Lecture 7: Advanced DQN

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Based on CS234 Reinforcement Learning
and Deep RL Bootcamp by DeepMind 2017

Refresh Your Knowledge

- 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

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**

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

  else

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

  end if
  $t = t + 1$
end loop

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)

Check Your Understanding: Mars Rover Model-Free Policy Evaluation

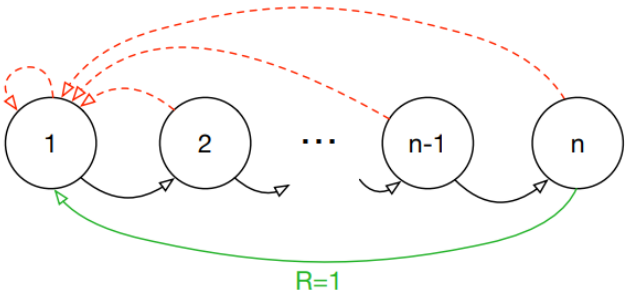
s_1	s_2	s_3	s_4	s_5	s_6	s_7
$R(s_1) = +1$ *Okay Field Site*	$R(s_2) = 0$	$R(s_3) = 0$	$R(s_4) = 0$	$R(s_5) = 0$	$R(s_6) = 0$	$R(s_7) = +10$ *Fantastic Field Site*

- $\pi(s) = a_1 \ \forall s$, $\gamma = 1$. 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, 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



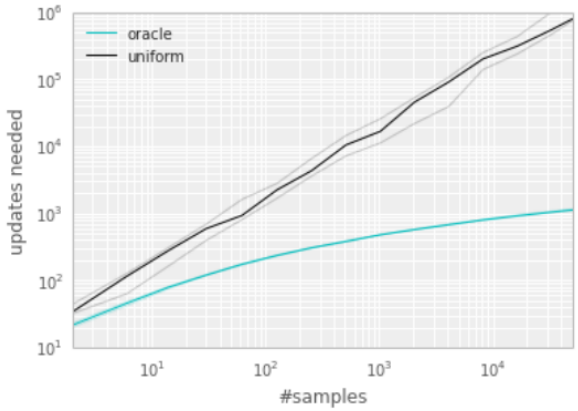


Figure: Schaul, Quan, Antonoglou, Silver ICLR 2016

- 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-the 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 0
- One method[1]: proportional (stochastic prioritization)

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

[1] See paper for details and an alternative

Exercise: Prioritized Replay

- Let i be the index of the i-the 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

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- Update p_i every update. p_i for new tuples is set to 0
- One method[1]: 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

