Deep Q-Networks

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DeepMind

Recap: Q-Learning

- Learning a parametric Q function: $Q_\theta(s, a)$
  - Remember: $\text{target}(s') = R(s, a, s') + \gamma \max_{a'} Q_{\theta_k}(s', a')$
  - Update: $\theta_{k+1} \leftarrow \theta_k - \alpha \nabla_\theta \mathbb{E}_{s' \sim P(s'|s,a)} \left[(Q_\theta(s, a) - \text{target}(s'))^2 \right] \big|_{\theta=\theta_k}$
  - For tabular function, $\theta \in \mathbb{R}^{||S|| \times ||A|}$, we recover the familiar update:

$$Q_{k+1}(s, a) \leftarrow (1 - \alpha) Q_k(s, a) + \alpha \left[\text{target}(s') \right]$$

    - Converges to optimal values (*)
  - Does it work with a neural network Q functions?
    - Yes but with some care

Recap: (Tabular) Q-Learning

Algorithm:

Start with $Q_0(s, a)$ for all s, a.

Get initial state s

For k = 1, 2, … till convergence

Sample action a, get next state s’

If s’ is terminal:

$$\text{target} = R(s, a, s')$$

Sample new initial state s’

else:

$$\text{target} = R(s, a, s') + \gamma \max_{a'} Q_k(s', a')$$

$$Q_{k+1}(s, a) \leftarrow (1 - \alpha) Q_k(s, a) + \alpha \left[\text{target}\right]$$

$$s \leftarrow s'$$

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Chasing a nonstationary target!

Updates are correlated within a trajectory!

DQN

- High-level idea - **make Q-learning look like supervised learning**.
- Two main ideas for stabilizing Q-learning.
- Apply Q-updates on batches of past experience instead of online:
  - **Experience replay** (Lin, 1993).
  - Previously used for better data efficiency.
  - Makes the data distribution more stationary.

- Use an older set of weights to compute the targets (**target network**):
  - Keeps the target function from changing too quickly.

$$L_i(\theta_i) = \mathbb{E}_{s,a,s',r\sim D}\left(\underbrace{r + \gamma \max_{a'} Q(s', a'; \theta_i^-)}_{\text{target}} - Q(s, a; \theta_i)\right)^2$$

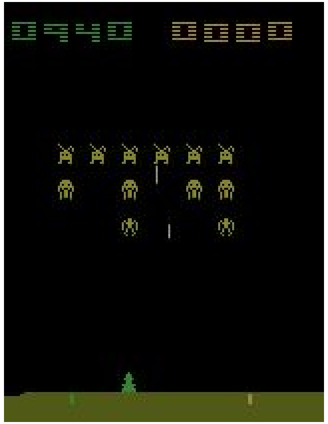
"Human-Level Control Through Deep Reinforcement Learning", Mnih, Kavukcuoglu, Silver et al. (2015)

Target Network Intuition

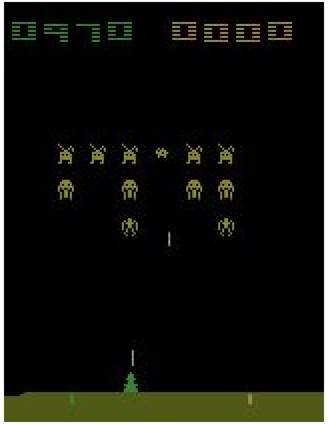
- Changing the value of one action will change the value of other actions and similar states.
- The network can end up chasing its own tail because of bootstrapping.
- Somewhat surprising fact - bigger networks are less prone to this because they alias less.

$$L_i(\theta_i) = \mathbb{E}_{s,a,s',r\sim D}\left(\underbrace{r + \gamma \max_{a'} Q(s', a'; \theta_i^-)}_{\text{target}} - Q(s, a; \theta_i)\right)^2$$

s



s'



DQN Training Algorithm

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N

Initialize action-value function Q with random weights θ

Initialize target action-value function $\hat{Q}$ with weights $\theta^- = \theta$

For episode $= 1, M$ **do**

  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$

  For $t = 1$,T **do**

    With probability ε select a random action a_t

    otherwise select $a_t = \mathrm{argmax}_a Q(\phi(s_t), a; \theta)$

    Execute action a_t in emulator and observe reward r_t and image x_{t+1}

    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$

    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D

    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D

    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$

    Perform a gradient descent step on $\left(y_j - Q(\phi_j, a_j; \theta)\right)^2$ with respect to the network parameters θ

