Playing Atari with Deep Reinforcement Learning Paper Review

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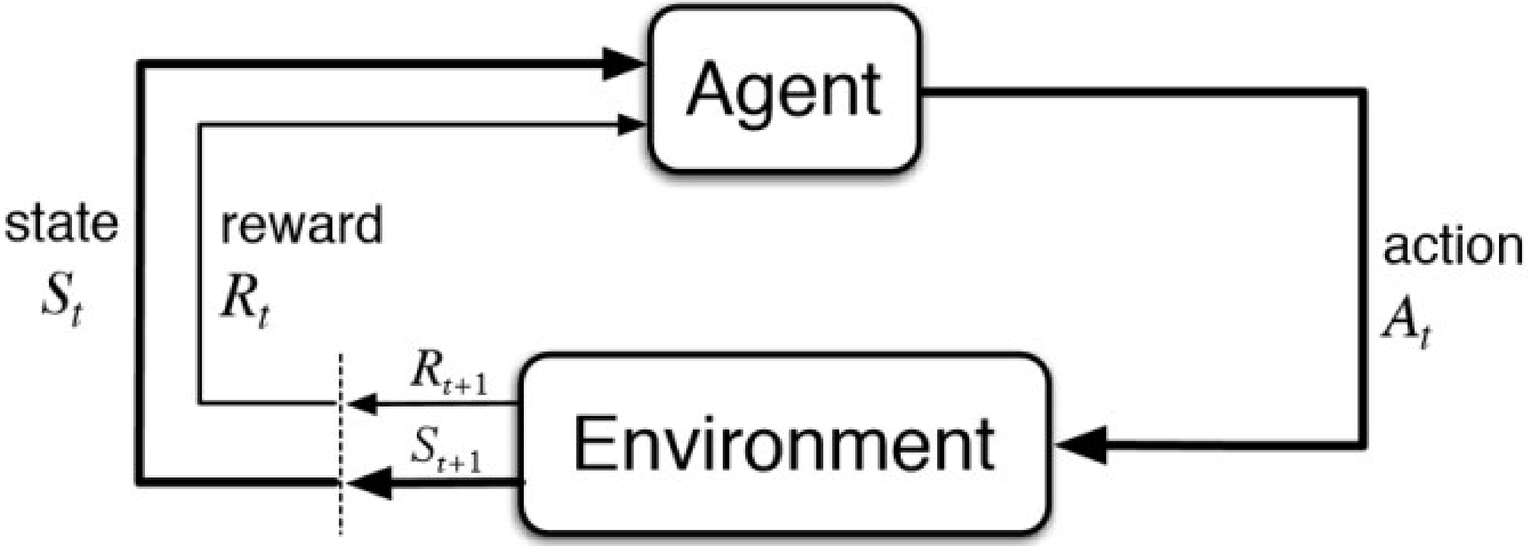
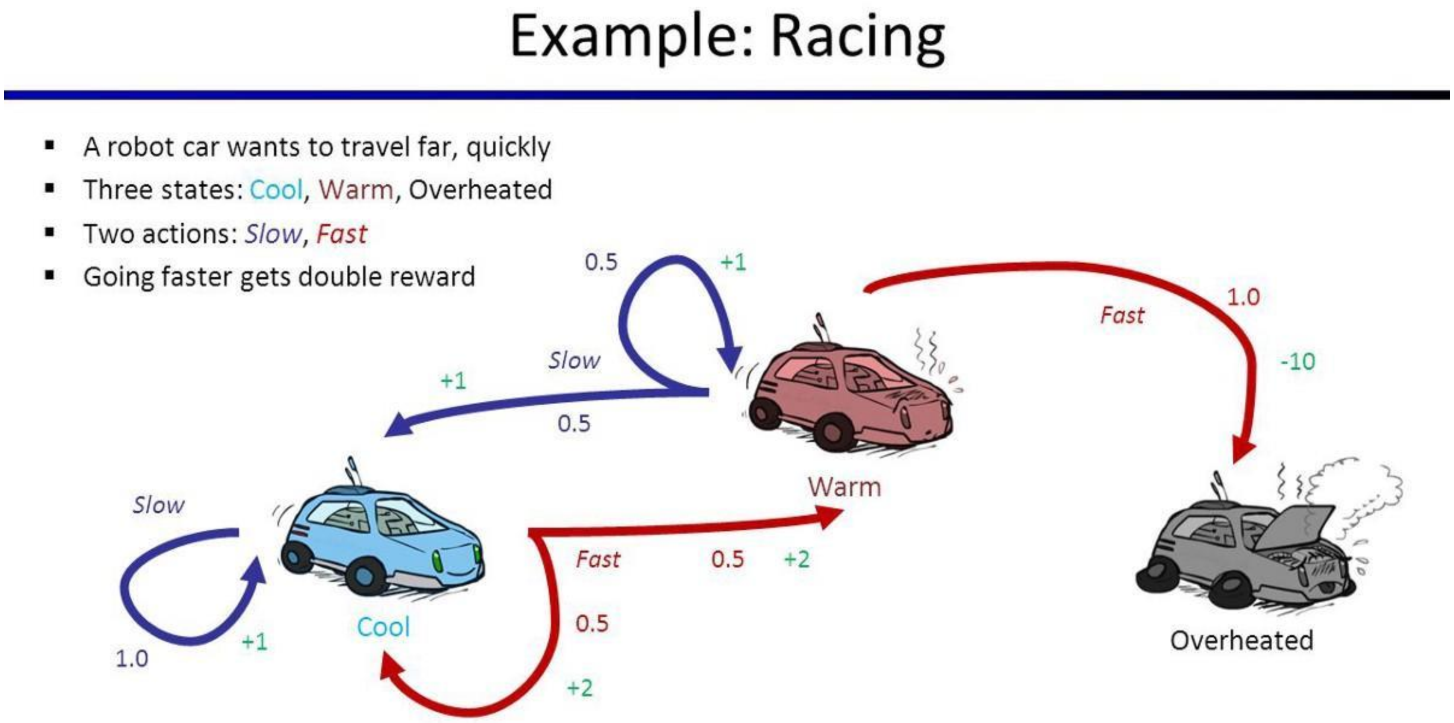
Reinforcement Learning Framework



