Lecture 7: Deep RL

CS234: RL

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Much of the content for this lecture is borrowed from Ruslan Salakhutdinov's class, Rich Sutton's class and David Silver's class on RL.

Goal: Build RL Agent to Play Atari

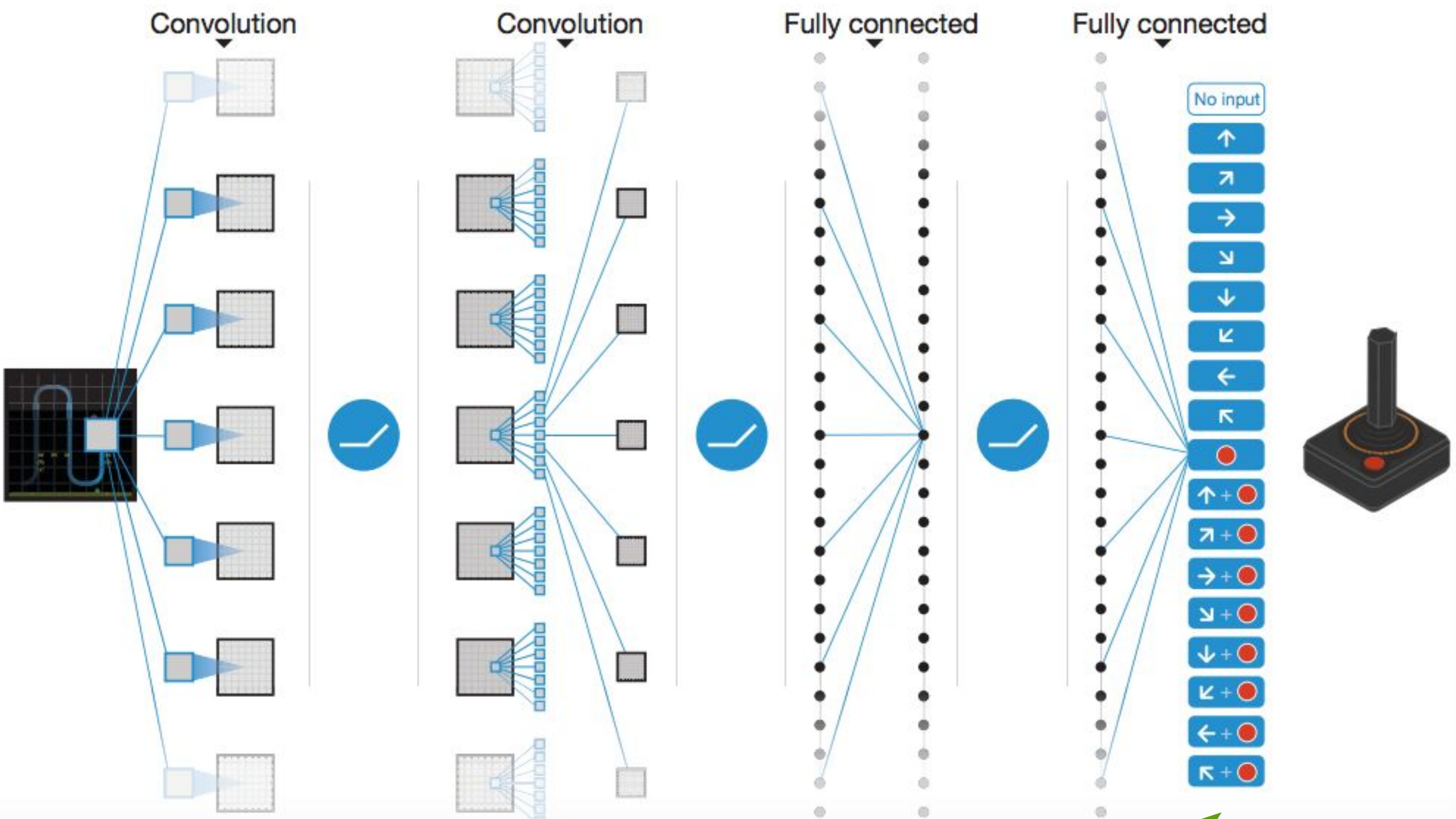
Generalization in RL

- Need some way to scale to large state spaces
- Important for planning
- Important for learning
- One approach: Model free RL
  - Use value function approximation
  - Discussed using linear weighted combination of features
  - Does this work for Atari?