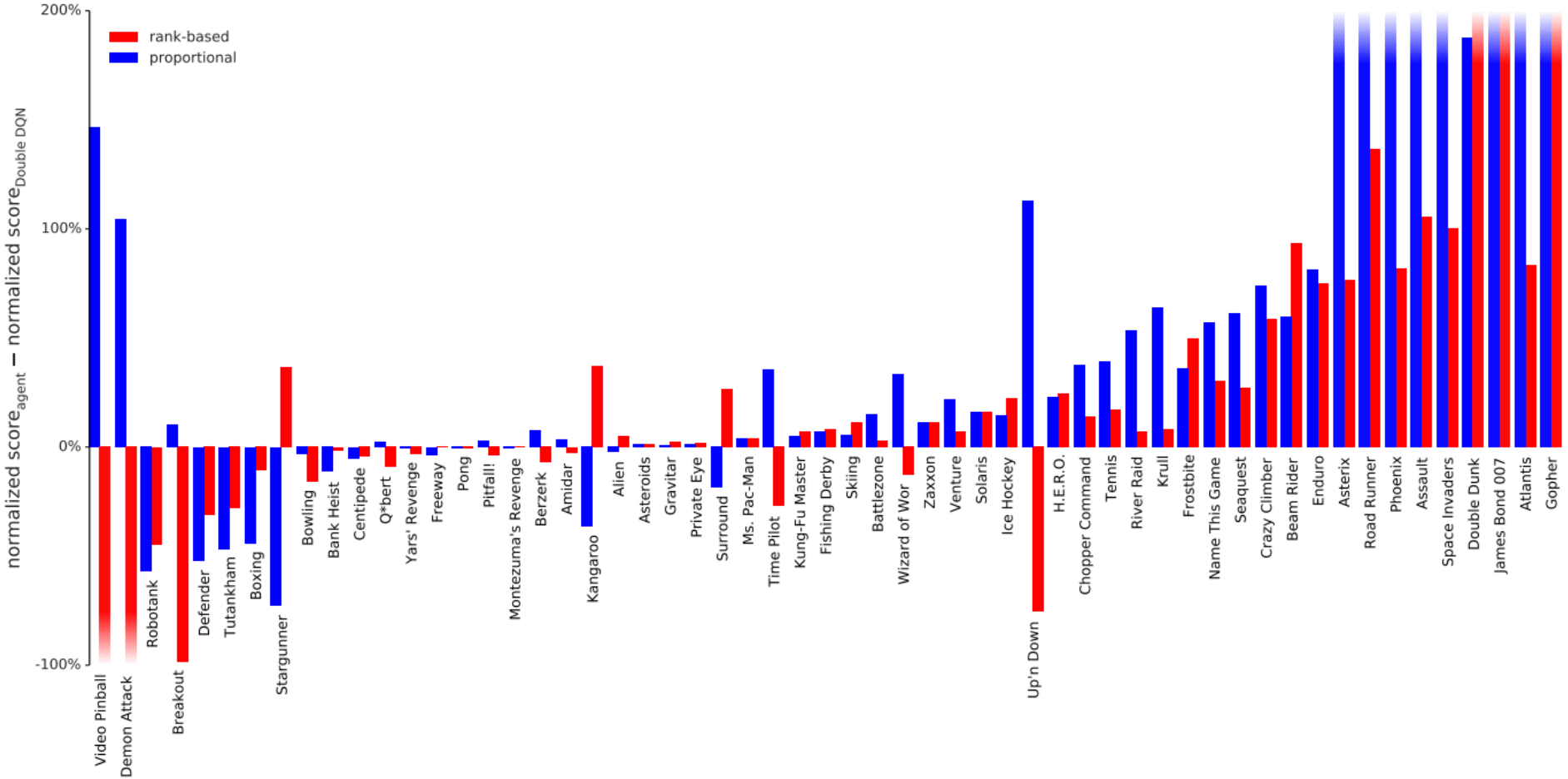

Figure: Schaul, Quan, Antonoglou, Silver ICLR 2016

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