Lecture 7: Deep RL Continued

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CS234 Reinforcement Learning.

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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 on 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

Refresh Your Knowledge 6 Solutions

- 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 on the tuples in the bank
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  3. Reduces the data efficiency of DQN
  4. Increases the computational cost
  5. Not sure

Answer: It increases the computational cost, it uses a bank of tuples and it samples them, it's likely to **improve** the data efficiency, and it does not have to always use the most recent history of tuples.

Class Structure

- Last time: CNNs and Deep Reinforcement learning
- This time: DRL
- Next time: Policy Search

Deep RL

- 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)

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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

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

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

  else

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

  end if
  $t = t + 1$
end loop

Double DQN

- Extend this idea to DQN
- Current Q-network $\boldsymbol{w}$ is used to select actions
- Older Q-network $\boldsymbol{w}^-$ is used to evaluate actions

$$\Delta \boldsymbol{w} = \alpha(r + \gamma \overbrace{\hat{Q}(\underbrace{\arg\max_{a'} \hat{Q}(s', a'; \boldsymbol{w})}_{\text{Action selection: } \boldsymbol{w}}; \boldsymbol{w}^-)}^{\text{Action evaluation: } \boldsymbol{w}^-} - \hat{Q}(s, a; \boldsymbol{w}))$$

Double DQN

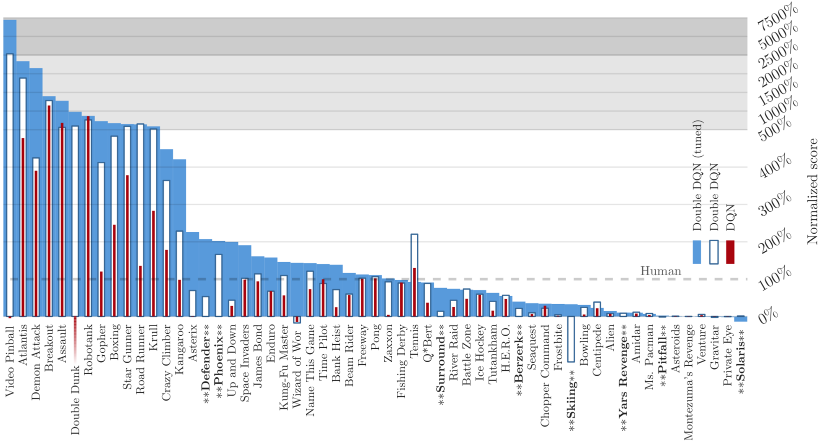

Figure: van Hasselt, Guez, Silver, 2015

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

- $\pi(s) = a_1 \ \forall s$, $\gamma = 1$. Any action from s_1 and s_7 terminates episode
- Trajectory $= (s_3, a_1, 0, s_2, a_1, 0, s_2, a_1, 0, s_1, a_1, 1, \text{terminal})$
- 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]
- Choose 2 additional "replay" backups to do. Which should we pick to get a V 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 $(s_2, a_1, 0, s_2)$
  4. $(s_2, a_1, 0, s_1)$ then $(s_3, a_1, 0, s_2)$
  5. Not sure

Check Your Understanding: Mars Rover Model-Free Policy Evaluation Solution

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

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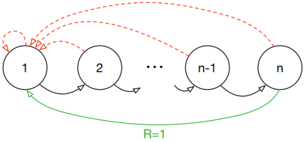
  Answer: $(s_2, a_1, 0, s_1)$, $(s_3, a_1, 0, s_2)$ yielding V =[1 1 1 0 0 0 0].

Impact of Replay?

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

Potential Impact of Ordering Episodic Replay Updates



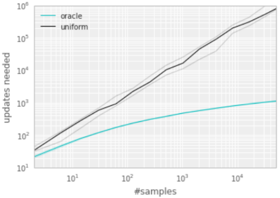


Figure: Schaul, Quan, Antonoglou, Silver ICLR 2016

- 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

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

- Update p_i every update. p_i for new tuples is set to maximum value
- One method[1]: proportional (stochastic prioritization)