Recap: Q-learning + Deep Learning

- Deep Q learning
  - Use deep learning to represent Q function
  - Learns directly from pixels to control

DQN Architecture



1 network, outputs Q value for each action

Recap: Q-learning + Deep Learning

- Challenge of using function approximation
  - Local updates (s,a,r,s') highly correlated
  - "Target" (approximation to true value of s') can change quickly and lead to instabilities
- Deep Q-learning
  - Experience replay of mix of prior (s_i,a_i,r_i,s_{i+1}) tuples to update Q
  - Fix target for number of steps

Recap: DQN

- Experience replay of mix of prior (s_i,a_i,r_i,s_{i+1}) tuples to update Q(w)
- Fix target Q (w–) for number of steps, then update
- Optimize MSE between current Q and Q target

$$\mathbb{E}_{s,a,r,s' \sim \mathcal{D}_i} \left[\left(\underbrace{r + \gamma \max_{a'} Q(s', a'; w_i^-)}_{\text{Q-learning target}} - \underbrace{Q(s, a; w_i)}_{\text{Q-network}} \right)^2 \right]$$

- Use stochastic gradient descent

Recap: Double Q-Learning

- Use 2 Q deep nets
- Switch between which network is used as target or for policy selection
- Significant improvement

Deep RL

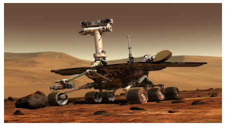
- Hugely expanding area
- Will discuss more later in course
- Today: 2 other influential model-free deep RL ideas

Which Aspects of DQN Were Important for Success?

Game	Linear	Deep netowrk	DQN with fixed Q	DQN with replay	DQN with replay and fixed Q
Breakout	3	3	10	241	317
Enduro	62	29	141	831	1006
River Raid	2345	1453	2868	4102	7447
Sequest	656	275	1003	823	2894
Space Invaders	301	302	373	826	1089

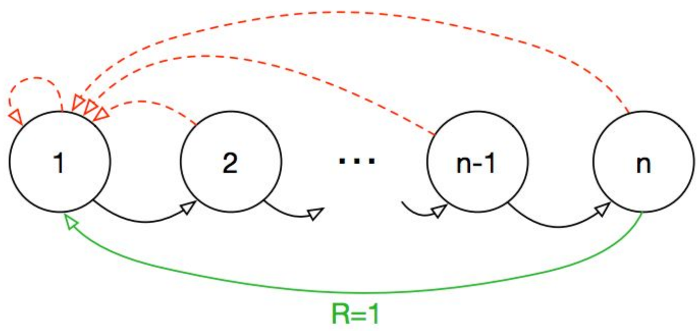
- Replay is **hugely** important

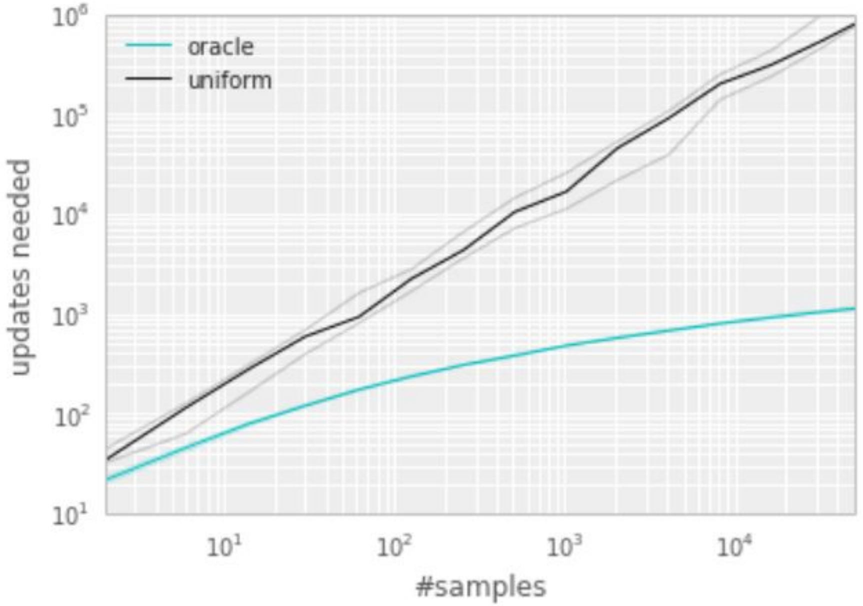
Order of Replay?

S1	S2	S3	S4	S5	S6	S7
Okay Field Site +1						Fantastic Field Site +10

- In tabular TD-learning, discussed replay could help speed learning
- Repeating some updates seem to better propagate info than others
- Systematic ways to prioritize updates?

How Much Might Ordering Updates Help?





