

Lecture 7: Imitation Learning in Large State Spaces¹

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CS234 Reinforcement Learning.

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¹With slides from Katerina Fragkiadaki and Pieter Abbeel

Refresh Your Knowledge 6

• Experience replay in deep Q-learning (select all):

- ① Involves using a bank of prior (s,a,r,s') tuples and doing Q-learning updates using all the tuples in the bank
- ② Always uses the most recent history of tuples
- ③ Reduces the data efficiency of DQN
- ④ Increases the computational cost
- ⑤ Not sure

- Success in Atari has led to huge excitement in using deep neural networks to do value function approximation in RL
- Some immediate improvements (many others!)
 - 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)

Class Structure

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

Double DQN

- Recall maximization bias challenge
 - Max of the estimated state-action values can be a biased estimate of the max
- Double Q-learning

Recall: Double Q-Learning

```
1: Initialize  $Q_1(s, a)$  and  $Q_2(s, a), \forall s \in S, a \in A$   $t = 0$ , initial state  $s_t = s_0$ 
2: loop
3:   Select  $a_t$  using  $\epsilon$ -greedy  $\pi(s) = \arg \max_a Q_1(s_t, a) + Q_2(s_t, a)$ 
4:   Observe  $(r_t, s_{t+1})$ 
5:   if (with 0.5 probability) then
6:
```

$$Q_1(s_t, a_t) \leftarrow Q_1(s_t, a_t) + \alpha(r_t + Q_1(s_{t+1}, \arg \max_{a'} Q_2(s_{t+1}, a')) - Q_1(s_t, a_t))$$

```
7:   else
8:
```

$$Q_2(s_t, a_t) \leftarrow Q_2(s_t, a_t) + \alpha(r_t + Q_2(s_{t+1}, \arg \max_{a'} Q_1(s_{t+1}, a')) - Q_2(s_t, a_t))$$

```
9:   end if
10:   $t = t + 1$ 
11: end loop
```

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Check Your Understanding: Mars Rover Model-Free Policy Evaluation

s_1	s_2	s_3	s_4	s_5	s_6	s_7
$R(s_1) = +1$ <i>Okay Field Site</i>	$R(s_2) = 0$	$R(s_3) = 0$	$R(s_4) = 0$	$R(s_5) = 0$	$R(s_6) = 0$	$R(s_7) = +10$ <i>Fantastic Field Site</i>

- $\pi(s) = a_1 \forall s, \gamma = 1$. Any action from s_1 and s_7 terminates episode
- Trajectory = ($s_3, a_1, 0, s_2, a_1, 0, s_2, a_1, 0, s_1, a_1, 1$, terminal)
- First visit MC estimate of V of each state? [1 1 1 0 0 0 0]
- TD estimate of all states (init at 0) with $\alpha = 1$ is [1 0 0 0 0 0 0]
- Chose 2 "replay" backups to do. Which should we pick to get estimate closest to MC first visit estimate?
 - 1 Doesn't matter, any will yield the same
 - 2 ($s_3, a_1, 0, s_2$) then ($s_2, a_1, 0, s_1$)
 - 3 ($s_2, a_1, 0, s_1$) then ($s_3, a_1, 0, s_2$)
 - 4 ($s_2, a_1, 0, s_1$) then ($s_3, a_1, 0, s_2$)
 - 5 Not sure

Impact of Replay?

- In tabular TD-learning, **order** of replaying updates could help speed learning
- Repeating some updates seem to better propagate info than others
- Systematic ways to prioritize updates?

Potential Impact of Ordering Episodic Replay Updates

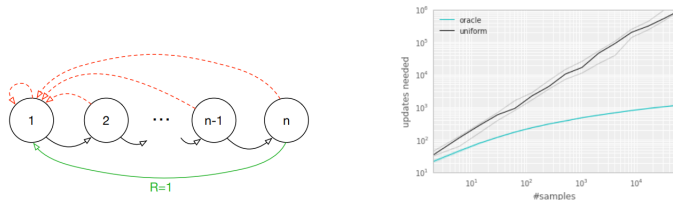


Figure: Schaul, Quan, Antonoglou, Silver ICLR 2016

- Schaul, Quan, Antonoglou, Silver ICLR 2016
- Oracle: picks (s, a, r, s') tuple to replay that will minimize global loss
- Exponential improvement in convergence
 - Number of updates needed to converge
- Oracle is not a practical method but illustrates impact of ordering