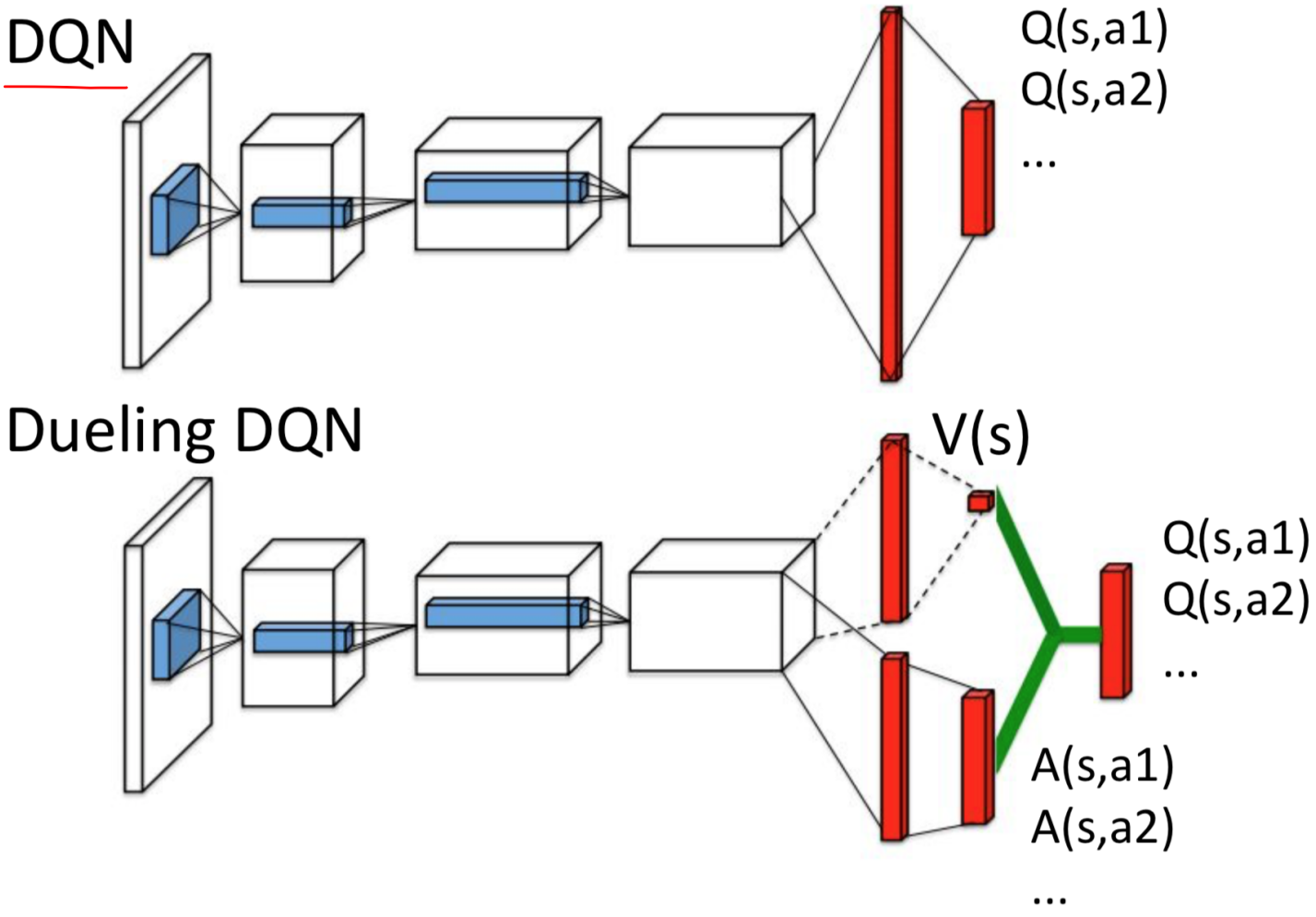
Value & Advantage Function

- Intuition: Features need to accurate 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