- Oracle: picks (s,a,r,s’) tuple that will minimize global loss
- **Exponential improvement in convergence!**
- Number of updates needed to converge
- Not practical but illustrates potential impact of order

Schaul, Quan, Antonoglou, Silver ICLR 2016

Prioritized Experience Replay

- Sample (s,a,r,s') tuple for update using priority
- Priority of a tuple is proportional to DQN error

$$\underbrace{\left| r + \gamma \max_{a'} Q(s', a', \mathbf{w}^-) - Q(s, a, w) \right|}$$

Stochastic Prioritization

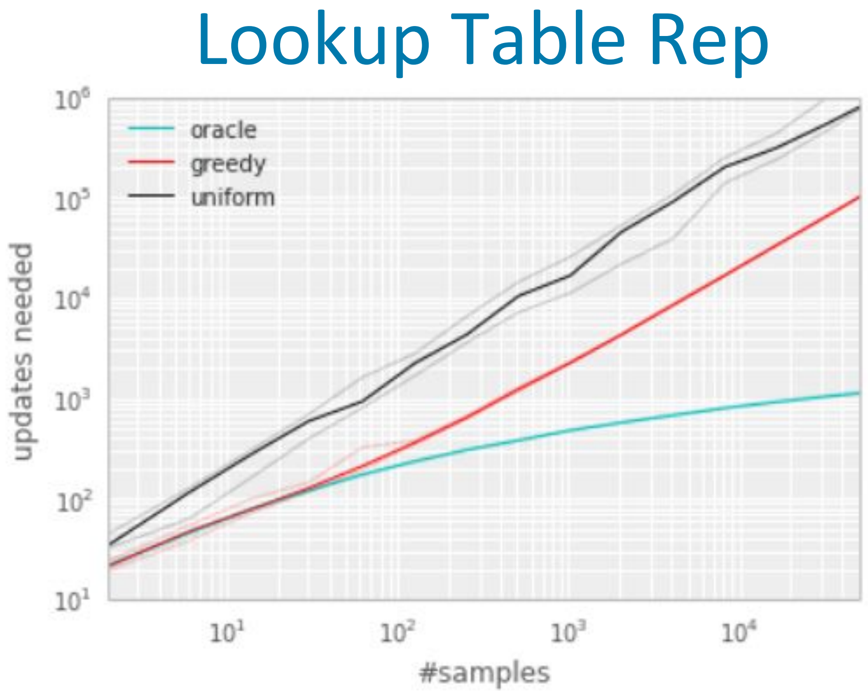
p_i is proportional to DQN error

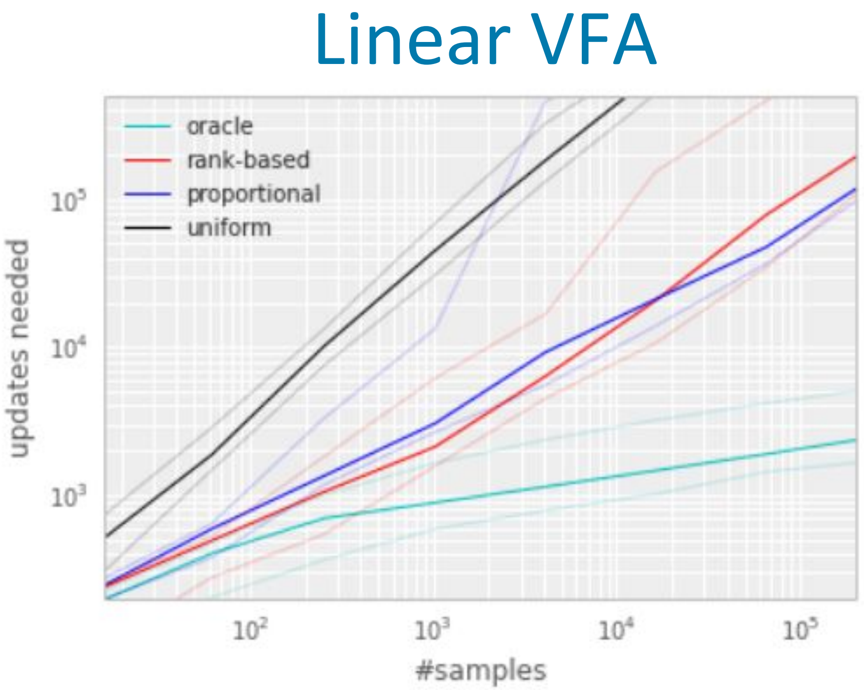
$$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$$