    Every C steps reset $\hat{Q} = Q$

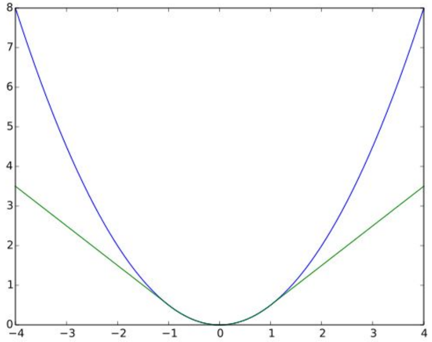
  End For

End For

DQN Details

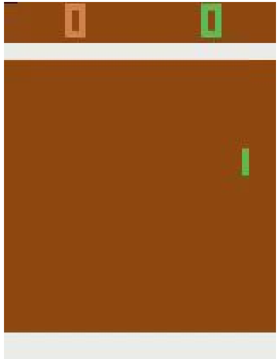
- Uses Huber loss instead of squared loss on Bellman error:

$$L_\delta(a) = \begin{cases} \frac{1}{2}a^2 & \text{for } |a| \le \delta, \\ \delta(|a| - \frac{1}{2}\delta), & \text{otherwise.} \end{cases}$$

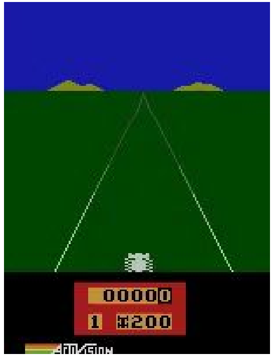


- Uses RMSProp instead of vanilla SGD.
  - Optimization in RL really matters.
- It helps to anneal the exploration rate.
  - Start ε at 1 and anneal it to 0.1 or 0.05 over the first million frames.

DQN on ATARI

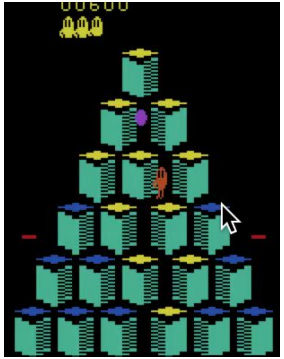


Pong



Enduro

Beamrider

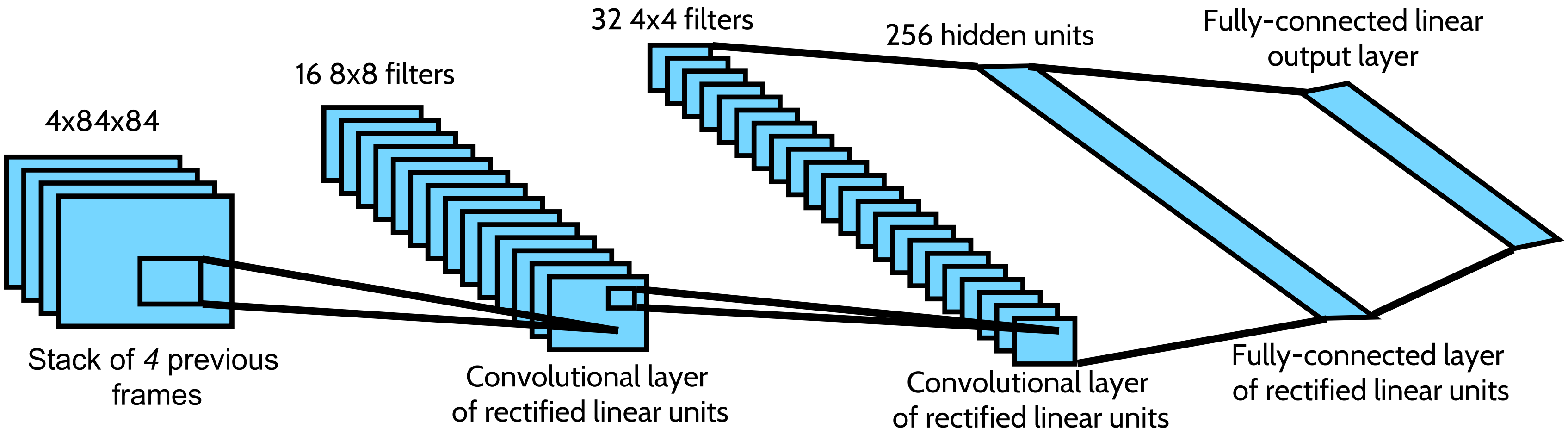


Q*bert

- 49 ATARI 2600 games
- From pixels to actions
- Same algorithm
- Same function approximator, w/ 3M free parameters
- Same hyperparameters
- Roughly human-level performance on 29 out of 49 games

