Q-Learning

- Optimal Q-values should obey Bellman equation

$$Q^*(s,a) = \mathbb{E}_{s'}\left[r + \gamma \max_{a'} Q(s',a')^* \mid s,a\right]$$

- Treat right-hand side $r + \gamma \max_{a'} Q(s',a',\mathbf{w})$ as a target
- Minimise MSE loss by stochastic gradient descent

$$I = \left(r + \gamma \max_{a} Q(s',a',\mathbf{w}) - Q(s,a,\mathbf{w})\right)^2$$

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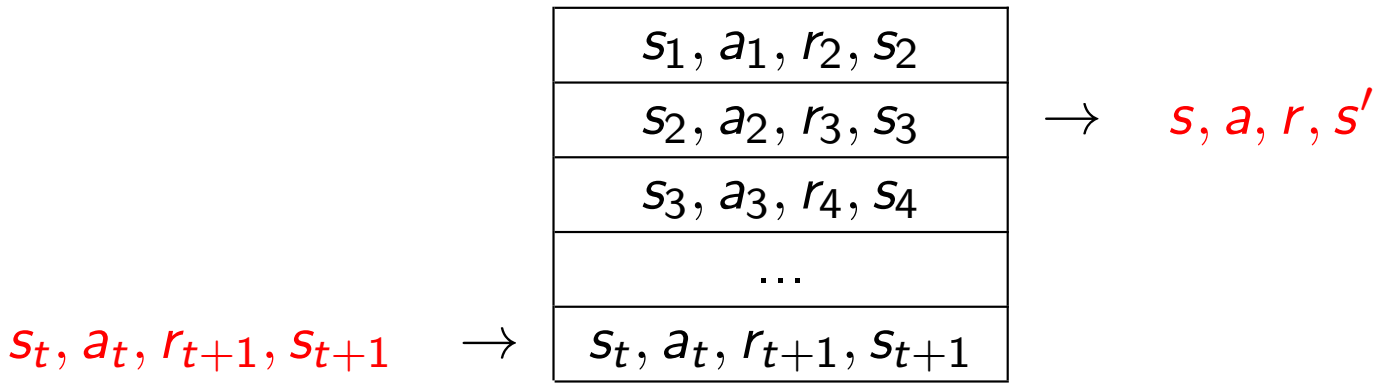
- Converges to Q^* using table lookup representation
- But diverges using neural networks due to:
  - Correlations between samples
  - Non-stationary targets