- α=0, uniform
- Update p_i every update
- p_i for new tuples set to 0

Schaul, Quan, Antonoglou, Silver ICLR 2016

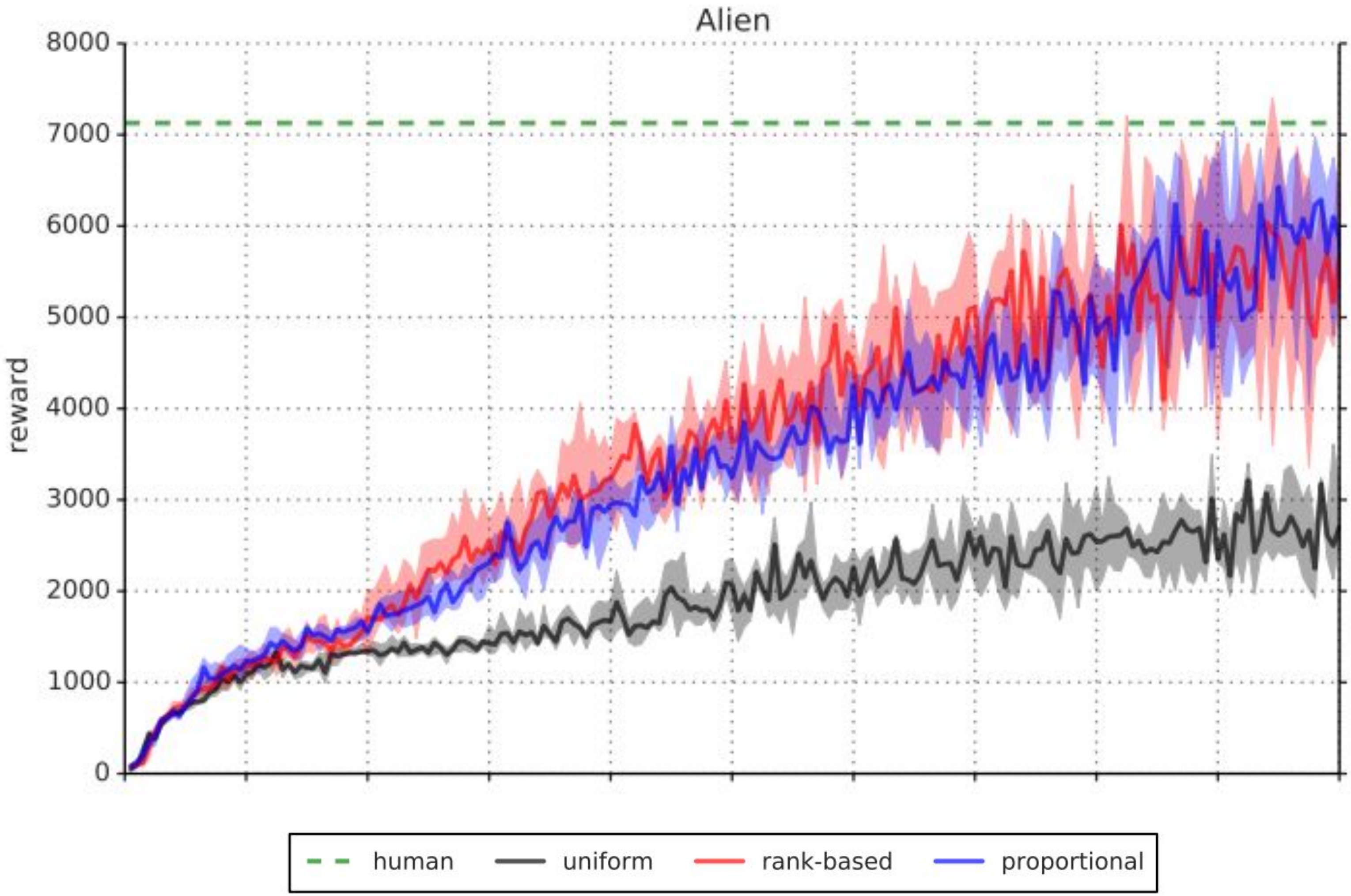
Impact of Order





- Note: prioritized replay changes distribution of data sampled, which introduces bias
- Can correct for this, see paper