ATARI Network Architecture

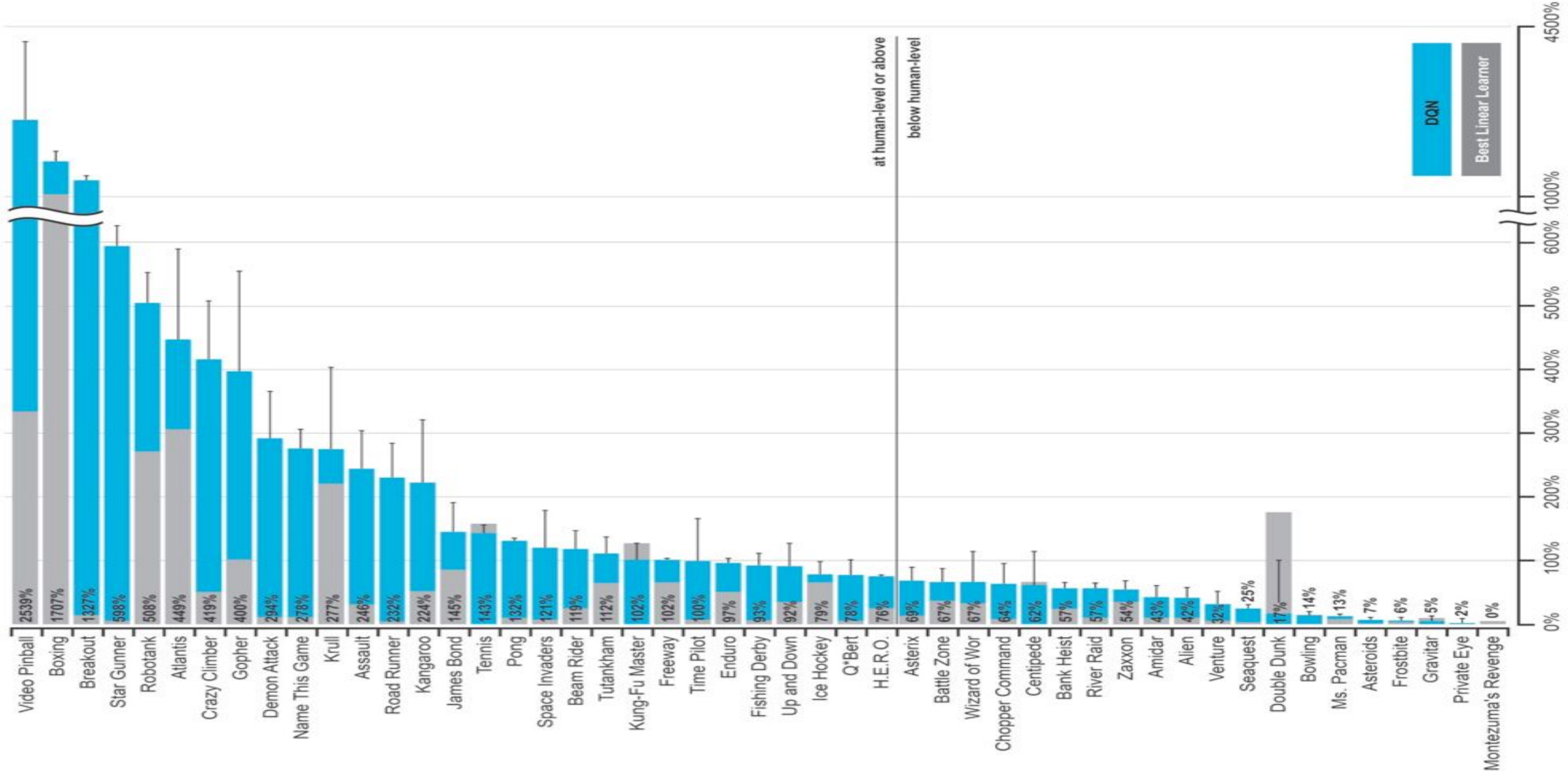
- Convolutional neural network architecture:
  - History of frames as input.
  - One output per action - expected reward for that action $Q(s, a)$.
  - Final results used a slightly bigger network (3 convolutional + 1 fully-connected hidden layers).