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

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

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

Dueling DQN V.S. Double DQN with Prioritized Replay

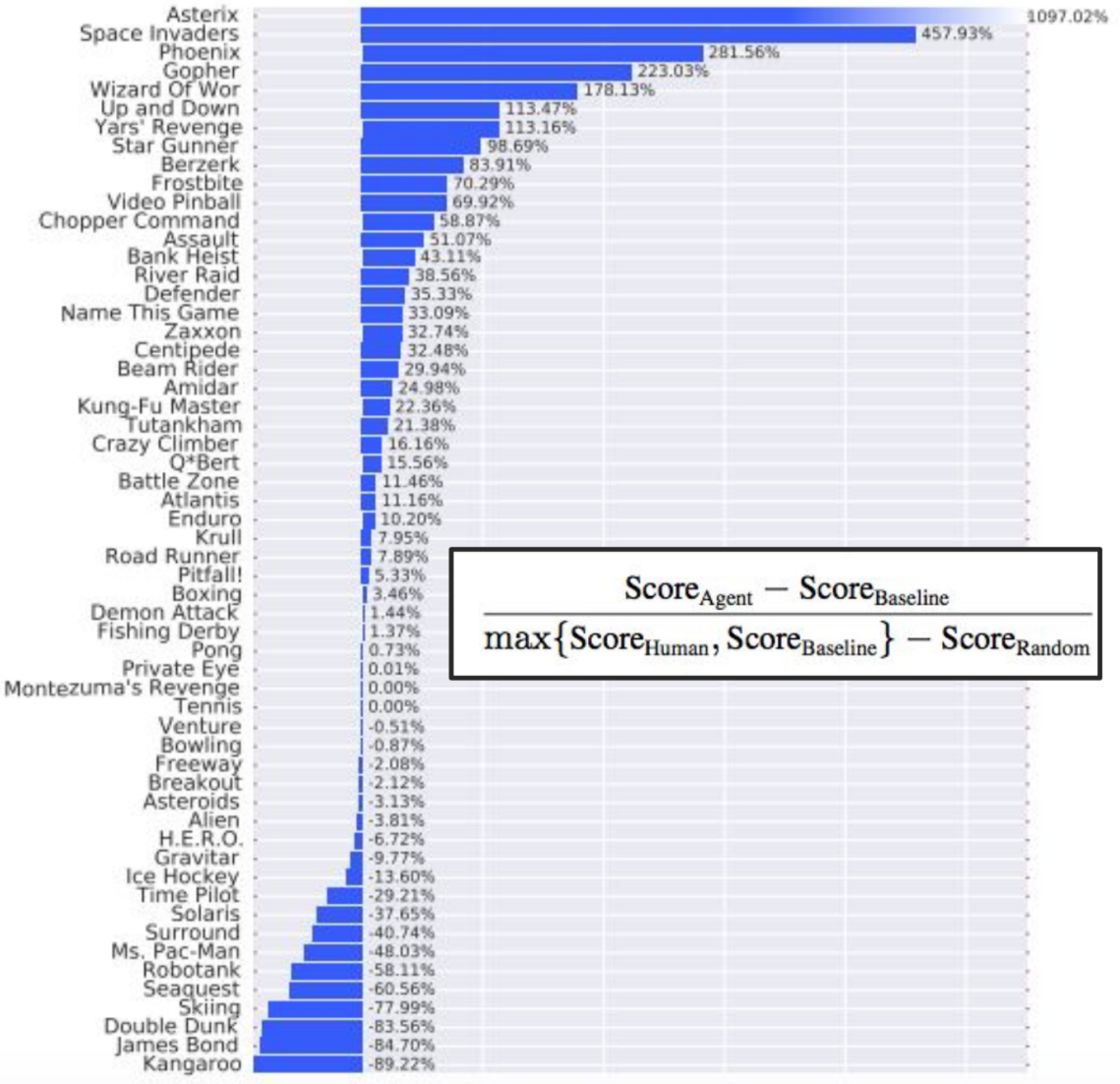


Figure: Wang et al, ICML 2016

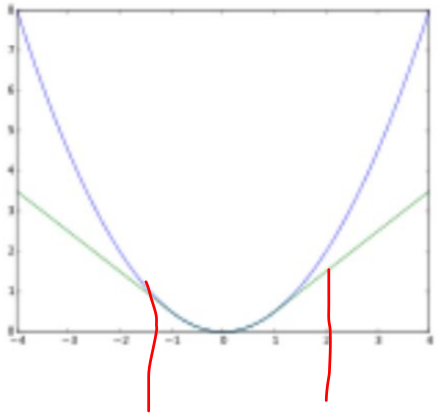
Practical Tips for DQN on Atari (from J. Schulman)

- 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

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

- Try Huber loss on Bellman error

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



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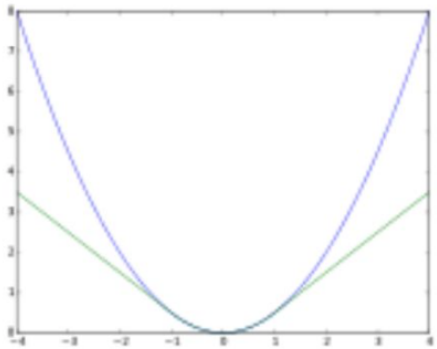

