# Reinforcement Learning

## Deep Reinforcement Learning

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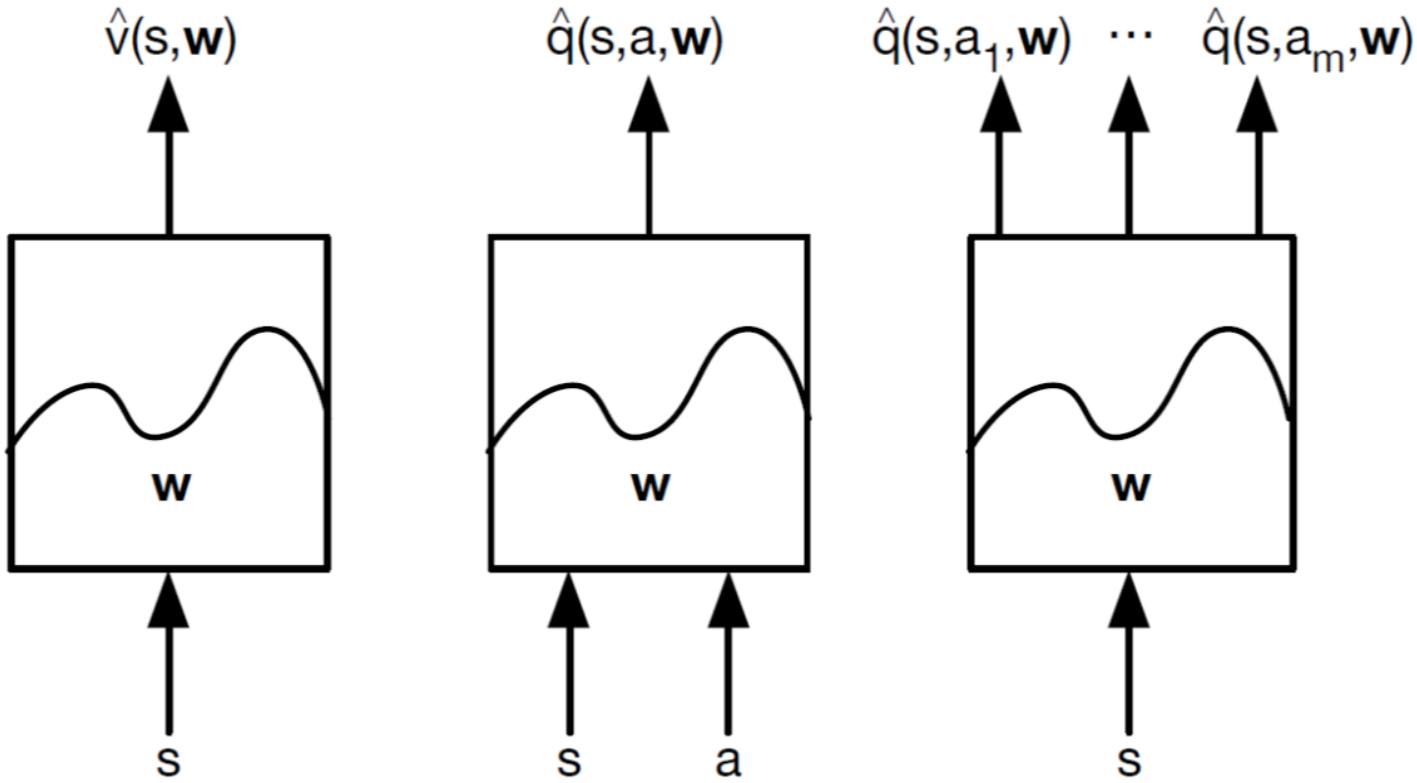
# Deep Neural Networks

# Use of Neural Networks for regression



# Recap of FA solutions

Two possible approaches for function approximation:

1. Incremental:
   - Pro: Learning on-line
   - Cons: No convergence due to (a) Data not i.i.d., that can lead to *catastrophic forgetting*, and (b) Moving target problem

# Recap of FA solutions

Two possible approaches for function approximation:

1. Incremental:
   - Pro: Learning on-line
   - Cons: No convergence due to (a) Data not i.i.d., that can lead to *catastrophic forgetting*, and (b) Moving target problem
2. Batch Learning:
   - Cons: Learn from collected dataset (not own experience)
   - Pro: Better convergence

# Fitted Q-learning

## Fitted Q-learning

Given $\mathcal{D}$ of size $T$ with examples $(s_t, a_t, r_{t+1}, s_{t+1})$, and regression algorithm, set $N$ to zero and $Q_N(s, a) = 0$ for all $a$ and $s$

**repeat**

$N \leftarrow N + 1$

Build training set $TS = \{\langle (s_t, a_t), r_{t+1} + \gamma \max_a Q_N(s_{t+1}, a)\rangle\}_{t=1}^{T}$

$Q_{N+1} \leftarrow$ regression algorithm on TS

**until** $Q_N \approx Q_{N+1}$ or $N >$ limit

**return** $\pi$ based on greedy evaluation of $Q_N$

# Neural Fitted Q-learning

## Neural Fitted Q-learning: Wrong version. Why?

Initialize weights $\theta$ for NN for regression
Collect $\mathcal{D}$ of size $T$ with examples $(s_t, a_t, r_{t+1}, s_{t+1})$
**repeat**
  Sample $\mathcal{B}$ mini-batch of $\mathcal{D}$
  $\theta \leftarrow \theta - \alpha \sum_{t \in \mathcal{B}} \frac{\partial Q_\theta}{\partial \theta}(s_t, a_t)\left(Q_\theta(s_t, a_t) - [r_{t+1} + \gamma \max_{a'} Q_\theta(s_{t+1}, a')]\right)$
**until** convergence on learning or maximum number of steps
**return** $\pi$ based on greedy evaluation of $Q_\theta$

- Does not work well
- It's not a Batch method. Can you see why?

# Neural Fitted Q-learning (Riedmiller, 2005)

## Neural Fitted Q-learning

Initialize weights $\theta$ for NN for regression
Collect $\mathcal{D}$ of size $T$ with examples $(s_t, a_t, r_{t+1}, s_{t+1})$
**repeat**
  $\theta' \leftarrow \theta$
  **repeat**
    Sample $\mathcal{B}$ mini-batch of $\mathcal{D}$
    $\theta \leftarrow \theta - \alpha \sum_{t \in \mathcal{B}} \frac{\partial Q_\theta}{\partial \theta}(s_t, a_t)\,(Q_\theta(s_t, a_t) - [r_{t+1} + \gamma \max_{a'} Q_{\theta'}(s_{t+1}, a')])$
  **until** convergence on learning or maximum number of steps
**until** maximum limit iterations
**return** $\pi$ based on greedy evaluation of $Q'_\theta$

- Notice target does not change during supervised regression

# Neural Fitted Q-learning: Another version

- That works, however the update of parameters is not smooth
- Alternative version to avoid moving target

**Fitted Q-learning avoiding moving target**

Initialize weights $\theta$ for NN for regression
Collect $\mathcal{D}$ of size $T$ with examples $(s_t, a_t, r_{t+1}, s_{t+1})$
**repeat**
  Sample $\mathcal{B}$ mini-batch of $\mathcal{D}$
  $\theta \leftarrow \theta - \alpha \sum_{t \in \mathcal{B}} \frac{\partial Q_\theta}{\partial \theta}(s_t, a_t) - (Q_\theta(s_t, a_t) - [r_{t+1} + \gamma \max_{a'} Q_{\theta'}(s_{t+1}, a')])$
  $\theta' \leftarrow \tau\theta' + (1-\tau)\theta$
**until** maximum limit iterations
**return** $\pi$ based on greedy evaluation of $Q'_\theta$

- Value of $\tau$ close to one (f.i. $\tau = 0.999$) reduces the "speed" of the moving target.