Stability Techniques

Game	With replay, with target Q	With replay, without target Q	Without replay, with target Q	Without replay, without target Q
Breakout	316.8	240.7	10.2	3.2
Enduro	1006.3	831.4	141.9	29.1
River Raid	7446.6	4102.8	2867.7	1453.0
Seaquest	2894.4	822.6	1003.0	275.8
Space Invaders	1088.9	826.3	373.2	302.0

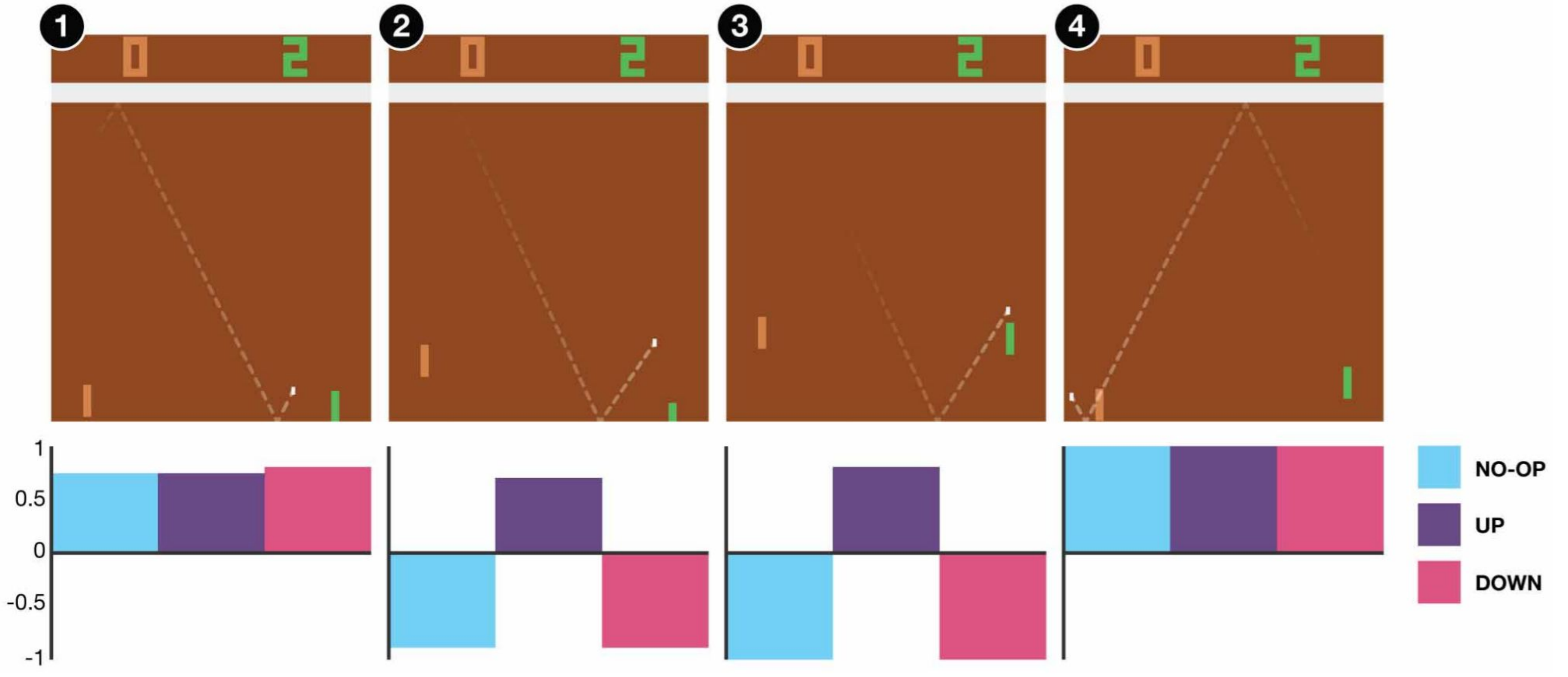
Atari Results



“Human-Level Control Through Deep Reinforcement Learning”, Mnih, Kavukcuoglu, Silver et al. (2015)