Substantially Improved Performance



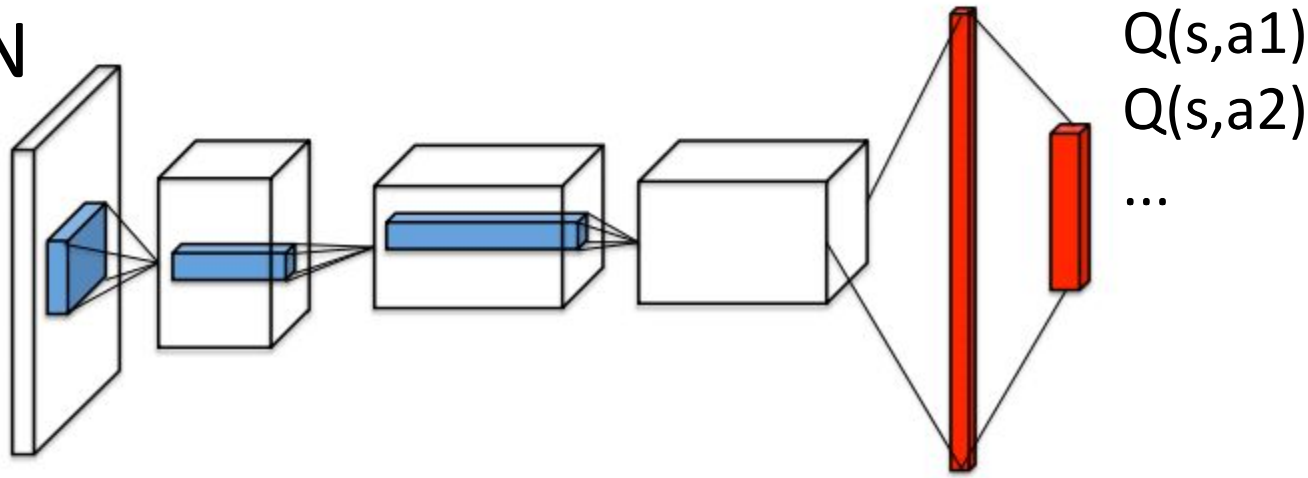
Value & Advantage Function

- Intuition: Features need to pay attention to determine value may be different than those need to determine action benefit
- E.g.
  - Game score may be relevant to predicting V(s)
  - But not necessarily in indicating relative action values
- Advantage function (Baird 1993)

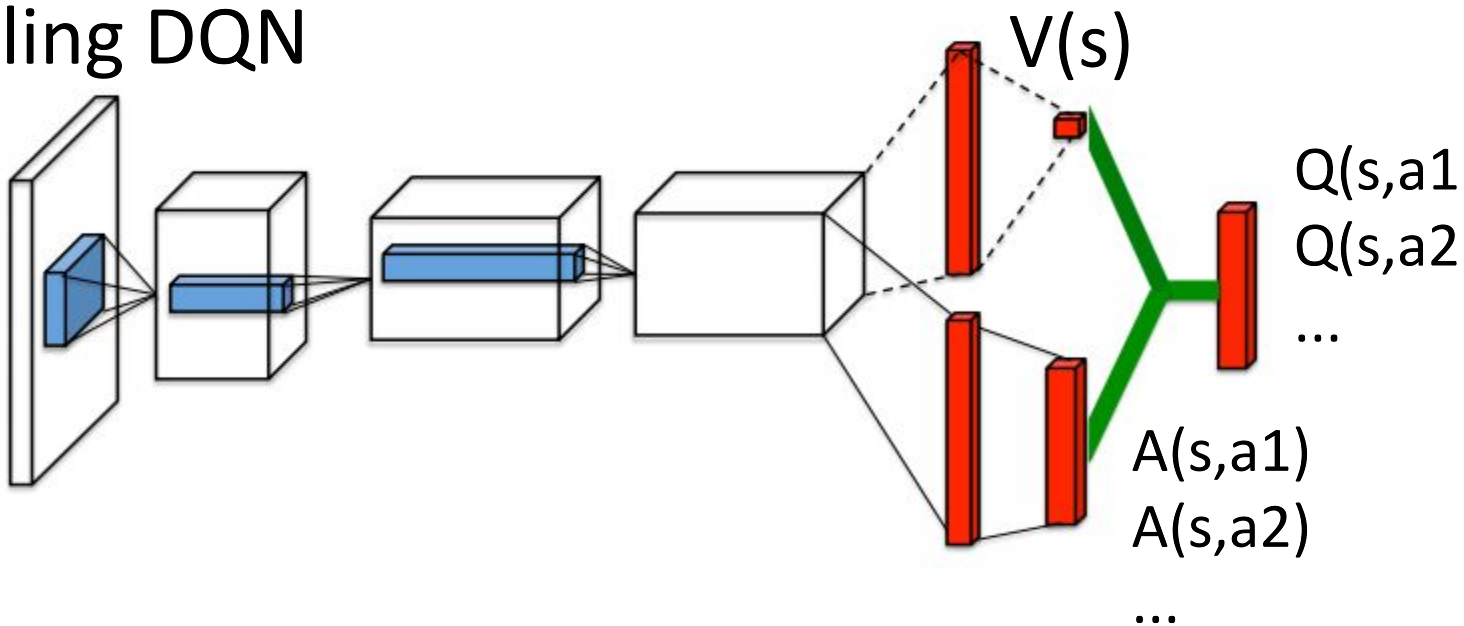
$$A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$$