# How to get the data?

- So now, we have learning stabilized just any batch method but using NN.
- However, now there is the problem of dependence of dataset $\mathcal{D}$. How we obtain the data?
- Data can be obtained using a random policy, but we want to minimize error on states visited by the policy!

$$L(\theta) = \mathbb{E}_\pi \left[ (V^\pi(s) - V_\theta(s))^2 \right] = \sum_{s \in \mathcal{S}} \mu^\pi(s) \left[ V^\pi(s) - V_\theta(s) \right]^2$$

where $\mu^\pi(s)$ is the time spent in state $s$ while following $\pi$

# How to get the data?

- Data should be generated by the policy
- But it also has to be probabilistic (to ensure exploration)
- So, collect data using the policy and add them to $\mathcal{D}$
- Also remove old data from $\mathcal{D}$.
  - Limit the size of the set
  - Remove examples obtained using old policies
- So, collect data using a *buffer* of limited size (we call **replay buffer**).

# When to get the data?

## Batch Q-learning with replay buffer and target network

Initialize weights $\theta$ for NN for regression
Collect $\mathcal{D}$ of size $T$ with examples $(s_t, a_t, r_{t+1}, s_{t+1})$ using random policy
**repeat**
  $\theta' \leftarrow \theta$
  **repeat**
    Collect $M$ experiences following $\epsilon$-greedy procedure and add them to **buffer** $\mathcal{D}$
    **repeat**
      Sample $\mathcal{B}$ mini-batch of $\mathcal{D}$
      $\theta \leftarrow \theta - \alpha \sum_{t \in \mathcal{B}} \frac{\partial Q_\theta}{\partial \theta}(s_t, a_t)\,(Q_\theta(s_t, a_t) - [r_{t+1} + \gamma \max_{a'} Q_{\theta'}(s_{t+1}, a')])$
    **until** maximum number of steps $K$
  **until** maximum number of iterations $N$
**until** maximum limit iterations
**return** $\pi$ based on greedy evaluation of $Q'_\theta$

# DQN algorithm (Mnih, et al. 2015)

- **Deep Q-Network** algorithm breakthrough
  - In 2015, Nature published DQN algorithm.
  - It takes profit of "then-recent" *Deep Neural Networks* and, in particular, of *Convolutional NNs* so successful for vision problems
  - Applied to Atari games directly from pixels of the screen (no hand made representation of the problem)
  - Very successful on a difficult task, surpassing in some cases human performance
- It is basically the previous algorithm with $K = 1$, and $M = 1$ that is applied *on the current state.*
- It goes back to incremental learning

