

Supervised learning assumes iid. (s, a) pairs and ignores temporal structure
Independent in time errors:



Error at time t with probability ϵ
$\mathbb{E}[\text{Total errors}] \leq \epsilon T$

Problem: Compounding Errors



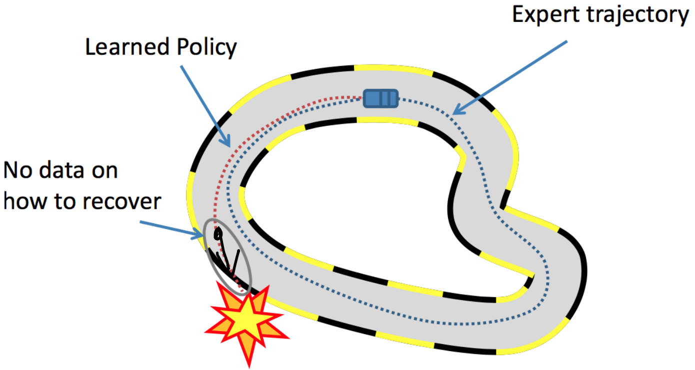
ϵT

Error at time t with probability ϵ

$\mathbb{E}[\text{Total errors}] \leq \epsilon(T + (T-1) + (T-2) \ldots + 1) \propto \underline{\epsilon T}^2$

A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning, Ross et al. 2011

Problem: Compounding Errors



Data distribution mismatch!

In supervised learning, $(x, y) \sim D$ during train **and** test. In MDPs:

- Train: $s_t \sim D_{\pi^*}$
- Test: $s_t \sim D_{\pi_\theta}$

DAGGER: Dataset Aggregation

Initialize $\mathcal{D} \leftarrow \emptyset$.
Initialize $\hat{\pi}_1$ to any policy in Π.
for $i = 1$ **to** N **do**
  Let $\pi_i = \beta_i \pi^* + (1 - \beta_i)\hat{\pi}_i$.   expert policy
  Sample T-step trajectories using π_i.
  Get dataset $\mathcal{D}_i = \{(s, \pi^*(s))\}$ of visited states by π_i
  and actions given by expert.
  Aggregate datasets: $\mathcal{D} \leftarrow \mathcal{D} \bigcup \mathcal{D}_i$.
  Train classifier $\hat{\pi}_{i+1}$ on $\mathcal{D}$.
end for
Return best $\hat{\pi}_i$ on validation.

- Idea: Get more labels of the expert action along the path taken by the policy computed by behavior cloning
- Obtains a stationary deterministic policy with good performance under its induced state distribution

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Feature Based Reward Function

- Given state space, action space, transition model $P(s' \mid s, a)$
- No reward function R
- Set of one or more teacher's demonstrations $(s_0, a_0, s_1, s_0, \ldots)$ (actions drawn from teacher's policy π^*)
- Goal: infer the reward function R
- With no assumptions on the optimality of the teacher's policy, what can be inferred about R?
- Now assume that the teacher's policy is optimal. What can be inferred about R?

0

not unique

Andrew Ng
Stuart Russell
2000

Linear Feature Reward Inverse RL

- Recall linear value function approximation
- Similarly, here consider when reward is linear over features
  - $R(s) = \boldsymbol{w}^T x(s)$ where $w \in \mathbb{R}^n, x : S \rightarrow \mathbb{R}^n$
- Goal: identify the weight vector $\boldsymbol{w}$ given a set of demonstrations
- The resulting value function for a policy π can be expressed as

$$V^\pi \underset{s \sim \pi}{=} \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t \underbrace{R(s_t)}_{w^T x(s_t)}] \quad (1)$$

Linear Feature Reward Inverse RL

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- Goal: identify the weight vector $\boldsymbol{w}$ given a set of demonstrations
- The resulting value function for a policy π can be expressed as

$$V^\pi = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t R(s_t) \mid \pi] \quad = \mathbb{E}[\textstyle\sum_{t=0}^{\infty} \gamma^t \underbrace{\boldsymbol{w}^T} \underbrace{x(s_t)} \mid \pi] \tag{2}$$

$$= w^T \mathbb{E}[\textstyle\sum_{t=0}^{\infty} \gamma^t x(s_t) \mid \pi] \tag{3}$$

$$= \boldsymbol{w}^T \mu(\pi) \tag{4}$$

- where $\mu(\pi)(s)$ is defined as the discounted weighted frequency of state features under policy π.