Deep Q-Networks (DQN): Experience Replay

To remove correlations, build data-set from agent's own experience

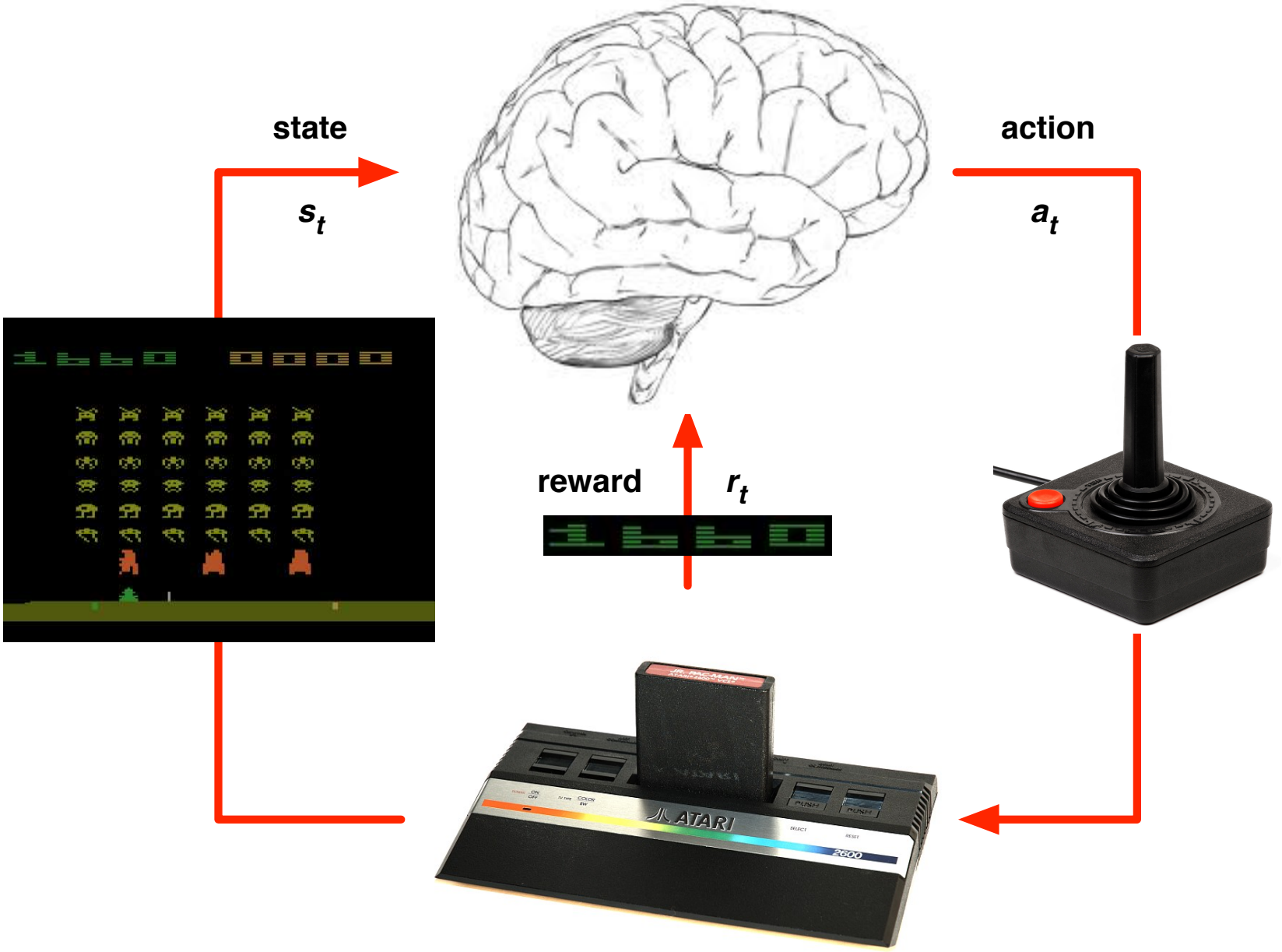


Sample experiences from data-set and apply update

$$I = \left(r + \gamma \max_{a'} Q(s', a', \mathbf{w}^-) - Q(s, a, \mathbf{w}) \right)^2$$

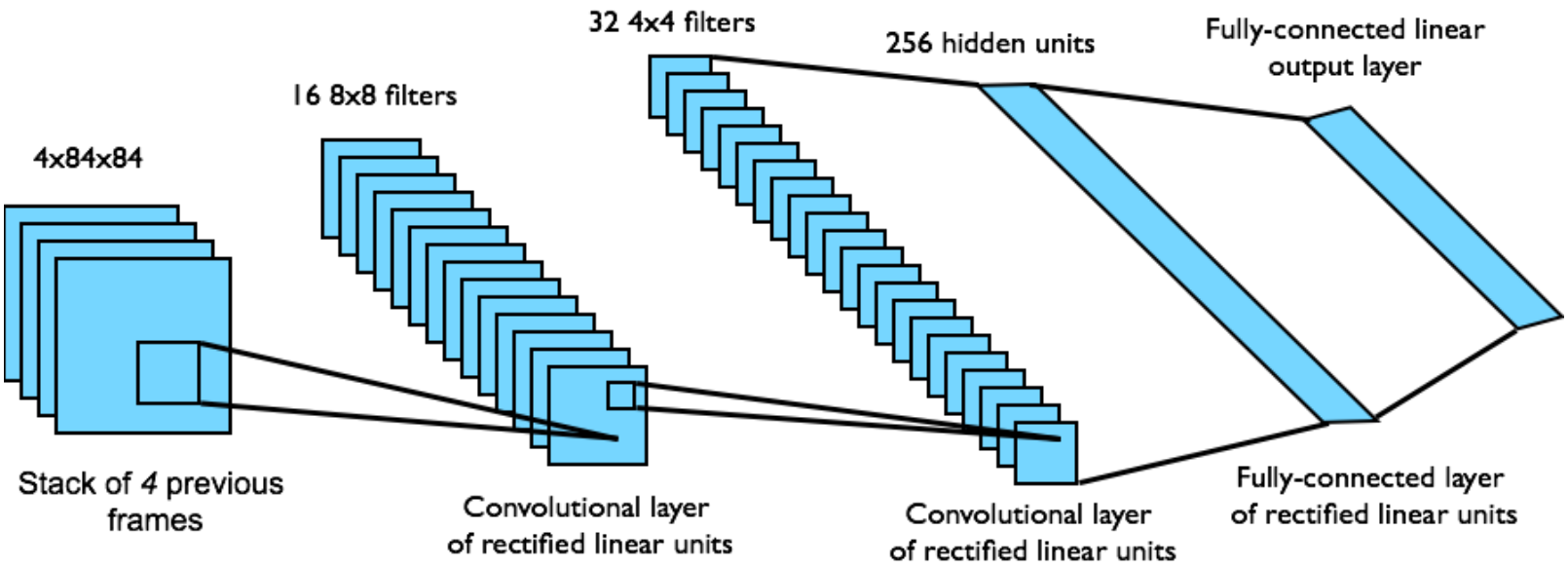
To deal with non-stationarity, target parameters $\mathbf{w}^-$ are held fixed