Wang et.al., ICML, 2016

DQN



Dueling DQN



Wang et.al., ICML, 2016

Identifiability

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

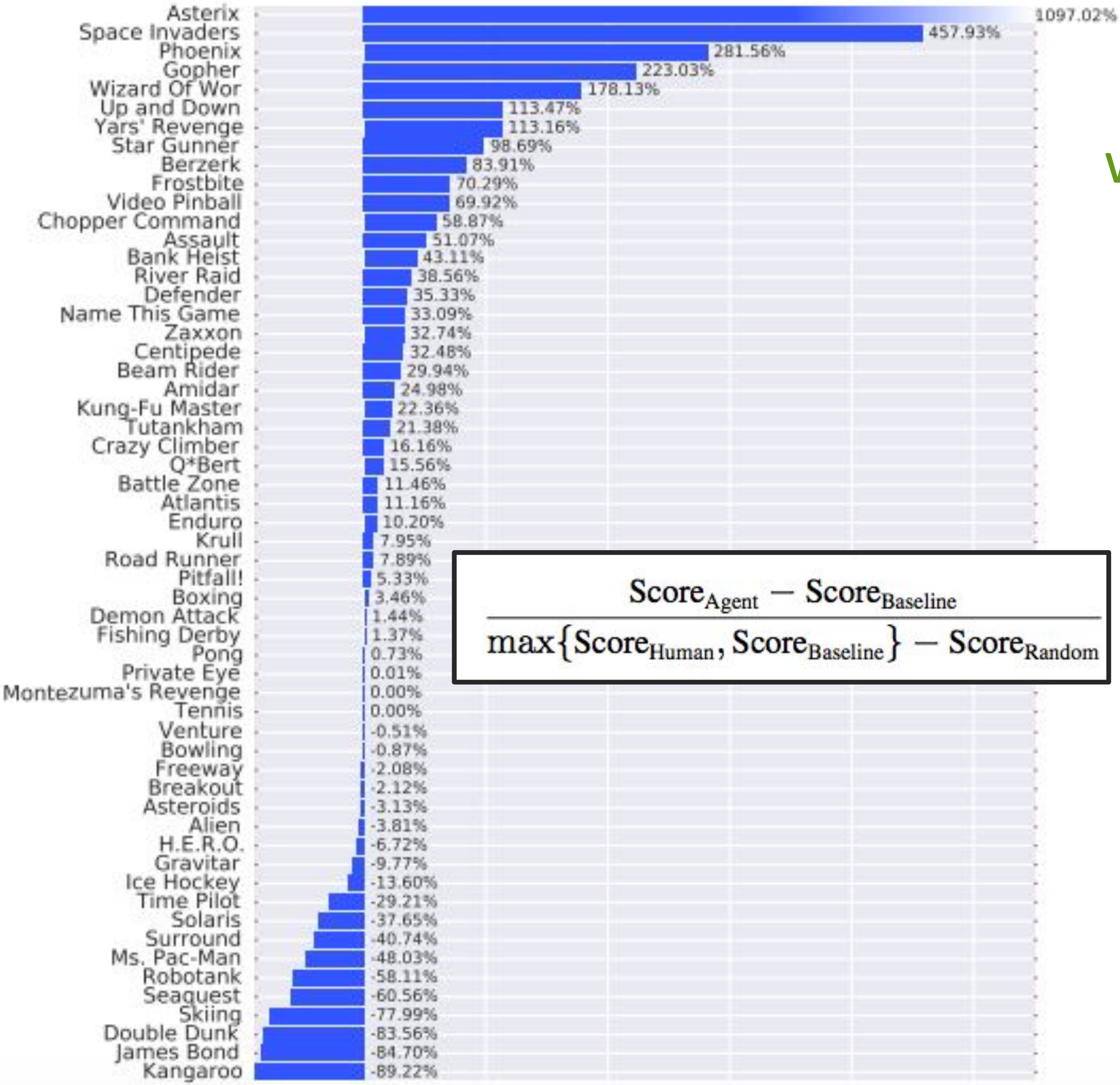
- Unidentifiable
- Option 1: Force A(s,a) = 0 if a is action taken

$$Q(s,a;\theta,\alpha,\beta) = V(s;\theta,\beta) + \left(A(s,a;\theta,\alpha) - \max_{a' \in |\mathcal{A}|} A(s,a';\theta,\alpha) \right)$$

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

$$Q(s,a;\theta,\alpha,\beta) = V(s;\theta,\beta) + \left(A(s,a;\theta,\alpha) - \frac{1}{|\mathcal{A}|} \sum_{a'} A(s,a';\theta,\alpha) \right)$$

Vs DDQN w/Prioritized Replay



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

Model Free Deep RL: Quick Summary

- Stabilize target (proxy for true reward)
- Reuse prior experience in prioritized way
- Separate value and advantage

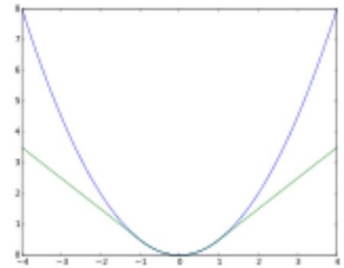
Practical Tips for DQN on Atari
(from J Schulman)

- 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 II
(from J Schulman)

- Try Huber loss on Bellman error

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



- Consider trying Double DQN—significant improvement from 3-line change in Tensorflow.
- To test out your data preprocessing, 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

Return to Model Free RL… Challenges of Target

$$\mathbb{E}_{s,a,r,s'\sim\mathcal{D}_i}\left[\left(\underbrace{r+\gamma\max_{a'}Q(s',a';w_i^-)}_{\text{Q-learning target}}-\underbrace{Q(s,a;w_i)}_{\text{Q-network}}\right)^2\right]$$

- Running stochastic gradient descent
- Ideally what should Q-learning target be?