# DQN algorithm (Mnih, et al. 2015)

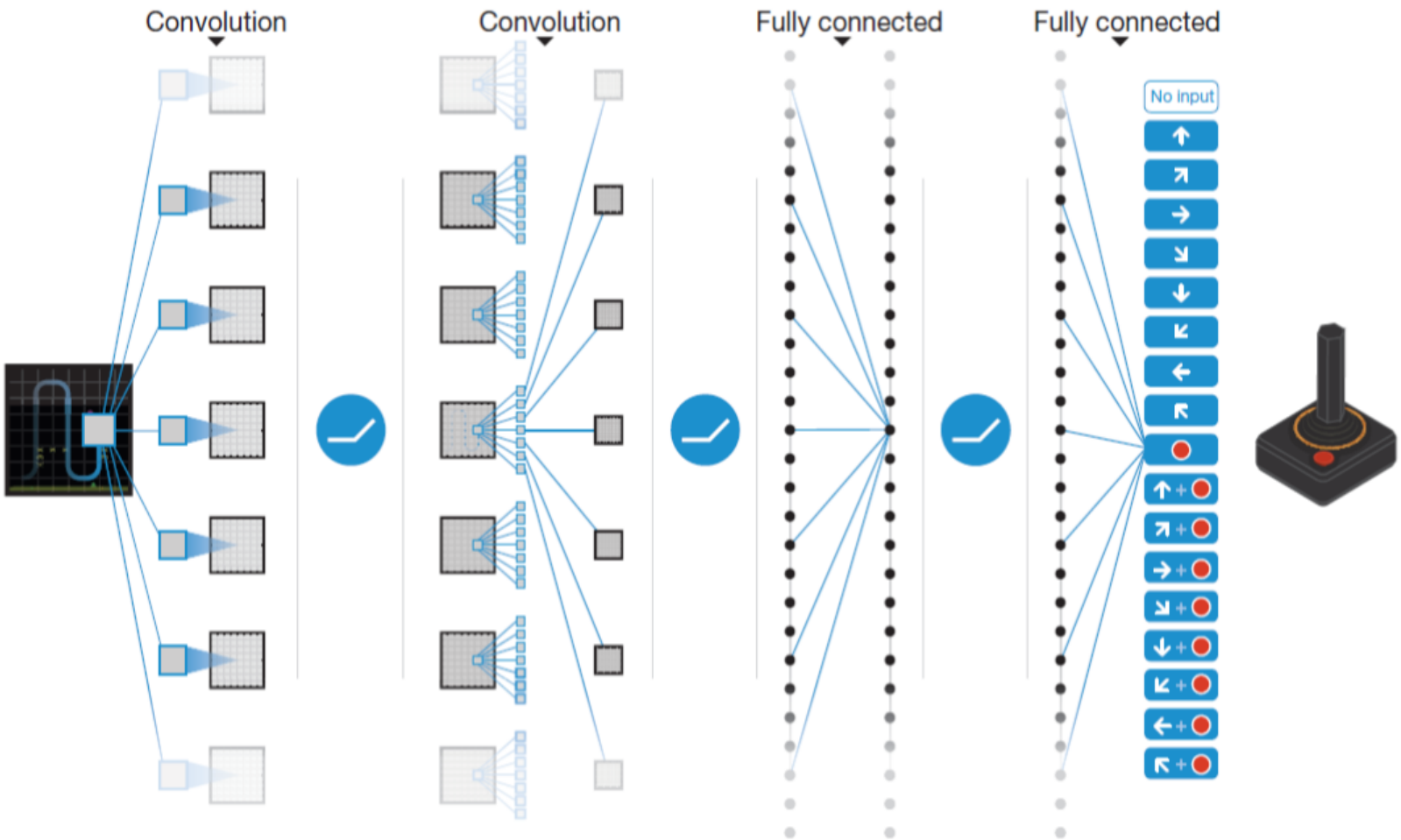
## DQN algorithm

Initialize weights $\theta$ for NN for regression
Set $s$ to initial state, and $k$ to zero
**repeat**
  Choose $a$ from $s$ using policy $\pi_\theta$ derived from $Q_\theta$ (e.g., $\epsilon$-greedy)
  $k \leftarrow k + 1$
  Execute action $a$, observe $r$, $s'$, and add $\langle s, a, r, s' \rangle$ to buffer $\mathcal{D}$
  Sample $\mathcal{B}$ mini-batch of $\mathcal{D}$
  $\theta \leftarrow \theta - \alpha \sum_{t \in \mathcal{B}} \frac{\partial Q_\theta}{\partial \theta}(s_t, a_t)\,(Q_\theta(s_t, a_t) - [r_{t+1} + \gamma \max_{a'} Q_{\theta'}(s_{t+1}, a')])$
  **if** k==N **then**
    $\theta' \leftarrow \theta$
    $k \leftarrow 0$
  **end if**
**until** maximum limit iterations
**return** $\pi$ based on greedy evaluation of $Q'_\theta$

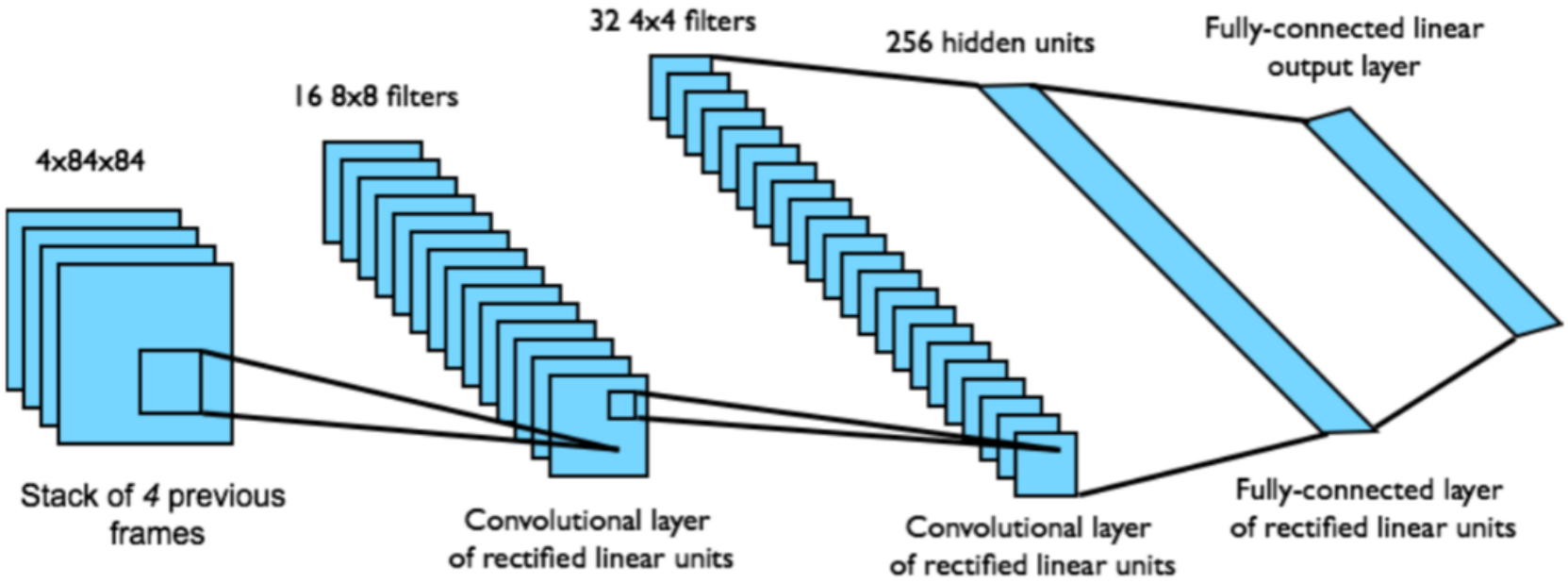
# DQN algorithm on Atari

- End-to-end learning of values Q(s; a) from pixels:
  - **State:** Input state s is stack of raw pixels from last 4 frames
  - **Actions:** Output is $Q(s, a)$ value for each of 18 joystick/button positions
  - **Reward:** Reward is direct change in score for that step
- Network architecture and hyper-parameters **fixed across all games**, No tuning!
- Clipping reward -1,0,1 to avoid problem of different magnitudes of score in each game

