Human-level control through deep reinforcement learning

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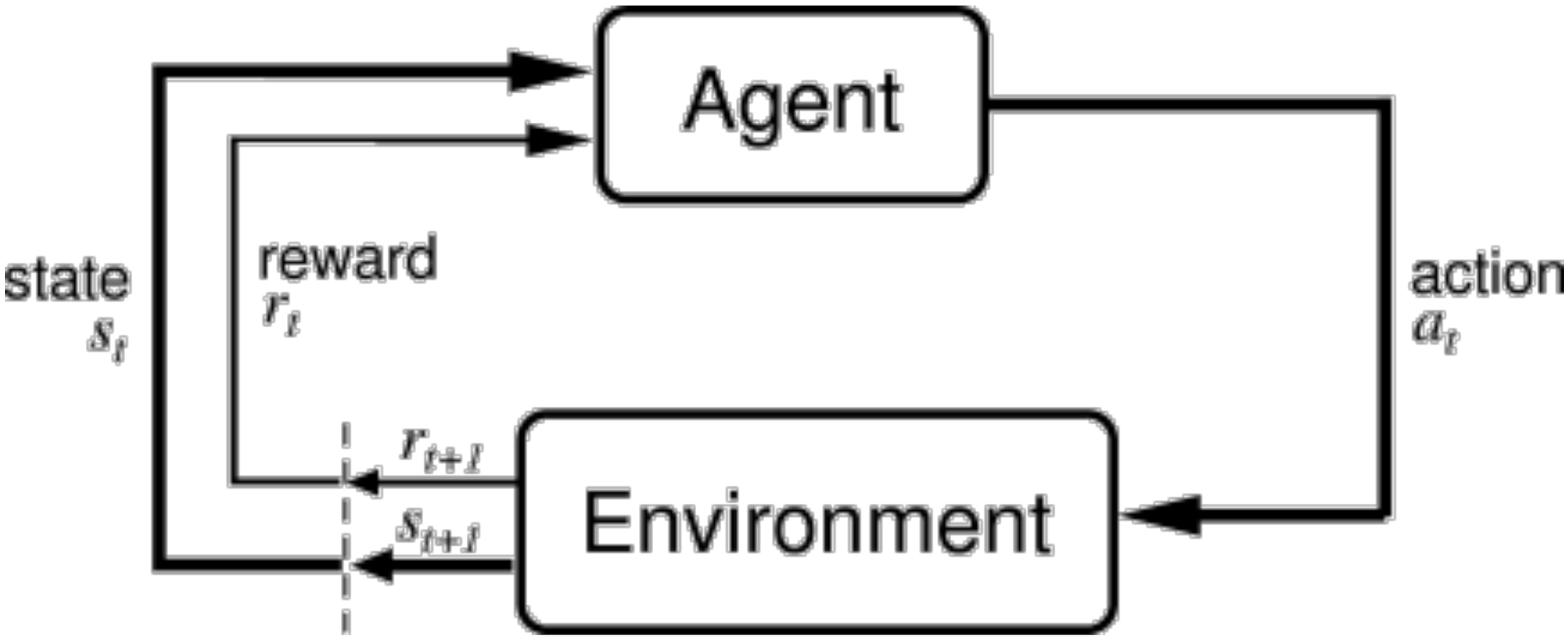
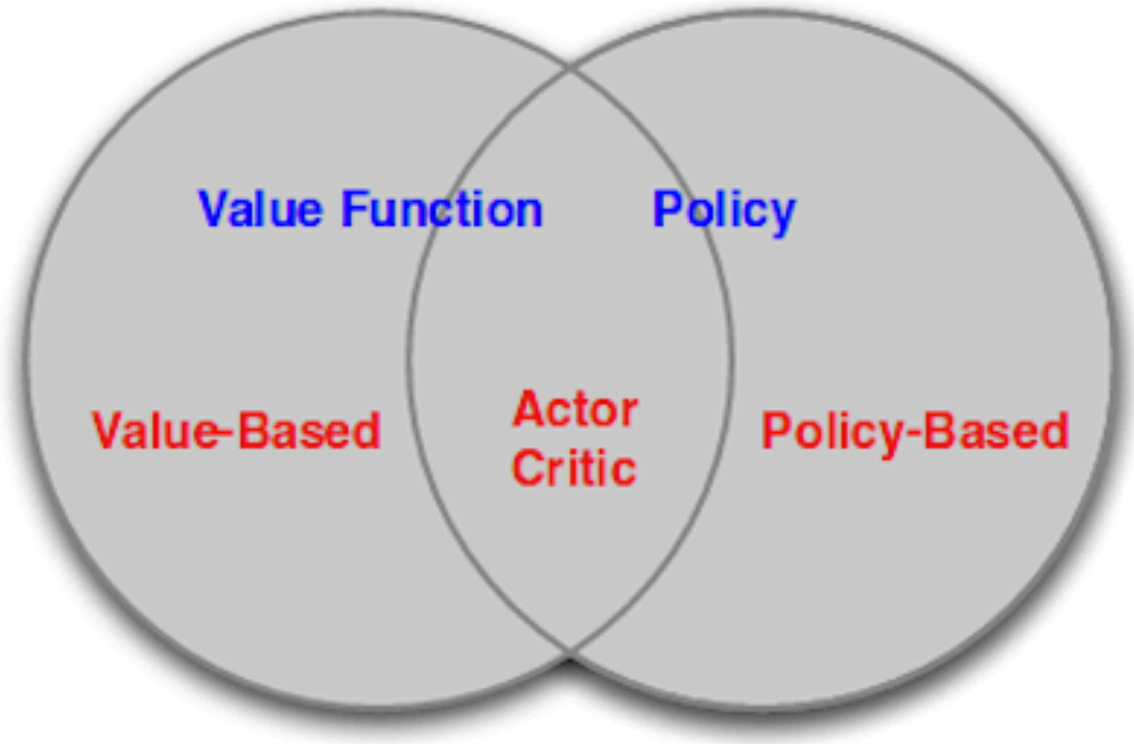
Reinforcement Learning