Prioritized Experience Replay

- Let i be the index of the i -th tuple of experience (s_i, a_i, r_i, s_{i+1})
- Sample tuples for update using priority function
- Priority of a tuple i is proportional to DQN error

$$p_i = \left| r + \gamma \max_{a'} Q(s_{i+1}, a'; \mathbf{w}^-) - Q(s_i, a_i; \mathbf{w}) \right|$$

- Update p_i every update. p_i for new tuples is set to 0
- One method¹: proportional (stochastic prioritization)

$$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$$

¹See paper for details and an alternative

Exercise: Prioritized Replay

- Let i be the index of the i -th tuple of experience (s_i, a_i, r_i, s_{i+1})
- Sample tuples for update using priority function
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- Update p_i every update. p_i for new tuples is set to 0
- One method¹: proportional (stochastic prioritization)

$$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$$

- $\alpha = 0$ yields what rule for selecting among existing tuples?
- Selects randomly
- Selects the one with the highest priority
- It depends on the priorities of the tuples
- Not Sure

Performance of Prioritized Replay vs Double DQN

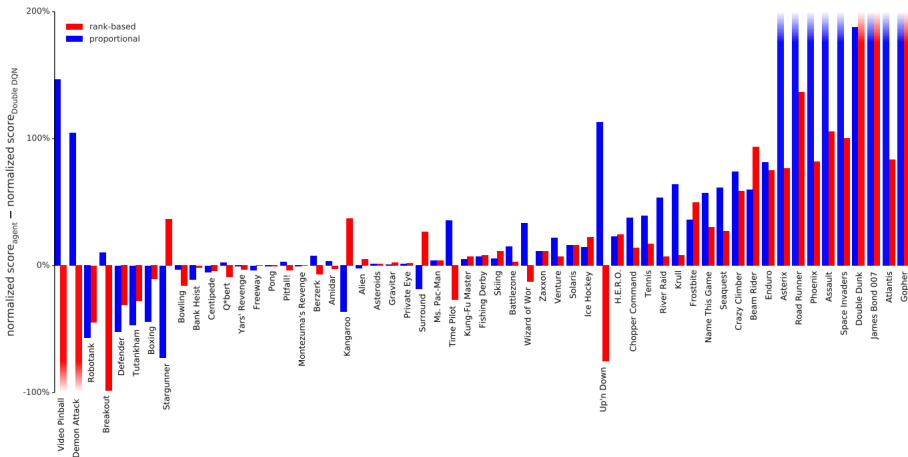


Figure: Schaul, Quan, Antonoglou, Silver ICLR 2016

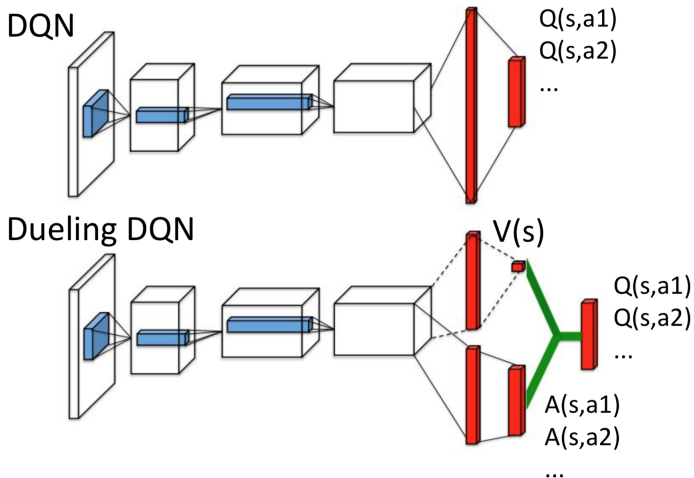
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Value & Advantage Function

- Intuition: Features need to accurately represent value may be different than those needed to specify difference in actions
- E.g.
 - Game score may help accurately predict $V(s)$
 - But not necessarily in indicating relative action values $Q(s, a_1)$ vs $Q(s, a_2)$
- Advantage function (Baird 1993)

$$A^\pi(s, a) = Q^\pi(s, a) - V^\pi(s)$$

Dueling DQN



Wang et.al., ICML, 2016

Check Understanding: Unique?