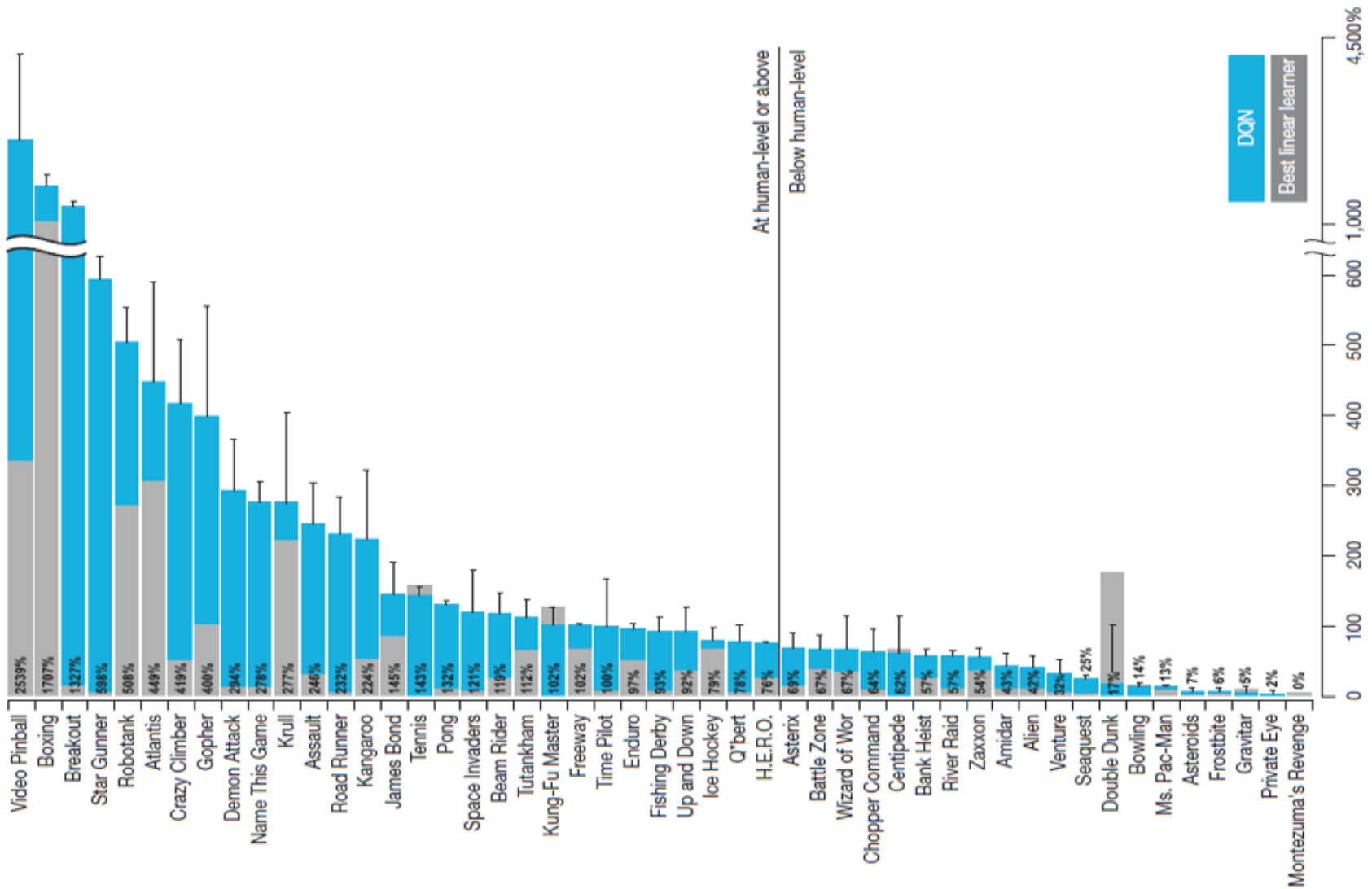
# DQN algorithm on Atari



# DQN algorithm on Atari



# DQN algorithm on Atari



# DQN algorithm on Atari

# DQN algorithm on Atari

- What is the effect of each trick on Atari games?

DQN

| | Q-learning | Q-learning + Target Q | Q-learning + Replay | Q-learning + Replay + Target Q |
|---|---|---|---|---|
| Breakout | 3 | 10 | 241 | **317** |
| Enduro | 29 | 142 | 831 | **1006** |
| River Raid | 1453 | 2868 | 4103 | **7447** |
| Seaquest | 276 | 1003 | 823 | **2894** |
| Space Invaders | 302 | 373 | 826 | **1089** |

# Overestimates: Double Q-learning

# Double Q-learning (Hasselt, et al. 2015)

- **Problem of overestimation of Q values**.
- We use "max" operator to compute the target in the minimization of:

$$L(s,a) = (Q(s,a) - (r + \gamma \max_{a'} Q(s',a')))^2$$

- Surprisingly here is a problem.
  1. Suppose $Q(s',a')$ is 0 for all actions, so $Q(s,a)$ should be $r$.
  2. But $\gamma \max_{a'} Q(s',a') \geq 0$ because random initialization and use of the max operator.
  3. So estimation $Q(s,a) \geq r$, overestimating true value
  4. All this because for max operator:

$$\mathbb{E}[\max_{a'} Q(s',a')] \geq \max_{a'} \mathbb{E}[Q(s',a')]$$

- This overestimation is propagated to other states.

# Double Q-learning

- Solution (Hasselt, 2010): Train 2 action-value functions: $Q_A$ and $Q_B$, and compute argmax with the other network
- Do Q-learning on both, but
  - never on the same time steps ($Q_A$ and $Q_B$ are independent)
  - *pick $Q_A$ or $Q_B$ at random to be updated on each step*
- Notice that:

$$r + \gamma \max_{a'} Q(s, a') = r + \gamma Q(s, \arg\max_{a'} Q(s', a'))$$

- When updating one network, use the values of the other network:

$$Q_A(s, a) \leftarrow r + \gamma Q_B(s, \arg\max_{a'} Q_A(s', a'))$$

$$Q_B(s, a) \leftarrow r + \gamma Q_A(s, \arg\max_{a'} Q_B(s', a'))$$

- Idea is that they should compensate mistakes of each other because they will be independent. When one network overestimate, probably, the other no, so they mutually cancel overestimation

# Double DQN (Hasselt, et al. 2015)

- In DQN, in fact, we have 2 value functions: $Q_\theta$ and $Q_{\theta'}$
- so, no need to add another one:
  - Current Q-network $\theta$ is used to select actions
  - Older Q-network $\theta'$ is used to evaluate actions
- Update in Double-DQN (Hasselt, et al. 2015):

$$Q_\theta(s,a) \leftarrow r + \gamma \overbrace{Q_{\theta'}(s, \underbrace{\arg\max_{a'} Q_\theta(s',a')}_{\text{Action Selection}})}^{\text{Action Evaluation}}$$

- Works well in practice.

# Prioritized Experience Replay

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

- Idea: sample transitions from replay buffer more cleverly
- Those states with poorer estimation in buffer will be selected with preference for update
- We will set probability for every transition. Let's use the absolute value of TD-error of transition as a probability!

$$p_i = |\text{TD-error}_i| = |Q_{\theta'}(s_i, a_i) - (r_i + \gamma Q_{\theta'}(s_i, \arg\max_{a'} Q_\theta(s_{i+1}, a'))|$$

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

where $P(i)$ is probability of selecting sample $i$ for the mini-batch, and $\alpha \geq 0$ is a new parameter ($\alpha = 0$ implies uniform probability)

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

- Do you see any problem?

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

- Do you see any problem?
- Now transitions are no i.i.d. and therefore we introduce a bias.
- Solution: we can correct the bias by using **importance-sampling** weights

$$w_i = \left( \frac{1}{N} \cdot \frac{1}{P(i)} \right)^{\beta}$$

- For numerical reasons, we also normalize weights by $\max_i w_i$
- When we put transition into experience replay, we set it to maximal priority $p_t = \max_{i<t} p_i$

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

**Algorithm 1** Double DQN with proportional prioritization

**Input:** minibatch $k$, step-size $\eta$, replay period $K$ and size $N$, exponents $\alpha$ and $\beta$, budget $T$.
Initialize replay memory $\mathcal{H} = \emptyset$, $\Delta = 0$, $p_1 = 1$
Observe $S_0$ and choose $A_0 \sim \pi_\theta(S_0)$
**for** $t = 1$ **to** $T$ **do**
  Observe $S_t, R_t, \gamma_t$
  Store transition $(S_{t-1}, A_{t-1}, R_t, \gamma_t, S_t)$ in $\mathcal{H}$ with maximal priority $p_t = \max_{i<t} p_i$
  **if** $t \equiv 0 \mod K$ **then**
    **for** $j = 1$ **to** $k$ **do**
      Sample transition $j \sim P(j) = p_j^\alpha / \sum_i p_i^\alpha$
      Compute importance-sampling weight $w_j = (N \cdot P(j))^{-\beta} / \max_i w_i$
      Compute TD-error $\delta_j = R_j + \gamma_j Q_{\text{target}}\left(S_j, \arg\max_a Q(S_j, a)\right) - Q(S_{j-1}, A_{j-1})$
      Update transition priority $p_j \leftarrow |\delta_j|$
      Accumulate weight-change $\Delta \leftarrow \Delta + w_j \cdot \delta_j \cdot \nabla_\theta Q(S_{j-1}, A_{j-1})$
    **end for**
    Update weights $\theta \leftarrow \theta + \eta \cdot \Delta$, reset $\Delta = 0$
    From time to time copy weights into target network $\theta_{\text{target}} \leftarrow \theta$
  **end if**
  Choose action $A_t \sim \pi_\theta(S_t)$
**end for**