Value-Based and Policy-Based RL

- Value Based
  - Learnt Value Function
  - Implicit policy (e.g. ϵ-greedy)
- Policy Based
  - No Value Function
  - Learnt Policy
- Actor-Critic
  - Learnt Value Function
  - Learnt Policy



Value Based Method

- DQN (Deep Q-Learning Network)
  - Double Deep Q-Learning
  - Continuous DQN (CDQN or NAF)
  - Dueling network DQN (Dueling DQN)
- Deep SARSA

Policy Based Method

- Policy Gradient
  - Deep Deterministic Policy Gradient (DDPG)
  - Cross-Entropy Method (CEM)
- Actor Critic
  - Asynchronous Advantage Actor-Critic (A3C)

Q-learning

$$Q(s_t, a_t) \leftarrow \underbrace{Q(s_t, a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \left(\overbrace{\underbrace{r_{t+1}}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\text{estimate of optimal future value}}}^{\text{learned value}} - \underbrace{Q(s_t, a_t)}_{\text{old value}} \right)$$

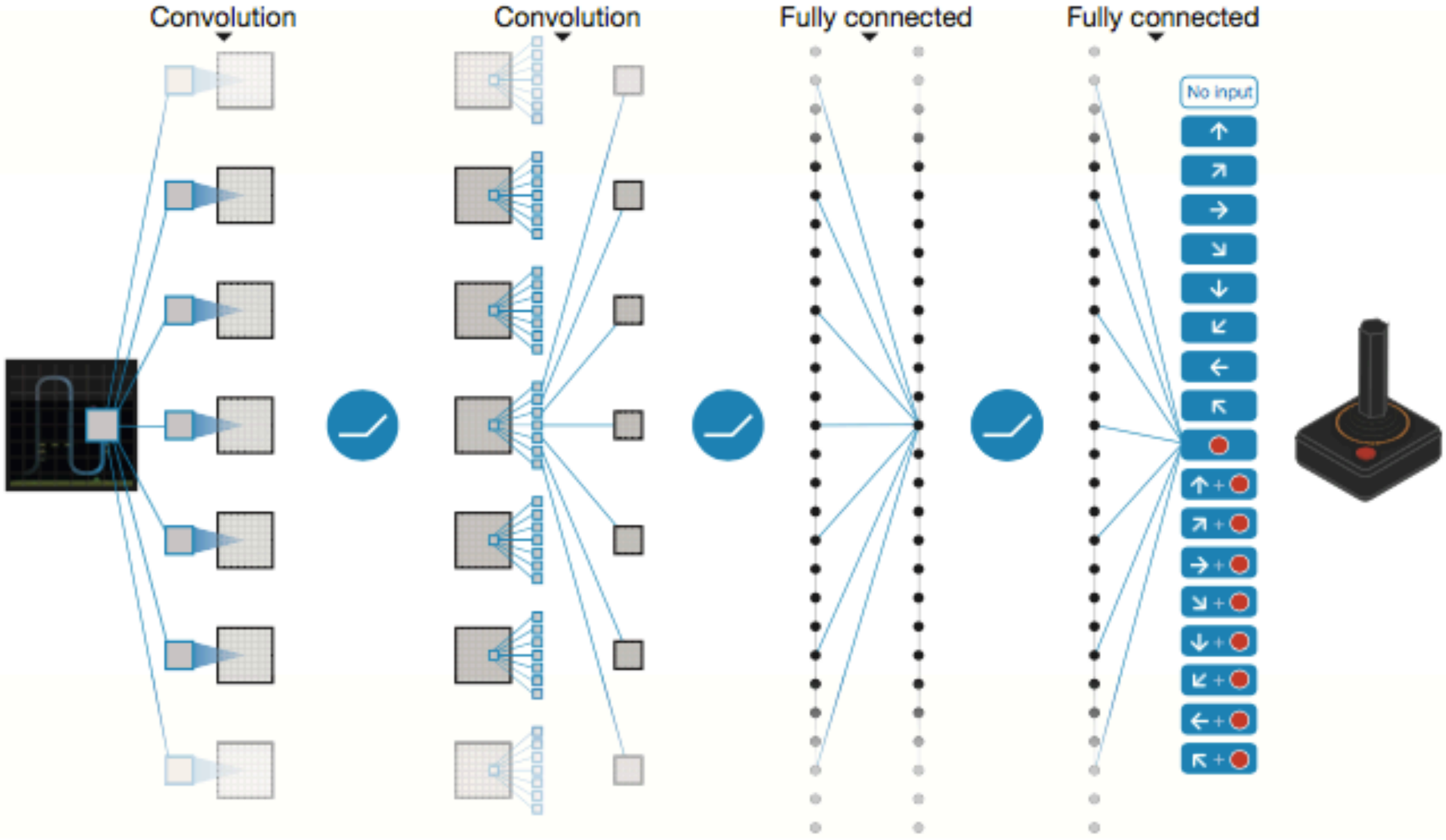
- Learning rate : 新資訊的重要程度，和一般機器學習的 learning rate 意義一樣
- Discount factor : 代表未來獎勵的重要程度
  - 0 : 看當前，短視近利
  - 1 : 看長期，需要注意的是，接近超過1時容易發散

Loss Function

Reward Decay Rate

$$loss = \left(\underbrace{r + \gamma \max_{a`} \hat{Q}(s, a`)}_{\text{Target}} - \underbrace{Q(s, a)}_{\text{Prediction}} \right)^2$$