- Advantage function

$$A^{\pi}(s, a) = Q^{\pi}(s, a) - V^{\pi}(s)$$

- For a given advantage function, is there a unique Q and V ?
 - 1 Yes
 - 2 No
 - 3 Not sure

Uniqueness

- Advantage function

$$A^\pi(s, a) = Q^\pi(s, a) - V^\pi(s)$$

- Not unique
- Option 1: Force $A(s, a) = 0$ if a is action taken

$$\hat{Q}(s, a; \mathbf{w}) = \hat{V}(s; \mathbf{w}) + \left(\hat{A}(s, a; \mathbf{w}) - \max_{a' \in \mathcal{A}} \hat{A}(s, a'; \mathbf{w}) \right)$$

- Option 2: Use mean as baseline (more stable)

$$\hat{Q}(s, a; \mathbf{w}) = \hat{V}(s; \mathbf{w}) + \left(\hat{A}(s, a; \mathbf{w}) - \frac{1}{|\mathcal{A}|} \sum_{a' \in \mathcal{A}} \hat{A}(s, a'; \mathbf{w}) \right)$$

Dueling DQN V.S. Double DQN with Prioritized Replay

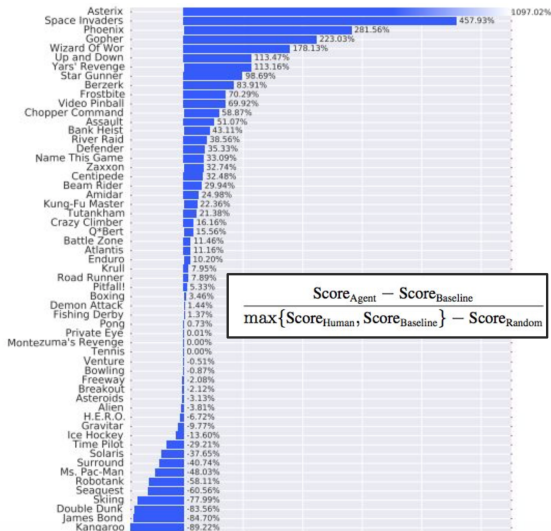


Figure: Wang et al, ICML 2016.

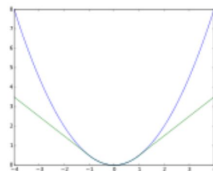
Practical Tips for DQN on Atari (from J. Schulman)

- DQN is more reliable on some Atari tasks than others. Pong is a reliable task: if it doesn't achieve good scores, something is wrong
- Large replay buffers improve robustness of DQN, and memory efficiency is key
 - Use uint8 images, don't duplicate data
- Be patient. DQN converges slowly—for ATARI it's often necessary to wait for 10-40M frames (couple of hours to a day of training on GPU) to see results significantly better than random policy
- In our Stanford class: Debug implementation on small test environment

Practical Tips for DQN on Atari (from J. Schulman) cont.

- Try Huber loss on Bellman error

$$L(x) = \begin{cases} \frac{x^2}{2} & \text{if } |x| \leq \delta \\ \delta|x| - \frac{\delta^2}{2} & \text{otherwise} \end{cases}$$

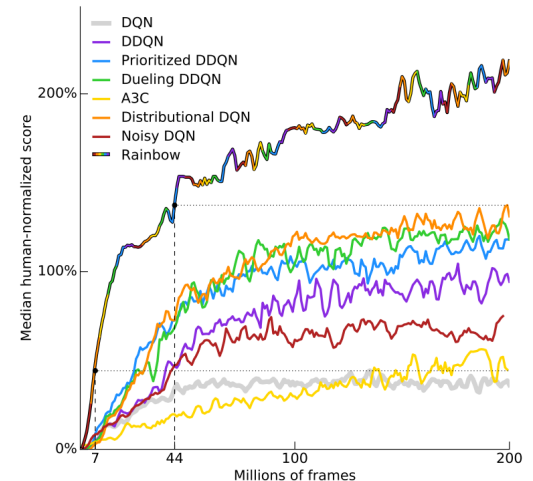


- Consider trying Double DQN—significant improvement from small code change in Tensorflow.
- To test out your data pre-processing, try your own skills at navigating the environment based on processed frames
- Always run at least two different seeds when experimenting
- Learning rate scheduling is beneficial. Try high learning rates in initial exploration period
- Try non-standard exploration schedules

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)
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Deep Reinforcement Learning



- Hessel, Matteo, et al. "Rainbow: Combining Improvements in Deep Reinforcement Learning."