Deep Reinforcement Learning in Atari



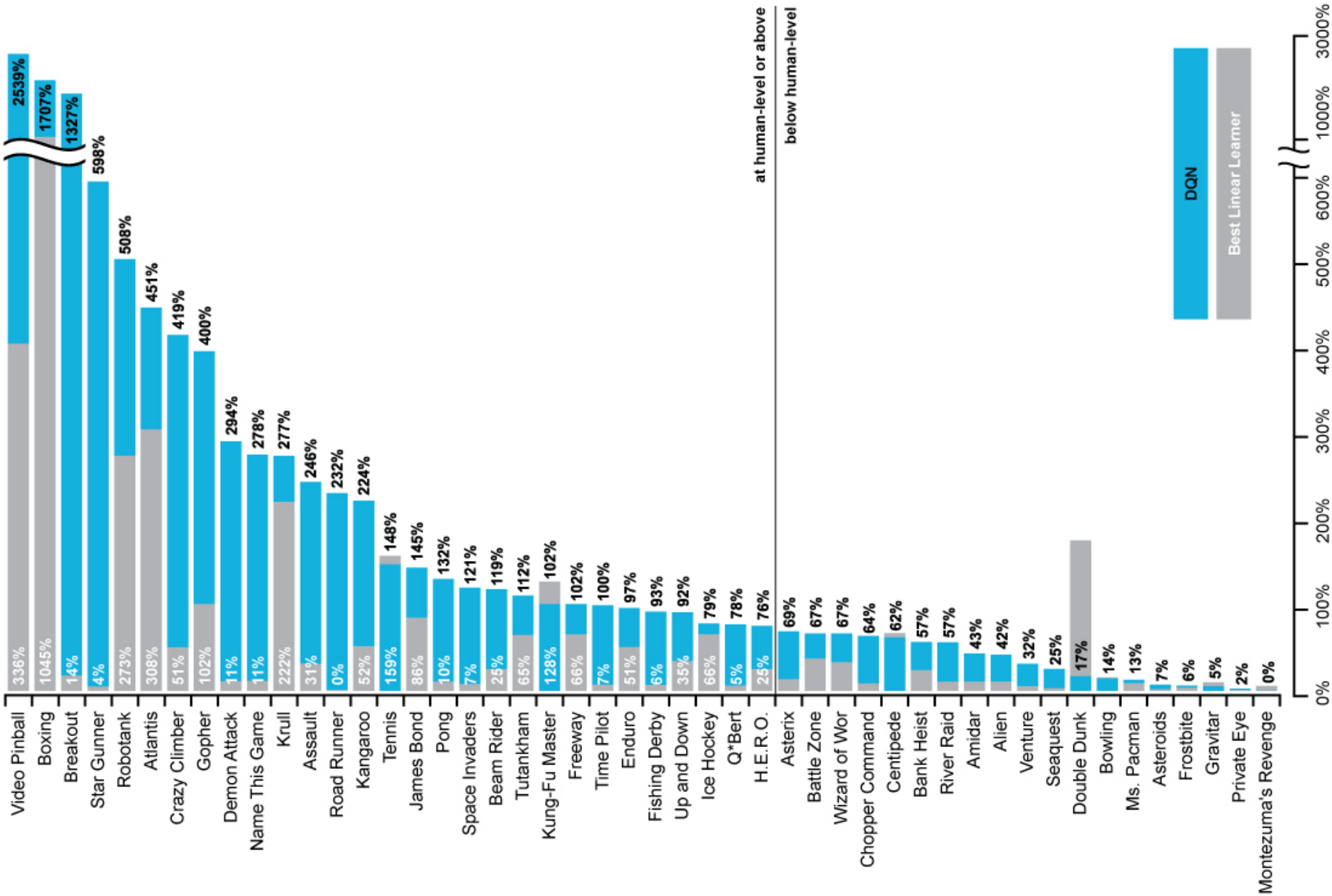
DQN in Atari

- End-to-end learning of values $Q(s, a)$ from pixels s
- Input state s is stack of raw pixels from last 4 frames
- Output is $Q(s, a)$ for 18 joystick/button positions
- Reward is change in score for that step



Network architecture and hyperparameters fixed across all games

DQN Results in Atari



DQN Atari Demo

DQN paper

www.nature.com/articles/nature14236

DQN source code:

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

Improvements since Nature DQN

- Double DQN: Remove upward bias caused by $\max_a Q(s, a, \mathbf{w})$
  - Current Q-network $\mathbf{w}$ is used to select actions
  - Older Q-network $\mathbf{w}^-$ is used to evaluate actions