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

[1] See paper for details and an alternative

Check Your Understanding: Prioritized Replay

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

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

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- Not Sure

Answer: Selects randomly

Performance of Prioritized Replay vs Double DQN

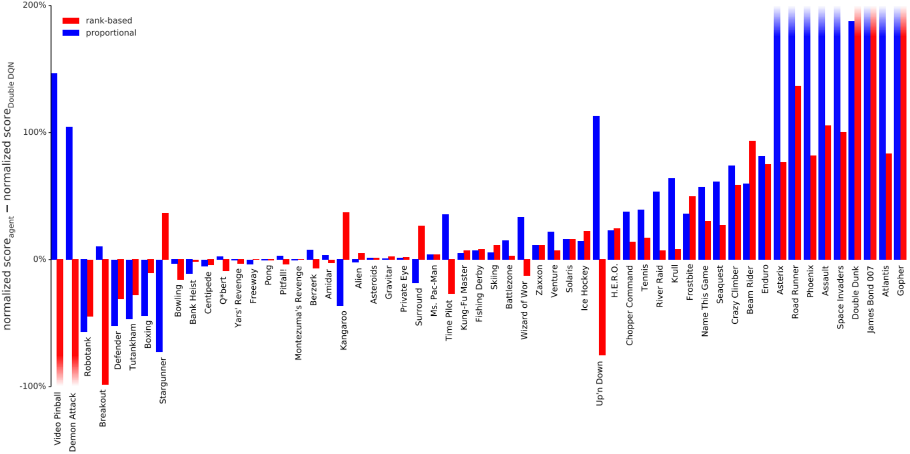

Figure: Schaul, Quan, Antonoglou, Silver ICLR 2016

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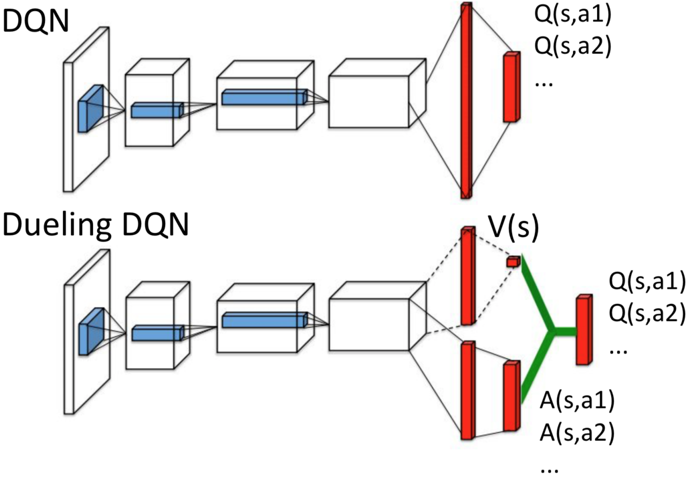
Value & Advantage Function

- Intuition: Features needed 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

Advantage Function and Training

- Advantage function

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

- Consider a network that outputs $V(s;\theta,\beta)$ as well as advantage $A(s,a;\theta,\lambda)$ where θ,β, and λ are parameters
- To construct Q could use $Q(s,a;\theta,\beta,\lambda) = V(s;\theta,\beta) + A(s,a;\theta,\lambda)$
- Do we expect that this architecture will result in learning a good estimate of true V or A?

Check Your Understanding: Unique?

- Advantage function

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

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

Check Your Understanding: Unique?

- Advantage function

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

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

  Answer: No. If we are just given a Q, there are many A and V that could satisfy this – for example, by shifting things by a constant. This can cause challenges for using the simple proposal before: $Q(s,a;\theta,\beta,\lambda) = V(s;\theta,\beta) + A(s,a;\theta,\lambda)$

Uniqueness

- Consider a network that outputs $V(s;\theta,\beta)$ as well as advantage $A(s,a;\theta,\lambda)$ where θ,β, and λ are parameters
- To construct Q could use $Q(s,a;\theta,\beta,\lambda) = V(s;\theta,\beta) + A(s,a;\theta,\lambda)$
- Option 1: Force $Q(s,a) = V(s)$ for the best action suggested by the advantage:

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

- This helps force the V network to approximate V

Uniqueness

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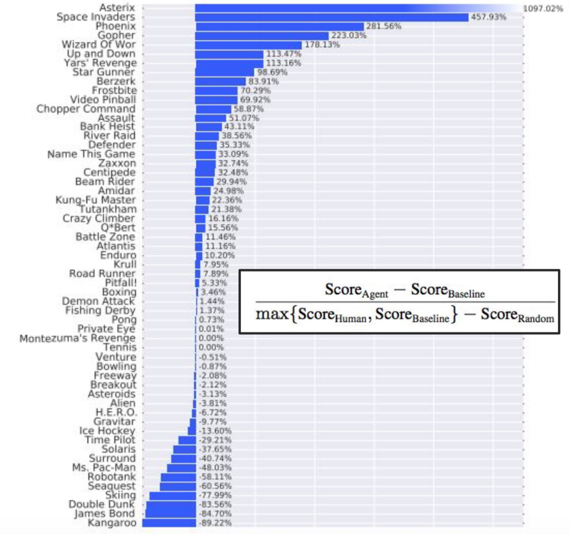
- This helps force the V network to approximate V
- Option 2: Use mean as baseline (more stable)

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

- More stable often because averaging over all advantages instead of the advantage of the current max action.

Dueling DQN V.S. Double DQN with Prioritized Replay



$$\frac{\text{Score}_{\text{Agent}} - \text{Score}_{\text{Baseline}}}{\max\{\text{Score}_{\text{Human}}, \text{Score}_{\text{Baseline}}\} - \text{Score}_{\text{Random}}}$$

Figure: Wang et al, ICML 2016

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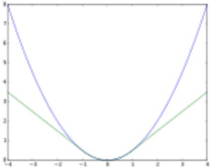
Practical Tips for DQN on Atari (from J. Schulman)

- 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

- Try Huber loss on Bellman error

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



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

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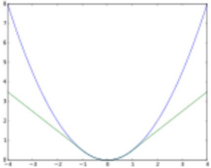

- Consider trying Double DQN—significant improvement from small code change
- To test out your data pre-processing, try your own skills at navigating the environment based on processed frames
- Always run at least two different seeds when experimenting
- Learning rate scheduling is beneficial. Try high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

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

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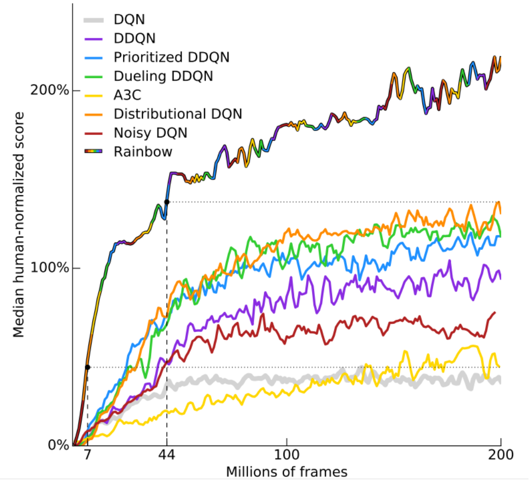
Deep Reinforcement Learning 2018



- Hessel, Matteo, et al. "Rainbow: Combining Improvements in Deep Reinforcement Learning."
- Very active area of research!

Summary of Model Free Value Function Approximation with DNN & What You Should Know

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

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