# Dueling Network Architectures

# Dueling Network Architectures (Wang, et al. 2016)

- Until now, use of generic NN for regression of Q-value function
- Now, specific Deep Architecture specific for RL
- *Advantage function* definition:

$$A(s, a) = Q(s, a) - V(s)$$

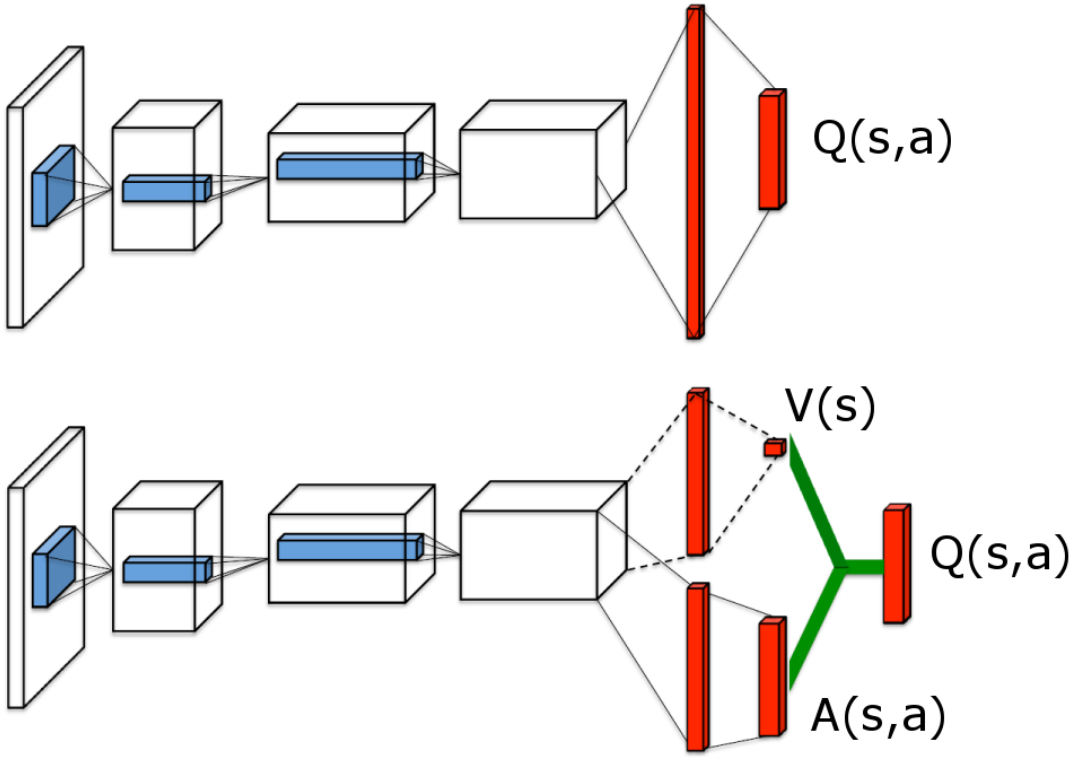
- So,

$$Q(s, a) = A(s, a) + V(s)$$

- Intuitively, Advantage function is relative measure of importance of each action

# Dueling Network Architectures (Wang, et al. 2016)

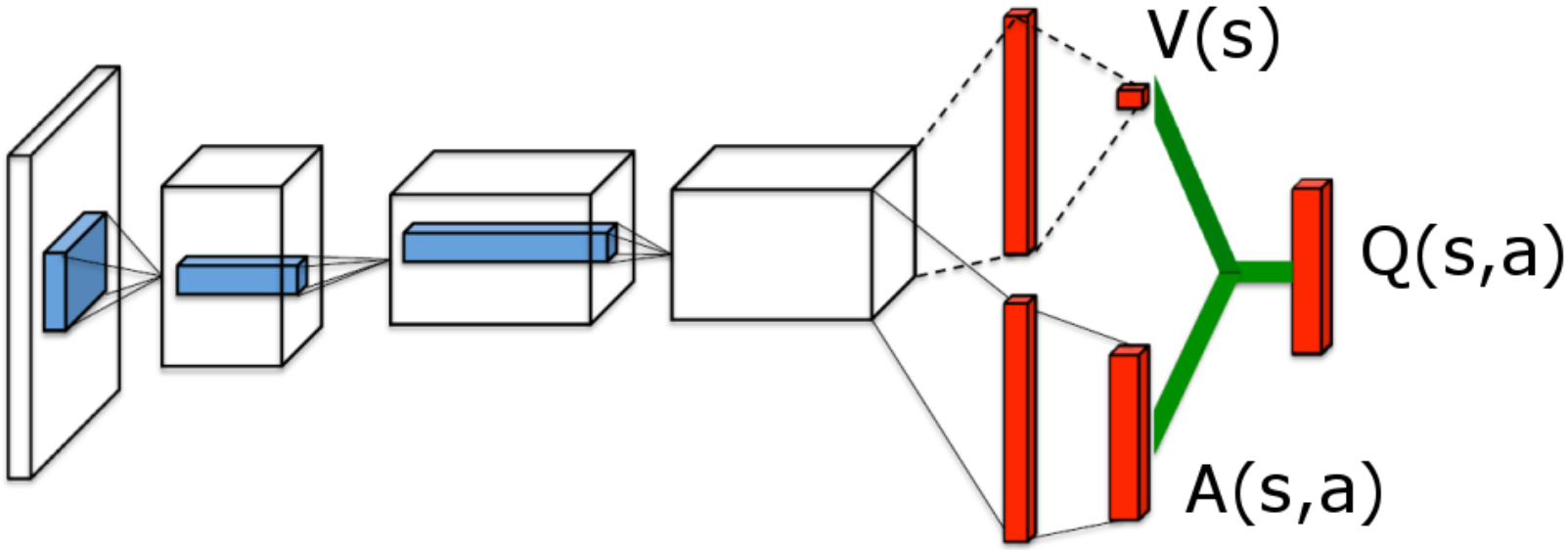
- Dueling network:




- Intuitive idea is that now we don't learn $Q(s, a)$ independently but share part that is $V(s)$ that improves generalization across actions