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- Prioritised replay: Weight experience according to surprise
  - Store experience in priority queue according to DQN error

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

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- Duelling network: Split Q-network into two channels
  - Action-independent value function $V(s, v)$
  - Action-dependent advantage function $A(s, a, \mathbf{w})$

$$Q(s, a) = V(s, v) + A(s, a, \mathbf{w})$$

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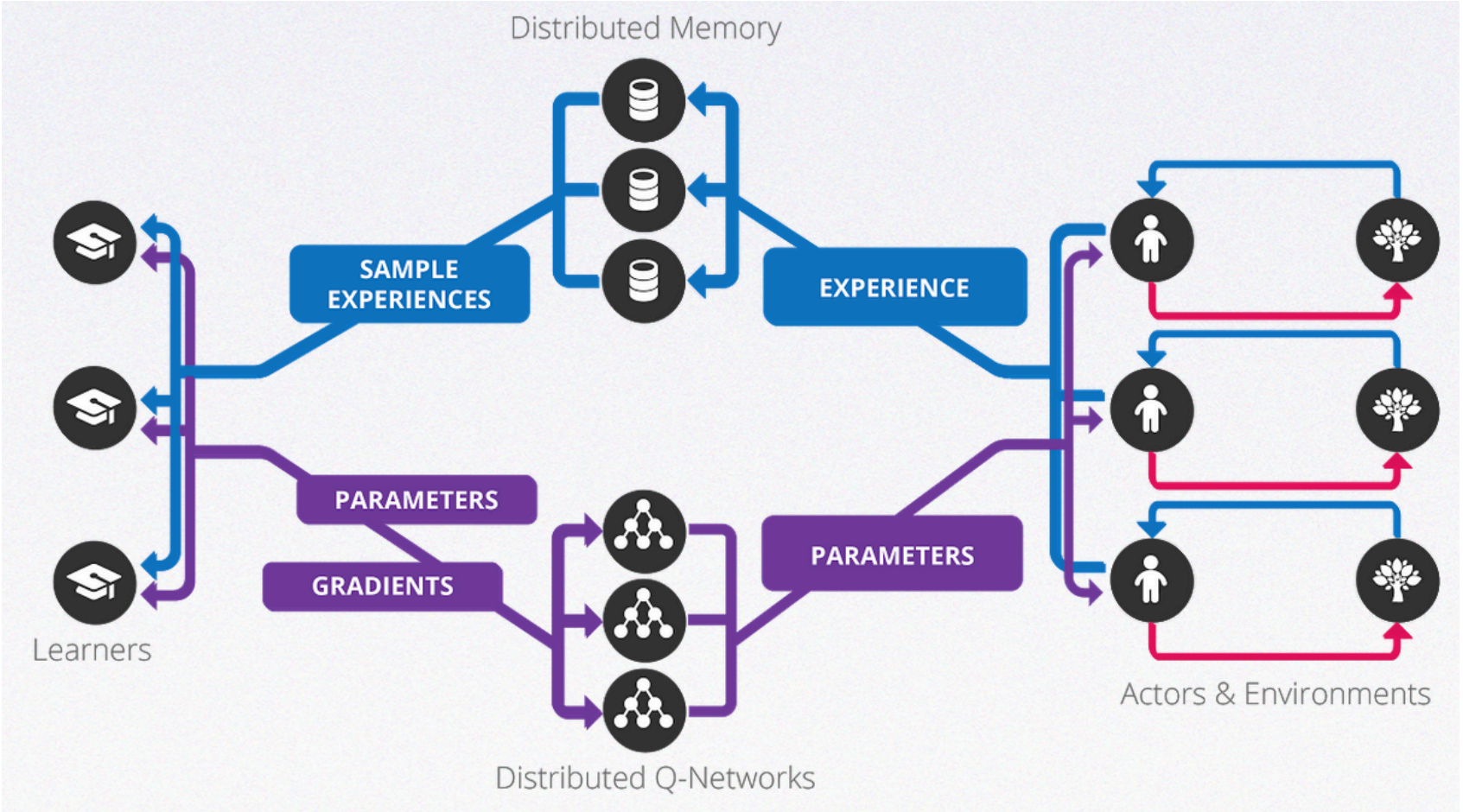
Combined algorithm: $3x$ mean Atari score vs Nature DQN

Gorila (General Reinforcement Learning Architecture)



- 10x faster than Nature DQN on 38 out of 49 Atari games
- Applied to recommender systems within Google

Asynchronous Reinforcement Learning

- Exploits multithreading of standard CPU
- Execute many instances of agent in parallel
- Network parameters shared between threads
- Parallelism decorrelates data
  - Viable alternative to experience replay
- Similar speedup to Gorila - on a single machine!