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
- 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

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 most successful?

- In simulation where data is cheap and parallelization is easy
- Harder when:
 - Execution of actions is slow
 - Very expensive or not tolerable to fail
 - 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]
- Parking lot navigation [Abbeel, Dolgov, Ng, and Thrun, IROS 2008]



Learning from Demonstrations

- 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 $P(s' | s, a)$
 - No reward function R
 - Set of one or more teacher's demonstrations $(s_0, a_0, s_1, s_0, \dots)$
(actions drawn from teacher's policy π^*)
- Behavioral Cloning:
 - Can we directly learn the teacher's policy using supervised learning?
- Inverse RL:
 - Can we recover R ?
- Apprenticeship learning via Inverse RL:
 - Can we use R to generate a good policy?

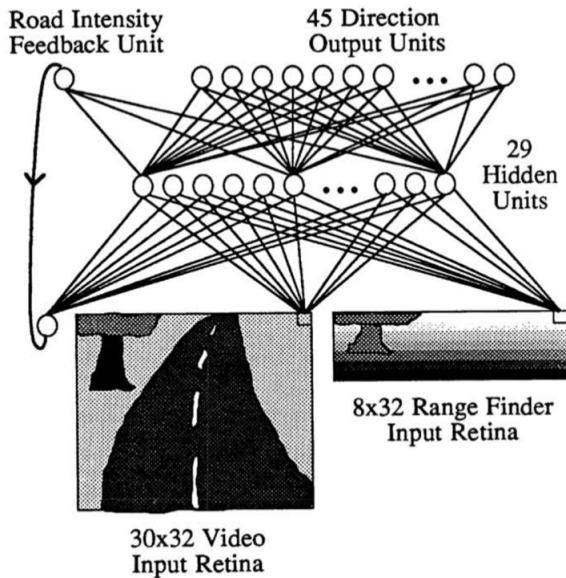
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1 Behavioral Cloning

2 Inverse Reinforcement Learning

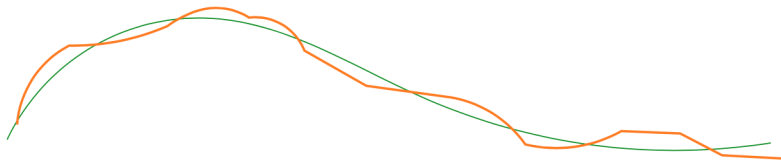
- Formulate problem as a standard machine learning problem:
 - Fix a policy class (e.g. neural network, decision tree, etc.)
 - Estimate a policy from training examples $(s_0, a_0), (s_1, a_1), (s_2, a_2), \dots$
- Two notable success stories:
 - Pomerleau, NIPS 1989: ALVINN
 - Summut et al., ICML 1992: Learning to fly in flight simulator

ALVINN



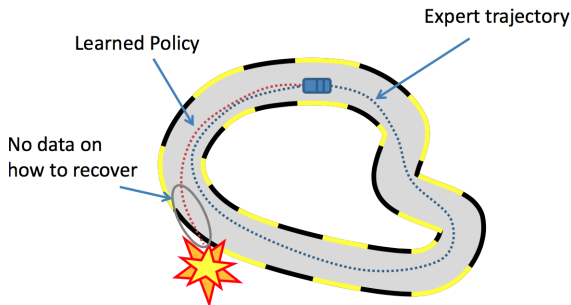
Problem: Compounding Errors

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



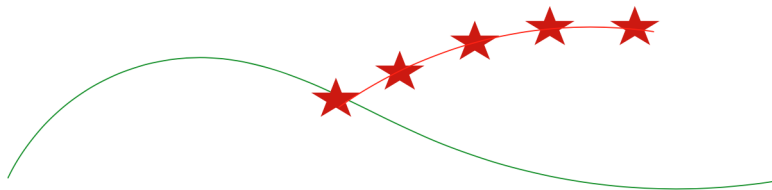
Data distribution mismatch!