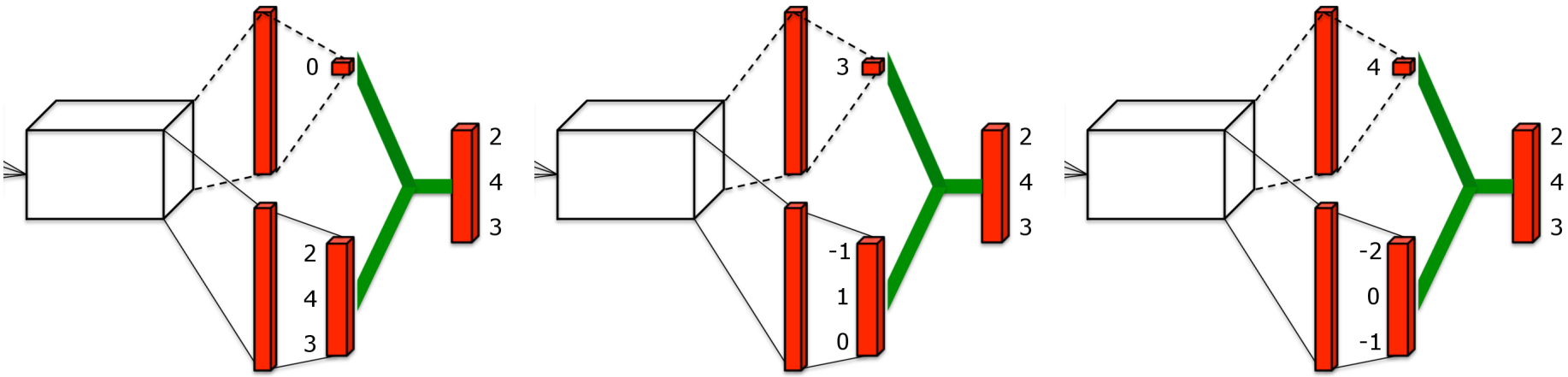
# Dueling Network Architectures (Wang, et al. 2016)

- We have now 3 sets of parameters:
  - $\theta$: Usual weights of NN until red section
  - $\beta$: Weights to compute $V(s)$
  - $\alpha$: Weights to compute $A(s, a)$
- Green part computes $A(s, a) + V(s)$



# Dueling Network Architectures (Wang, et al. 2016)

- However, there is a problem: one extra degree of freedom in targets!
- Example:



# Dueling Network Architectures (Wang, et al. 2016)

- Which is the correct one? Notice that:

$$\pi^*(s) = \arg\max_{a \in \mathcal{A}} \; Q^*(s,a)$$

and that,

$$V^*(s) = \max_{a \in \mathcal{A}} Q^*(s,a)$$

- So,

$$\begin{aligned} \max_{a \in \mathcal{A}} A(s,a) &= \max_{a \in \mathcal{A}} (Q(s,a) - V(s)) \\ &= \max_{a \in \mathcal{A}} Q(s,a) - V(s) \\ &= 0 \end{aligned}$$

- Of course, for actions $a \neq a^*$ $A(s,a) \leq 0$

# Dueling Network Architectures (Wang, et al. 2016)

- **Solution**: require $\max_a A(s,a)$ to be equal to zero!
- So the Q-function computes as:

$$Q_{\theta,\alpha,\beta}(s,a) = V_{\theta,\beta}(s) + \left( A_{\theta,\alpha}(s,a) - \max_{a' \in \mathcal{A}} A_{\theta,\alpha}(s,a') \right)$$

- In practice, the authors propose to implement

$$Q_{\theta,\alpha,\beta}(s,a) = V_{\theta,\beta}(s) + \left( A_{\theta,\alpha}(s,a) - \frac{1}{|A|} \sum_{a' \in \mathcal{A}} A_{\theta,\alpha}(s,a') \right)$$

- This variant increases stability of the optimization because now depends on softer measure (*average* instead of *max*)
- Now Q-values loses original semantics, but it not important. The important thing is a *reference* between actions

# Multi-step learning

# Multi-step learning

- Idea: instead of using TD(0), use n-steps estimators like we described in lecture 2
- In buffer we should store experiences:

$$\left\langle s_t, a_t, r_t, \sum_{i=0}^{n} \gamma^{i-1} r_{t+1} + \gamma^n \max_{a'} Q_{\theta'}(s_{t+n}, a') \right\rangle$$

# Multi-step learning

- Idea: instead of using TD(0), use n-steps estimators like we described in lecture 2
- In buffer we should store experiences:

$$\left\langle s_t, a_t, r_t, \sum_{i=0}^{n} \gamma^{i-1} r_{t+1} + \gamma^n \max_{a'} Q_{\theta'}(s_{t+n}, a') \right\rangle$$

- Again, there is a problem!
- Only correct when learning on-policy! (not an issue when $n = 1$)
- How to fix that?
  - Ignore the problem (often works well)
  - Dynamically choose $n$ to get only on-policy data (Store data until not policy action taken)
  - Use importance sampling (Munos et al, 2016)

# Rainbow: Combining Improvements in Deep Reinforcement Learning

# Rainbow (Hessel et al. 2017)

- Idea: Let's try to investigate how each of the different improvements over DQN help to improve performance on the Atari games
- Over DQN, they added the following modifications:
  - Double Q-learning
  - Prioritized replay
  - Dueling networks
  - Multi-step learning
  - Distributional RL
  - Noisy Nets
- They perform an ablation study where over the complete set of improvement, they disable one an measure the performance