DQN Playing ATARI

Action Values on Pong



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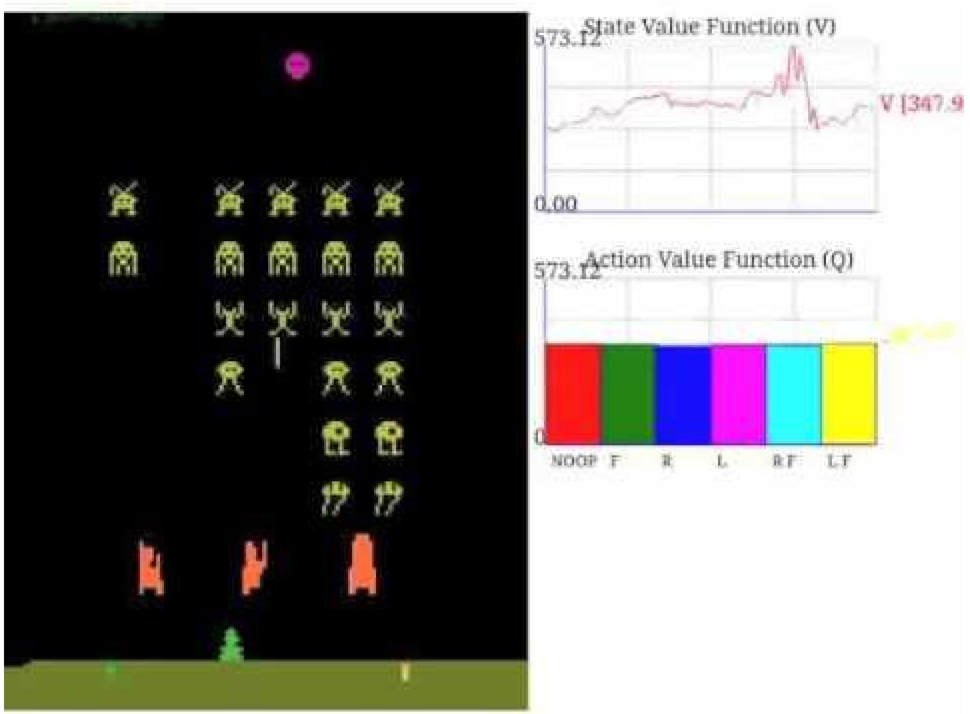
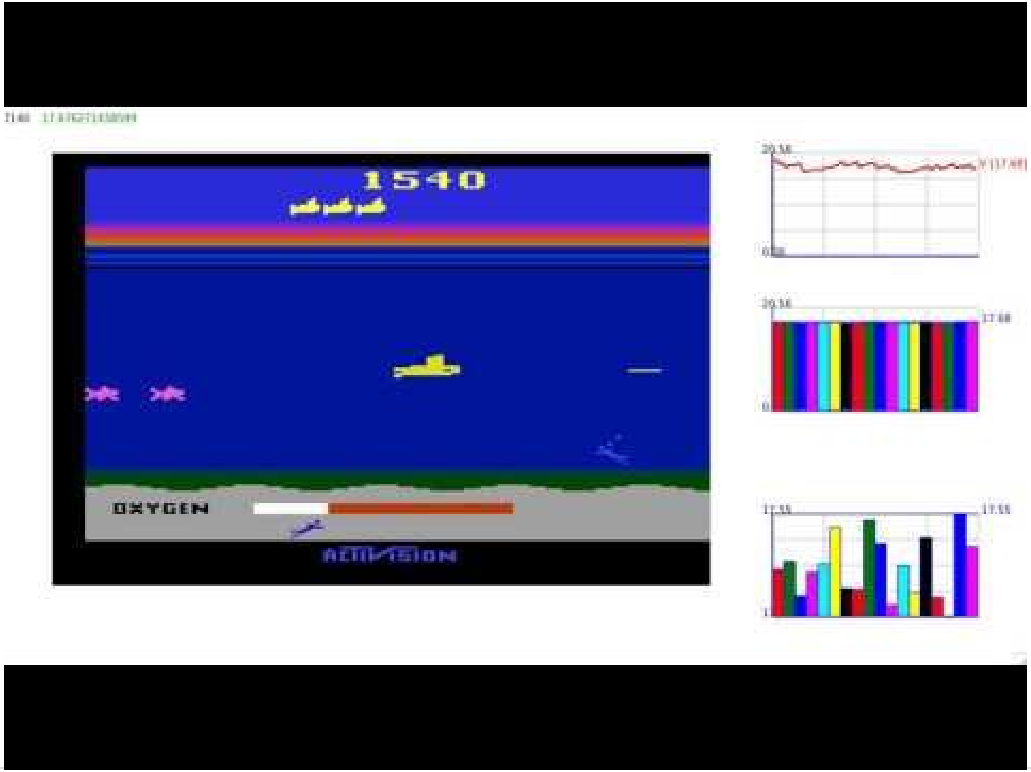
Learned Value Functions