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

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

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

Problem: Compounding Errors



Error at time t with probability ϵ

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

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

DAGGER: Dataset Aggregation

```
Initialize  $\mathcal{D} \leftarrow \emptyset$ .  
Initialize  $\hat{\pi}_1$  to any policy in  $\Pi$ .  
for  $i = 1$  to  $N$  do  
    Let  $\pi_i = \beta_i \pi^* + (1 - \beta_i) \hat{\pi}_i$ .  
    Sample  $T$ -step trajectories using  $\pi_i$ .  
    Get dataset  $\mathcal{D}_i = \{(s, \pi^*(s))\}$  of visited states by  $\pi_i$   
    and actions given by expert.  
    Aggregate datasets:  $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_i$ .  
    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
- Key limitation?

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1 Behavioral Cloning

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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 $(s_0, a_0, s_1, s_0, \dots)$
(actions drawn from teacher's policy π^*)
- Goal: infer the reward function R
- Assume that the teacher's policy is optimal. What can be inferred about R ?

Check Your Understanding: Feature Based Reward Function

- Given state space, action space, transition model $P(s' | s, a)$
 - No reward function R
 - Set of one or more teacher's demonstrations $(s_0, a_0, s_1, s_0, \dots)$ (actions drawn from teacher's policy π^*)
 - Goal: infer the reward function R
 - Assume that the teacher's policy is optimal.
-
- 1 There is a single unique R that makes teacher's policy optimal
 - 2 There are many possible R that makes teacher's policy optimal
 - 3 It depends on the MDP
 - 4 Not sure

Linear Feature Reward Inverse RL

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

$$V^\pi = \mathbb{E}_{s \sim \pi} \left[\sum_{t=0}^{\infty} \gamma^t R(s_t) \right]$$

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$$\begin{aligned} V^\pi &= \mathbb{E}_{s \sim \pi} \left[\sum_{t=0}^{\infty} \gamma^t R(s_t) \mid \pi \right] = \mathbb{E}_{s \sim \pi} \left[\sum_{t=0}^{\infty} \gamma^t \mathbf{w}^T \mathbf{x}(s_t) \mid \pi \right] \\ &= \mathbf{w}^T \mathbb{E}_{s \sim \pi} \left[\sum_{t=0}^{\infty} \gamma^t \mathbf{x}(s_t) \mid \pi \right] \\ &= \mathbf{w}^T \mu(\pi) \end{aligned}$$

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

Relating Frequencies to Optimality

- Assume $R(s) = \mathbf{w}^T \mathbf{x}(s)$ where $\mathbf{w} \in \mathbb{R}^n, \mathbf{x} : S \rightarrow \mathbb{R}^n$
- Goal: identify the weight vector $\mathbf{w}$ given a set of demonstrations
- $V^\pi = \mathbb{E}_{s \sim \pi} [\sum_{t=0}^{\infty} \gamma^t R^*(s_t) \mid \pi] = \mathbf{w}^T \mu(\pi)$ where $\mu(\pi)(s) =$ discounted weighted frequency of state s under policy π .

$$V^* \geq V^\pi$$

Relating Frequencies to Optimality

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

$$V^\pi = \mathbf{w}^T \mu(\pi)$$

- $\mu(\pi)(s) =$ discounted weighted frequency of state s under policy π .

$$\mathbb{E}_{s \sim \pi^*} \left[\sum_{t=0}^{\infty} \gamma^t R^*(s_t) \mid \pi^* \right] = V^* \geq V^\pi = \mathbb{E}_{s \sim \pi} \left[\sum_{t=0}^{\infty} \gamma^t R^*(s_t) \mid \pi \right] \quad \forall \pi$$

- Therefore if the expert's demonstrations are from the optimal policy, to identify $\mathbf{w}$ it is sufficient to find $\mathbf{w}^*$ such that

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

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^* , sufficient if its discounted summed feature expectations match the expert's policy [Abbeel & Ng, 2004].
- More precisely, if

$$\|\mu(\pi) - \mu(\pi^*)\|_1 \leq \epsilon$$

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

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

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?

Learning from Demonstration / Imitation Learning Pointers

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

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
- For a look into some of the theory between imitation learning and RL, see Sun, Venkatraman, Gordon, Boots, Bagnell (ICML 2017)

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