# Rainbow (Hessel et al. 2017)

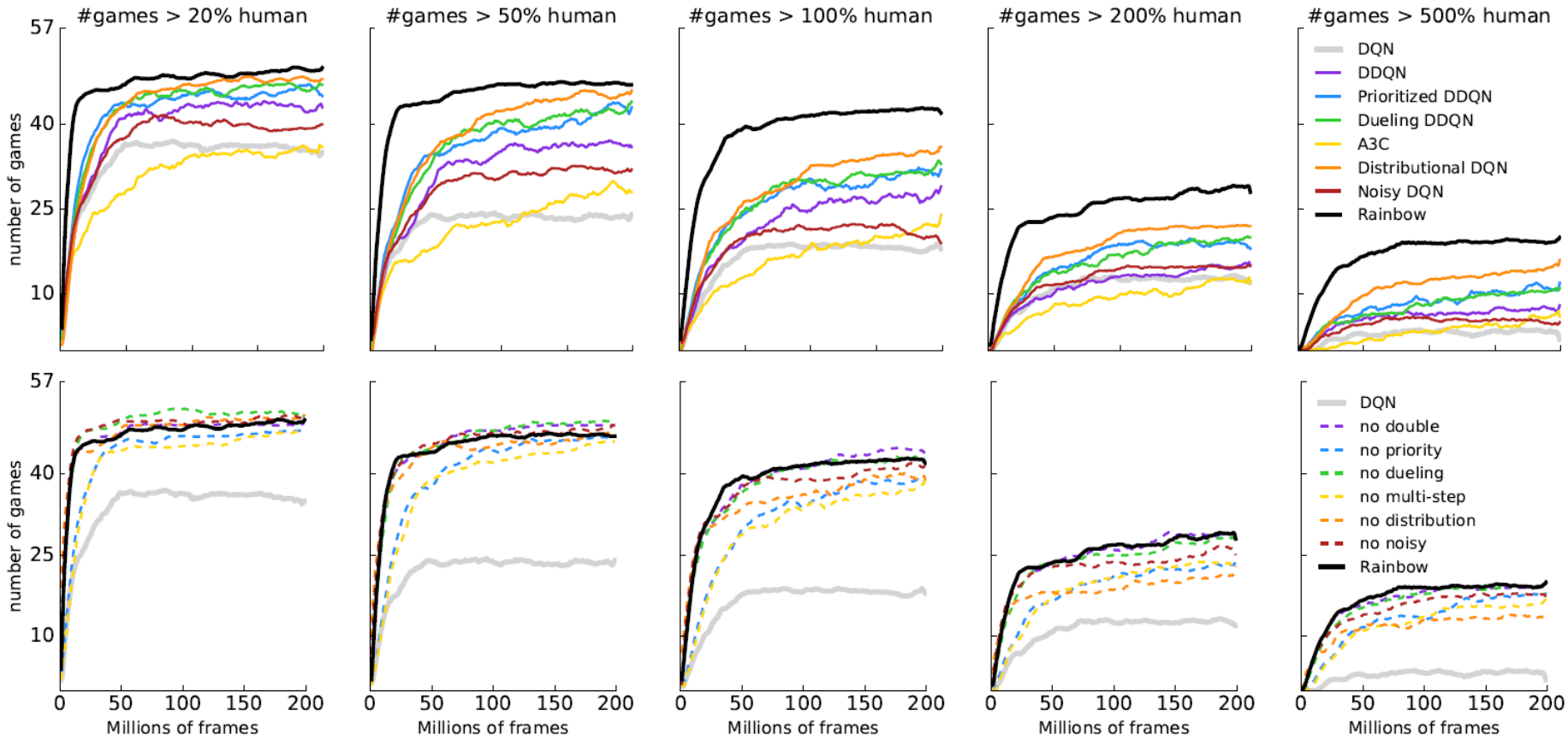
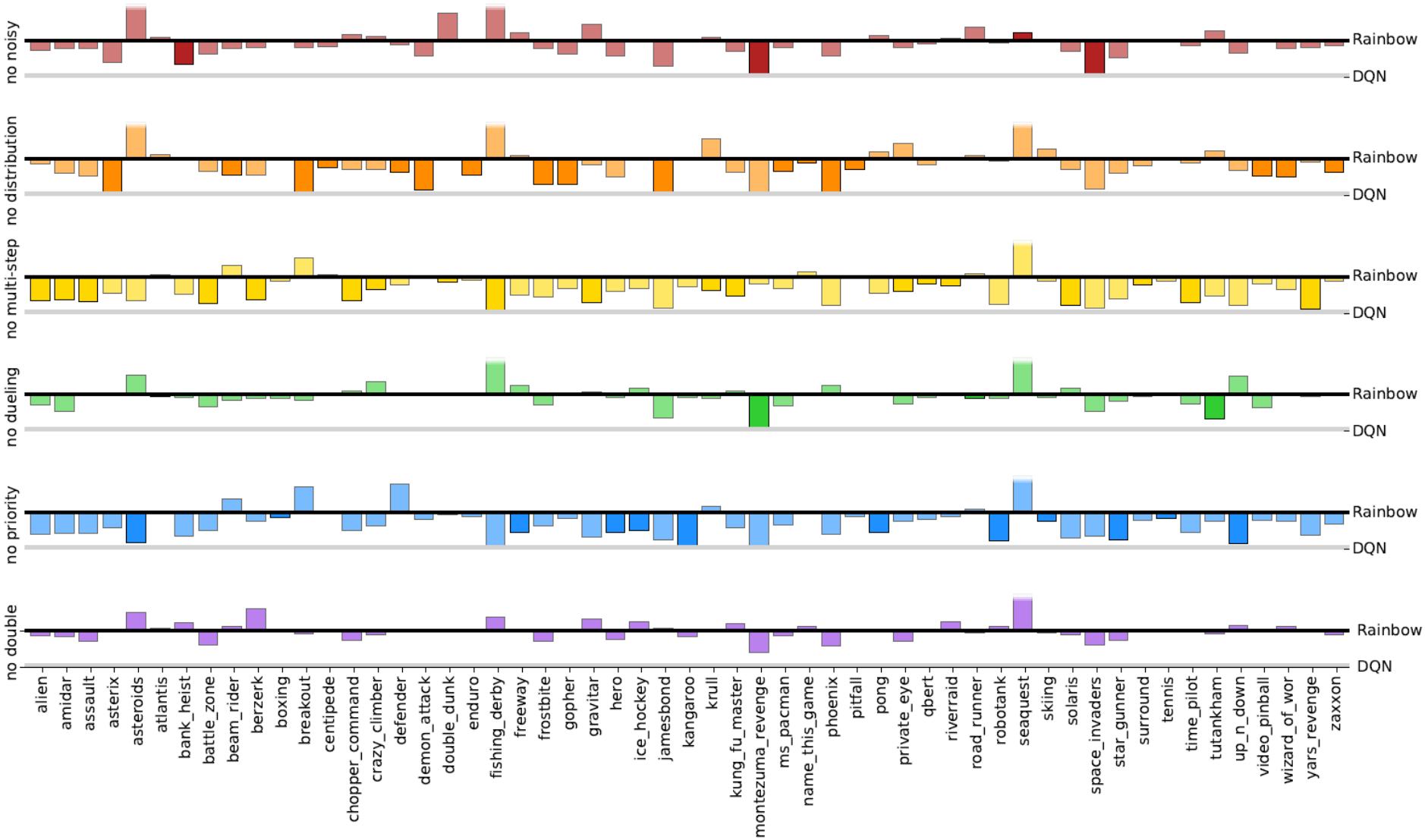



Figure 2: Each plot shows, for several agents, the number of games where they have achieved at least a given fraction of human performance, as a function of time. From left to right we consider the 20%, 50%, 100%, 200% and 500% thresholds. On the first row we compare Rainbow to the baselines. On the second row we compare Rainbow to its ablations.

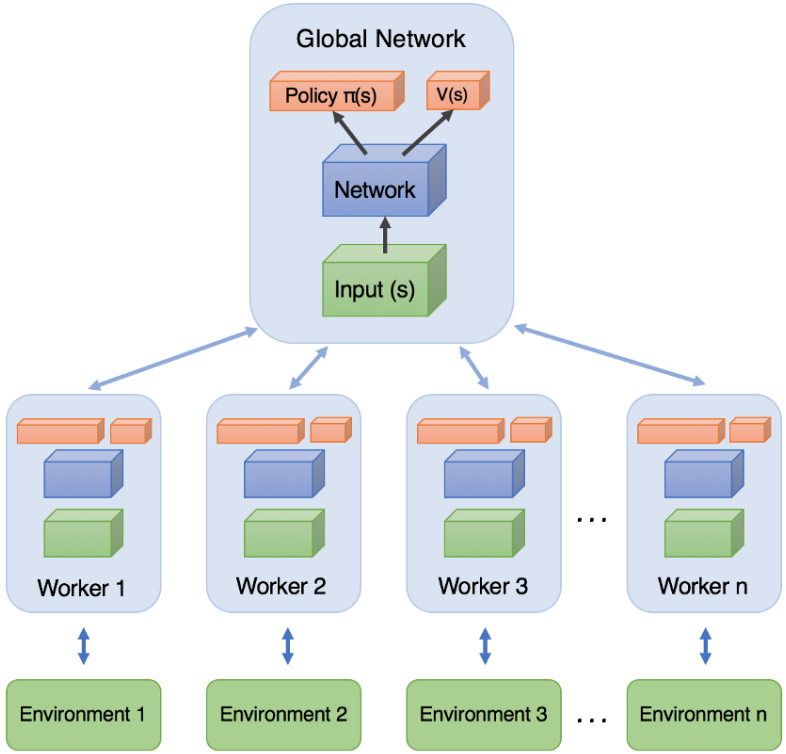
# Rainbow (Hessel et al. 2017)