Sacrificing Immediate Rewards



DQN Source Code

- The DQN source code (in Lua+Torch) is available:

  https://sites.google.com/a/deepmind.com/dqn/

Neural Fitted Q Iteration

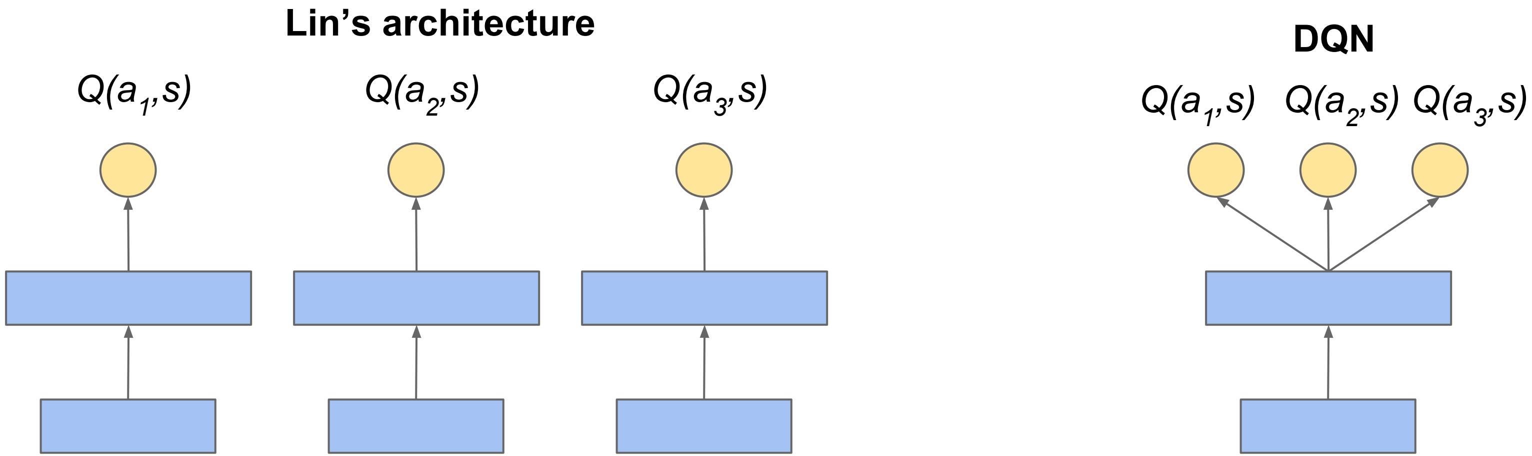
- NFQ (Riedmiller, 2005) trains neural networks with Q-learning.
- Alternates between collecting new data and fitting a new Q-function to all previous experience with batch gradient descent.

NFQ_main() {
input: a set of transition samples D; output: Q-value function Q_N
  k=0
  init_MLP() $\rightarrow Q_0$;
  Do {
    generate_pattern_set $P = \{(input^l, target^l), l = 1, \ldots, \#D\}$ where:
      $input^l = s^l, u^l,$
      $target^l = c(s^l, u^l, s'^l) + \gamma \, min_b Q_k(s'^l, b)$
    Rprop_training(P) $\rightarrow Q_{k+1}$
    k:= k+1
  } WHILE ($k < N$)

- DQN can be seen as an online variant of NFQ.