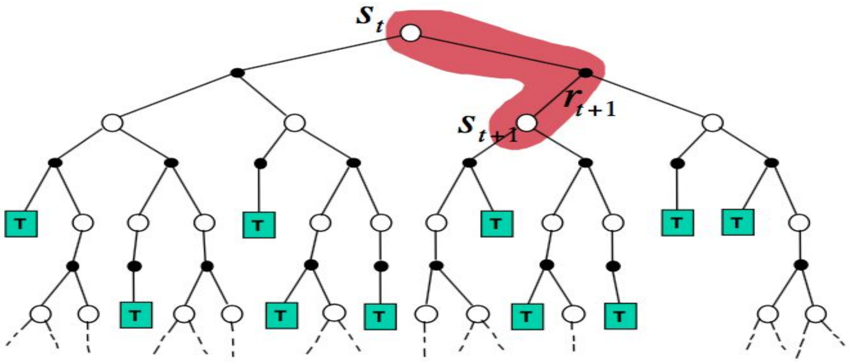
Return to Model Free RL…
Challenges of Target

$$\mathbb{E}_{s,a,r,s'\sim\mathcal{D}_i}\left[\left(\underbrace{r+\gamma\max_{a'}Q(s',a';w_i^-)}_{\text{Q-learning target}}-\underbrace{Q(s,a;w_i)}_{\text{Q-network}}\right)^2\right]$$

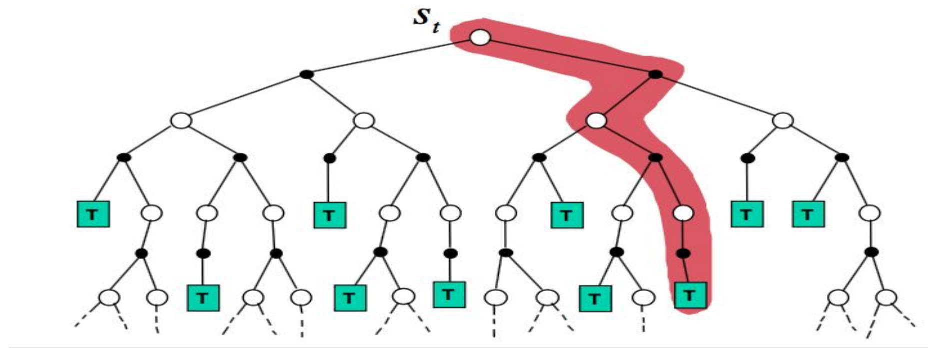
- Running stochastic gradient descent
- Ideally what should Q-learning target be?
  - V(s')
  - But we don't know that
  - Could be use Monte Carlo estimate (sum of rewards to the end of the episode)

TD vs Monte Carlo

$$V(S_t) \leftarrow V(S_t) + \alpha \left(R_{t+1} + \gamma V(S_{t+1}) - V(S_t) \right)$$



$$V(S_t) \leftarrow V(S_t) + \alpha \left(G_t - V(S_t) \right)$$



Monte Carlo vs TD Learning

- Computational complexity
- Memory requirements
- Convergence & Q representation
  - Convergence guaranteed?
  - Performance of convergence point?
  - Rate of convergence?
- In on policy case?
  - When evaluating the value of a fixed policy
- In off policy case?
  - When using data to evaluate value of a different $\boldsymbol{\pi}$

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Monte Carlo vs TD Learning: Convergence in On Policy Case

- Evaluating value of a single policy

$$MSVE(w) = \sum_{s \in S} d(s) \left(V^{\pi}(s) - \tilde{V}^{\pi}(s, w) \right)^2$$

- where
  - d(s) is generally the on-policy $\boldsymbol{\pi}$ stationary distrib
  - ~V(s,w) is the value function approximation

Tsitsiklis and Van Roy. An Analysis of Temporal-Difference Learning with Function Approximation. 1997

Monte Carlo Convergence: Linear VFA
(*Note: correction from prior slides)

- Evaluating value of a single policy

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  - ~V(s,w) is the value function approximation
- Linear VFA: $V(s) = \sum_i w_i f_i(s)$
- **Monte Carlo converges to min MSE possible!**

$$MSVE(w_{MC}) = \min_w \sum_{s \in S} d(s) \left(V^{\pi}(s) - \tilde{V}^{\pi}(s, w) \right)^2$$

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TD Learning Convergence: Linear VFA

(*Note: correction from prior slides)