- Consider trying Double DQN—significant improvement from small code change in Tensorflow.
- To test out your data pre-processing, try your own skills at navigating the environment based on processed frames
- Always run at least two different seeds when experimenting
- Learning rate scheduling is beneficial.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

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

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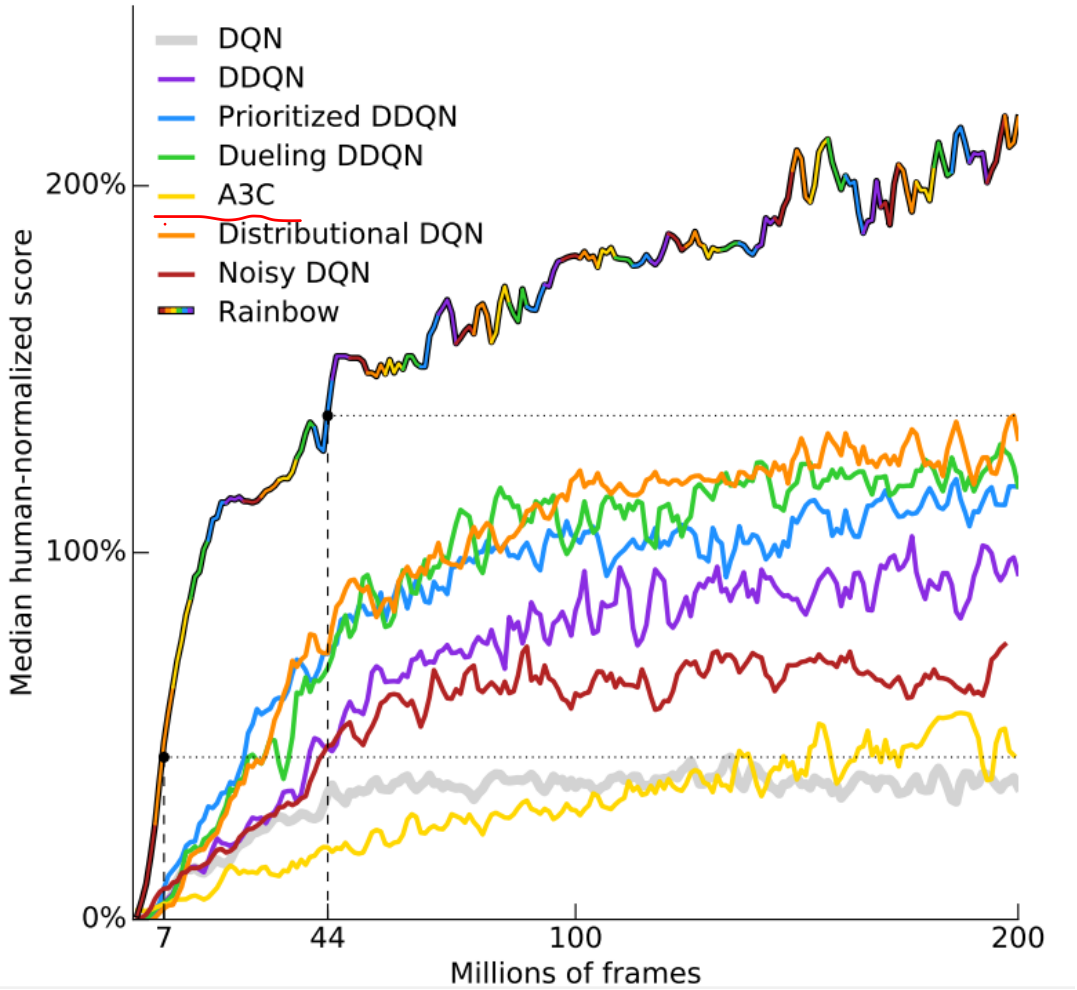
Deep Reinforcement Learning



- 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 and variants
- 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
- 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, . . .)