Lin's Networks

- Long-Ji Lin's thesis "Reinforcement Learning for Robots using Neural Networks" (1993) also trained neural nets with Q-learning.
- Introduced experience replay among other things.
- Lin's networks did not share parameters among actions.

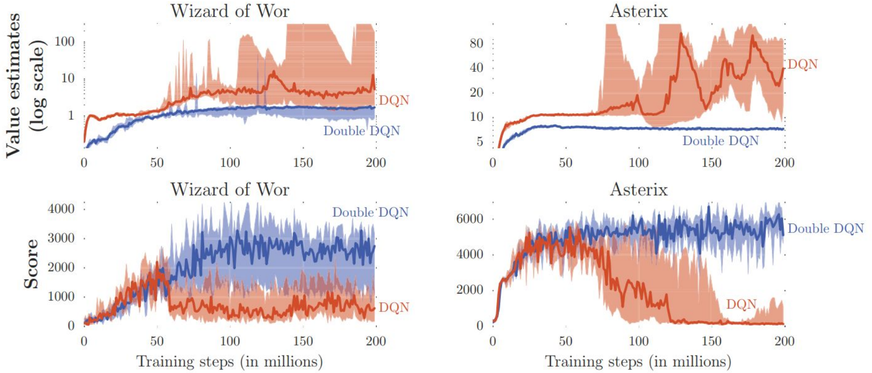


Double DQN

- There is an upward bias in $\max_a Q(s, a; \theta)$.
- DQN maintains two sets of weight θ and θ^-, so reduce bias by using:
  - θ for selecting the best action.
  - θ^- for evaluating the best action.
- Double DQN loss:

$$L_i(\theta_i) = \mathbb{E}_{s,a,s',r \sim D}\left(r + \gamma Q(s', \arg\max_{a'} Q(s', a'; \theta); \theta_i^-) - Q(s, a; \theta_i)\right)^2$$

	no ops		human starts		
	DQN	DDQN	DQN	DDQN	DDQN (tuned)
Median	93%	**115%**	47%	88%	**117%**
Mean	241%	**330%**	122%	273%	**475%**



“Double Reinforcement Learning with Double Q-Learning”, van Hasselt et al. (2016)

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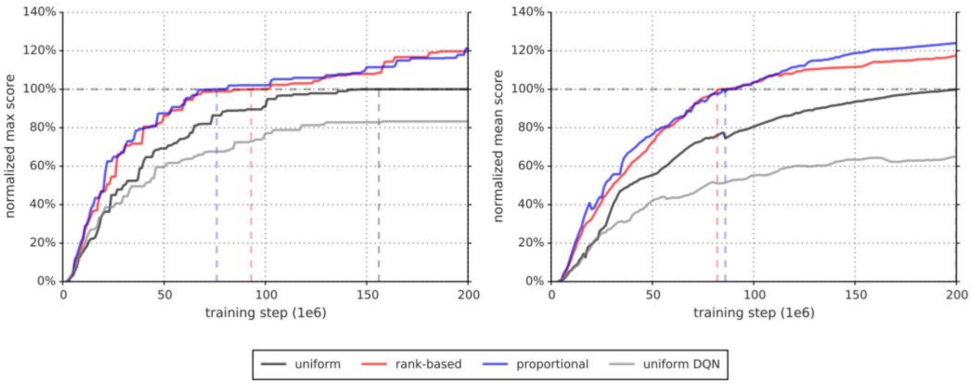
Prioritized Experience Replay

- Replaying all transitions with equal probability is highly suboptimal.
- Replay transitions in proportion to absolute Bellman error:

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

- Leads to much faster learning.

	DQN		Double DQN (tuned)		
	baseline	rank-based	baseline	rank-based	proportional
Median	48%	106%	111%	113%	128%
Mean	122%	355%	418%	454%	551%
> baseline	–	41	–	38	42
> human	15	25	30	33	33
# games	49	49	57	57	57



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"Prioritized Experience Replay", Schaul et al. (2016)