- Evaluating value of a single policy

$$MSVE(w) = \sum_{s \in S} d(s) \left(V^{\pi}(s) - \tilde{V}^{\pi}(s, w) \right)^2$$

- where
  - d(s) is generally the on-policy π stationary distrib
  - ~V(s,w) is the value function approximation
- Linear VFA: $V(s) = \sum_i w_i f_i(s)$
- **TD converges to constant factor of best MSE**

$$\begin{aligned} MSVE(w_{TD}) &= \frac{1}{1-\gamma} \min_w \sum_{s \in S} d(s) \left(V^{\pi}(s) - \tilde{V}^{\pi}(s, w) \right)^2 \\ &= \frac{1}{1-\gamma} MSVE(w_{MC}) \end{aligned}$$

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TD Learning vs Monte Carlo: Linear VFA Convergence Point

- Linear VFA: $V(s) = \sum_i w_i f_i(s)$
- Monte Carlo estimate:
- $$MSVE(w_{MC}) = \min_w \sum_{s \in S} d(s) \left(V^\pi(s) - \tilde{V}^\pi(s, w) \right)^2$$
- TD converges to constant factor of best MSE

$$MSVE(w_{TD}) = \frac{1}{1-\gamma} MSVE(w_{MC})$$

- In look up table case what does this say about MSVE of MC and TD?

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TD Learning vs Monte Carlo: Convergence Rate

- Which converges faster?
- Not (to my knowledge) definitively understood
- Practically TD learning often converges faster to its fixed point

Tsitsiklis and Van Roy. An Analysis of Temporal-Difference Learning with Function Approximation. 1997

TD Learning vs Monte Carlo:

Finite Data, Lookup Table, Which is Preferable?

- MC Estimates
- vs TD learning with (infinite) experience replay

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TD Learning vs Monte Carlo:
Finite Data, Lookup Table, Which is Preferable?

- MC Estimates
- vs TD learning with (infinite) experience replay
- 8 episodes, all of 1 or 2 steps duration
  - 1st episode: A, 0, B, 0
  - 6 episodes where observe: B, 1
  - 8th episode: B, 0
- Assume discount factor = 1
- What is a good estimate for V(B)?

Example 6.4, Sutton and Barto

TD Learning vs Monte Carlo:

Finite Data, Lookup Table, Which is Preferable?

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  - 1st episode: A, 0, B, 0
  - 6 episodes where observe: B, 1
  - 8th episode: B, 0
- Assume discount factor = 1
- What is a good estimate for V(B)?
  - Observed total reward of 1 6 times
  - Observed total reward of 0 2 times
  - Reasonable estimate V(B) = 6/8 = 3/4

Example 6.4, Sutton and Barto

TD Learning vs Monte Carlo:

Finite Data, Lookup Table, Which is Preferable?

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- Assume discount factor = 1
- What is a good estimate for V(B)? ¾
- What is a good estimate of V(A)?
  - What would TD learning w/infinite replay give?
  - What would MC estimate give?

Example 6.4, Sutton and Barto

TD Learning & Monte Carlo: Off Policy

- In Q-learning follow one policy while learning about value of optimal policy
- How do we do this with Monte Carlo estimation?
  - Recall that in MC estimation, just average sum of future rewards from a state
  - Assumes always following same policy

Example 6.4, Sutton and Barto

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- How do we do this with Monte Carlo estimation?
  - Recall that in MC estimation, just average sum of future rewards from a state
  - Assumes always following same policy
- Solution for off policy MC: Importance Sampling!

Example 6.4, Sutton and Barto

TD Learning & Monte Carlo: Off Policy

- With lookup table representation
  - Both Q-learning and Monte Carlo estimation (with importance sampling) will converge to value of optimal policy
  - Requires mild conditions over behavior policy (e.g. infinitely visiting each state--action pair is one sufficient condition)
- What about with function approximation?

Example 6.4, Sutton and Barto

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  - Requires mild conditions over behavior policy (e.g. infinitely visiting each state--action pair is one sufficient condition)
- What about with function approximation?
  - Target update is wrong
  - Distribution of samples is wrong

Example 6.4, Sutton and Barto

TD Learning & Monte Carlo: Off Policy

- With lookup table representation
  - Both Q-learning and Monte Carlo estimation (with importance sampling) will converge to value of optimal policy
  - Requires mild conditions over behavior policy (e.g. infinitely visiting each state--action pair is one sufficient condition)
- What about with function approximation?
  - Q-learning with function approximation can diverge
    - See examples in Chapter 11 (Sutton and Barto)
  - But in practice often does very well

Example 6.4, Sutton and Barto

Summary: What You Should Known

- Deep learning for model-free RL
  - Understand how to implement DQN
  - 2 challenges solving and how it solves them
  - What benefits double DQN and dueling offer
  - Convergence guarantees
- MC vs TD
  - Benefits of TD over MC
  - Benefits of MC over TD