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Linear Feature Reward Inverse RL

- Recall linear value function approximation
- Similarly, here consider when reward is linear over features
  - $R(s) = \boldsymbol{w}^T x(s)$ where $w \in \mathbb{R}^n, x : S \to \mathbb{R}^n$
- Goal: identify the weight vector $\boldsymbol{w}$ given a set of demonstrations
- The resulting value function for a policy π can be expressed as

$$V^\pi = \boldsymbol{w}^T \mu(\pi) \tag{5}$$

- where $\mu(\pi)(s)$ is defined as the discounted weighted frequency of features/state s under policy π.
- Note
  $\mathbb{E}[\sum_{t=0}^{\infty} \gamma^t R^*(s_t) \mid \pi^*] = V^* \geq V^\pi = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t R^*(s_t) \mid \pi] \quad \forall \pi,$
- Therefore if the expert's demonstrations are from the optimal policy, to identify $\boldsymbol{w}$ it is sufficient to find w^* such that

demo

$$w^{*T} \mu(\pi^*) \geq w^{*T} \mu(\pi), \forall \pi \neq \pi^* \tag{6}$$

Feature Matching

- Want to find a reward function such that the expert policy outperforms other policies.
- For a policy π to be guaranteed to perform as well as the expert policy π^*, it suffices that we have a policy such that its discounted summed feature expectations match the expert's policy[42].
- More precisely, if

demonstrations

$$\|\mu(\pi)^{(s)} - \mu(\pi^*)_{(s)}\|_1 \le \epsilon \tag{7}$$

then for all w with $\|w\|_\infty \le 1$:

$$|w^T\mu(\pi) - w^T\mu(\pi^*)| \le \epsilon$$

[42] Abbeel and Ng, 2004

Apprenticeship Learning

- This observation leads to the following algorithm for learning a policy that is as good as the expert policy
- Assumption: $R(s) = w^T x(s)$
- Initialize policy π_0
- For $i = 1, 2 \ldots$ w
  - Find a reward function such that the teacher maximally outperforms all previous controllers:

$$\arg\max_{\boldsymbol{w}} \max_{\gamma} s.t. w^T \mu(\pi^*) \geq w^T \mu(\pi) + \gamma \quad \forall \pi \in \{\pi_0, \pi_1, \ldots, \pi_{i-1}\} \tag{8}$$

  - s.t. $\|w\|_2 \leq 1$
  - Find optimal control policy π_i for the current $\boldsymbol{w}$
  - Exit if $\gamma \leq \epsilon/2$

Feature Expectation Matching

- If expert policy is suboptimal then the resulting policy is a mixture of somewhat arbitrary policies which have expert in the convex hull
- In practice: pick the best one of this set and pick the corresponding reward function.

Ambiguity

- There is an infinite number of reward functions with the same optimal policy.
- There are infinitely many stochastic policies that can match feature counts
- Which one should be chosen?

- Many different approaches
- Two of the key papers are:
  - Maximumum Entropy Inverse Reinforcement Learning (Ziebart et al. AAAI 2008)
  - Generative adversarial imitation learning (Ho and Ermon, NeurIPS 2016)   DNN

GAIL

Transition model unknown

Summary

- Imitation learning can greatly reduce the amount of data need to learn a good policy
- Challenges remain and one exciting area is combining inverse RL / learning from demonstration and online reinforcement learning

Class Structure

- Last time: Deep reinforcement learning
- This time: Imitation Learning
- Next time: Policy Search