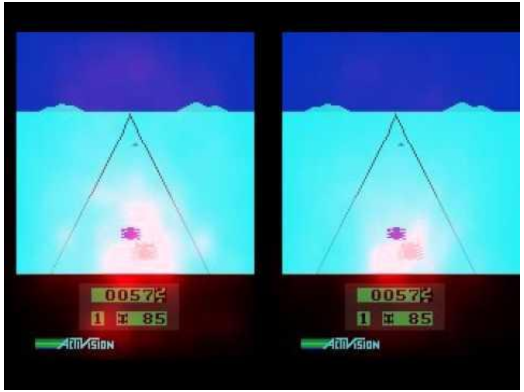
Dueling DQN

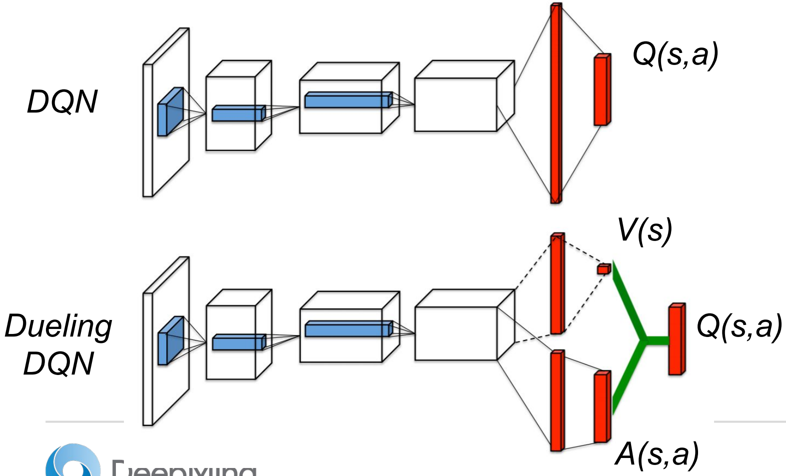
- Value-Advantage decomposition of Q:

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

- Dueling DQN (Wang et al., 2015):

$$Q(s,a) = V(s) + A(s,a) - \frac{1}{|\mathcal{A}|}\sum_{a=1}^{|\mathcal{A}|} A(s,a)$$





Atari Results

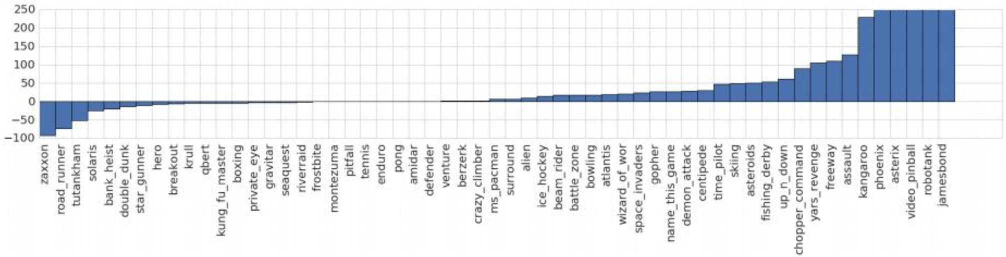
	30 no-ops		Human Starts	
	Mean	Median	Mean	Median
Prior. Duel Clip	**591.9%**	**172.1%**	**567.0%**	**115.3%**
Prior. Single	434.6%	123.7%	386.7%	112.9%
Duel Clip	**373.1%**	**151.5%**	**343.8%**	**117.1%**
Single Clip	341.2%	132.6%	302.8%	114.1%
Single	307.3%	117.8%	332.9%	110.9%
Nature DQN	227.9%	79.1%	219.6%	68.5%

"Dueling Network Architectures for Deep Reinforcement Learning", Wang et al. (2016)

Noisy Nets for Exploration

- Add noise to network parameters for better exploration [Fortunato, Azar, Piot et al. (2017)].
- Standard linear layer: $y = wx + b$
- Noisy linear layer: $y \stackrel{\text{def}}{=} (\mu^w + \sigma^w \odot \varepsilon^w)x + \mu^b + \sigma^b \odot \varepsilon^b$
- ε^w and ε^b contain noise.
- σ^w and σ^b are learned parameters that determine the amount of noise.

	Baseline		NoisyNet	
	Mean	Median	Mean	Median
DQN	213	47	**1210**	**89**
A3C	418	93	**1112**	**121**
Dueling	**2102**	126	1908	**154**



“Noisy Nets for Exploration”, Fortunato, Azar, Piot et al. (2017)
Also see “Parameter Space Noise for Exploration”, Plappert et al. (2017)