Convolutional Neural Network



Deep Q-learning

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

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

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

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

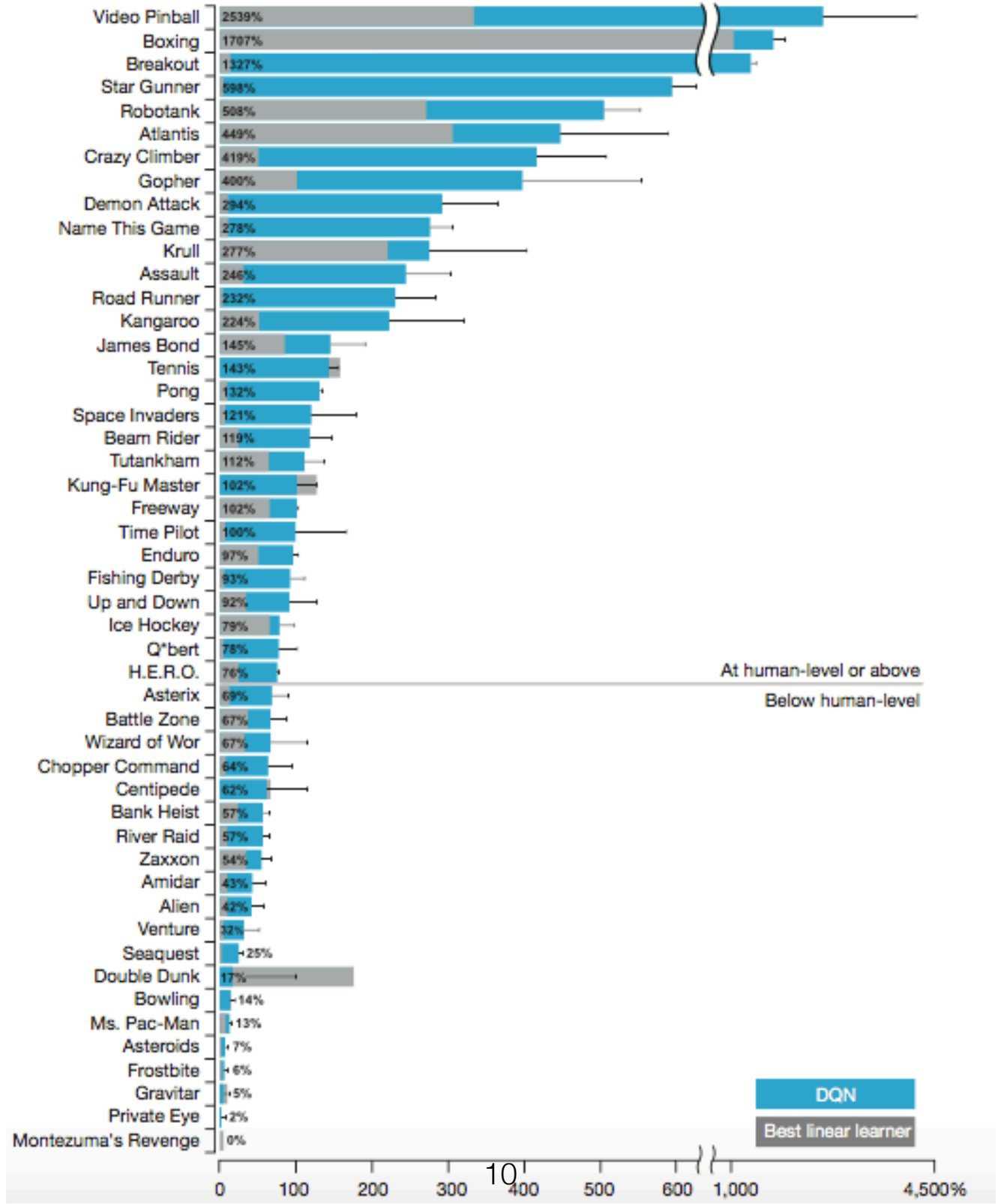
    Perform a gradient descent step on $\left(y_j - Q\left(\phi_j, a_j; \theta\right)\right)^2$ with respect to the network parameters θ

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

  End For

End For

Q-Learning V.S. DQN



Demo - Breakout