# Asynchronous Q-learning

# Asynchronous Q-learning (Mnih et al. 2016)

- Idea: Parallelize learning with several workers




- After some time steps, the worker passes gradients to the global network

# Asynchronous Q-learning (Mnih et al. 2016)

**Algorithm 1** Asynchronous one-step Q-learning - pseudocode for each actor-learner thread.

*// Assume global shared* $\theta$, $\theta^-$, *and counter* $T = 0$.
Initialize thread step counter $t \leftarrow 0$
Initialize target network weights $\theta^- \leftarrow \theta$
Initialize network gradients $d\theta \leftarrow 0$
Get initial state $s$
**repeat**
  Take action $a$ with $\epsilon$-greedy policy based on $Q(s, a; \theta)$
  Receive new state $s'$ and reward $r$

$$y = \begin{cases} r & \text{for terminal } s' \\ r + \gamma \max_{a'} Q(s', a'; \theta^-) & \text{for non-terminal } s' \end{cases}$$

  Accumulate gradients wrt $\theta$: $d\theta \leftarrow d\theta + \frac{\partial (y - Q(s,a;\theta))^2}{\partial \theta}$
  $s = s'$
  $T \leftarrow T + 1$ and $t \leftarrow t + 1$
  **if** $T \mod I_{target} == 0$ **then**
    Update the target network $\theta^- \leftarrow \theta$
  **end if**
  **if** $t \mod I_{AsyncUpdate} == 0$ or $s$ is terminal **then**
    Perform asynchronous update of $\theta$ using $d\theta$.
    Clear gradients $d\theta \leftarrow 0$.
  **end if**
**until** $T > T_{max}$

# Faster Deep RL by optimality tightening

# Faster Deep RL by optimality tightening (He, et al. 2016)

- From Bellman equation we will obtain a bound for a given Q-value:

$$
\begin{aligned}
Q(s_t, a_t) &= \mathbb{E}\left[r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a')\right] \\
&\geq \mathbb{E}\left[r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots + \gamma^k \max_{a'} Q(s_{t+k+1}, a')\right] \\
&\geq \mathbb{E}\left[\underbrace{r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots + \gamma^k Q(s_{t+k+1}, a_{t+k+1})}_{\text{Lower bound } L^{max}}\right]
\end{aligned}
$$

# Faster Deep RL by optimality tightening (He, et al. 2016)

- Also we can do this backwards in time. Notice that we had

$$Q(s_t, a_t) \quad \geq \quad r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots + \gamma^k Q(s_{t+k+1}, a_{t+k+1})$$

- Changing indexes

$$Q(s_{t-k-1}, a_{t-k-1}) \quad \geq \quad r_{t-k} + \gamma r_{t-k+1} + \gamma^2 r_{t-k+2} + \ldots + \gamma^k Q(s_t, a_t)$$

- So,

$$\begin{aligned} Q(s_{t-k-1}, a_{t-k-1}) - r_{t-k} - \gamma r_{t-k+1} - \gamma^2 r_{t-k+2} - \ldots \quad &\geq \quad \gamma^k Q(s_t, a_t) \\ \gamma^{-k} \left[ Q(s_{t-k-1}, a_{t-k-1}) - r_{t-k} - \gamma r_{t-k+1} - \gamma^2 r_{t-k+2} - \ldots \right] \quad &\geq \quad Q(s_t, a_t) \end{aligned}$$

- So, finally we have an upper bound:

$$Q(s_t, a_t) \quad \leq \quad \underbrace{\gamma^{-k} Q(s_{t-k}, a_{t-k}) - \gamma^{-k} r_{t-k} - \gamma^{-(k-1)} r_{t-(k-1)} - \ldots - \gamma r_{t-1}}_{\text{Upper bound } U^{min}}$$

# Faster Deep RL by optimality tightening (He, et al. 2016)

- And now we can modify our loss function using these bounds:

$$
\begin{aligned}
y &= r + \gamma Q_{\theta'}(s', \arg\max_a Q_\theta(s', a)) \\
L(\theta) &= \mathbb{E}\left[(Q_\theta(s,a) - y)^2 + \lambda (L^{max} - Q_\theta(s,a))_+^2 + \lambda (Q_\theta(s,a) - U^{min})_+^2\right]
\end{aligned}
$$

  where $\lambda$ is a penalization parameter like $C$ in SVMs

- Eq, minimize the original Bellman error. but also *penalizes breaking the bounds*
- Accelerates over an order of magnitude with respect original DQN in number of experiences needed for learning

# Practical tricks

# Practical tricks

- DQN is more reliable on some tasks than others. Test your implementation on reliable tasks like Pong and Breakout: if it doesn't achieve good scores, something is wrong.
- Large replay buffers improve robustness of DQN, and memory efficiency is key.
- SGD can be slow .. rely on RMSprop (or any new optimizer)
- Convolutional models are more ecient then MLPs
- DQN uses action repeat set to 4 (because fps too high - speeds training time)
- DQN receives 4 frames of the game at a time (grayscale)
- $\epsilon$ is anealled from 1 to .1

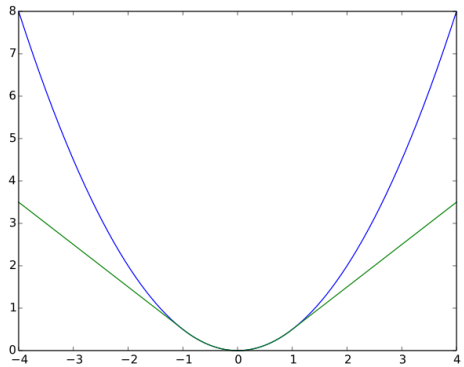
# Practical tricks

- Patience. Training takes time (roughly hours to day on GPU training to see improvement)
- Always use Double DQN (3 lines of difference from DQN)
- Learning rate scheduling is benecial. Try high learning rates in initial exploration period.
- *Exploration* is key: Try non-standard exploration schedules.
- Always run at least two different seeds when experimenting

# Practical tricks

- Bellman errors can be big. Clip gradients or use Huber loss on Bellman error

$$L_\delta(y, f(x)) = \begin{cases} \frac{(y-f(x))^2}{2}, & \text{when } |y - f(x)| \leq \delta \\ \delta|y - f(x)| - \frac{\delta^2}{2}, & \text{otherwise} \end{cases}$$




- Very large $\gamma$ or set it to 1 to avoid myopic reward (very large sequences before reward)
- n-steps return **helps** but careful