Markov Decision Process

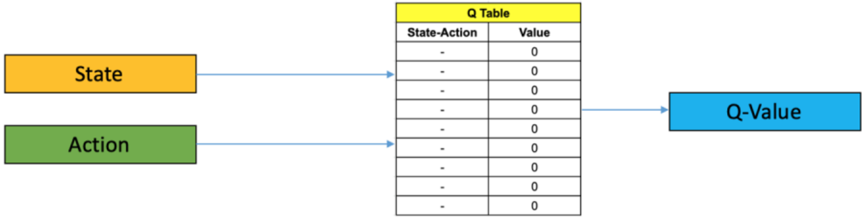


Bellman Equation, Q-learning

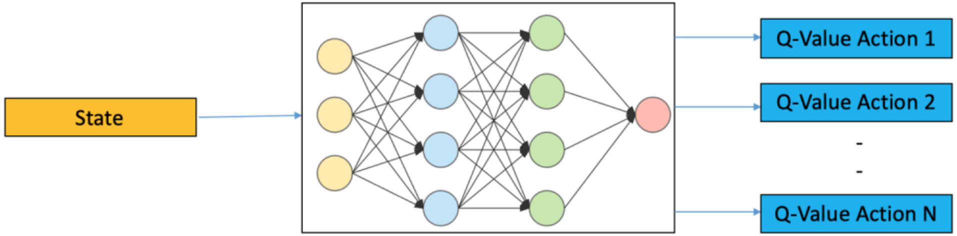
$$\boxed{\text{New } Q(s,a)} = \boxed{Q(s,a)} + \boxed{\alpha}\,\boxed{[R(s,a)} + \boxed{\gamma}\,\boxed{\max Q'(s',a')} - \boxed{Q(s,a)}]$$

- New Q Value for that state and the action
- Learning Rate
- Reward for taking that action at that state
- Current Q Values
- Maximum expected future reward given the new state (s') and all possible actions at that new state.
- Discount Rate

Deep Q Network vs Q-Learning

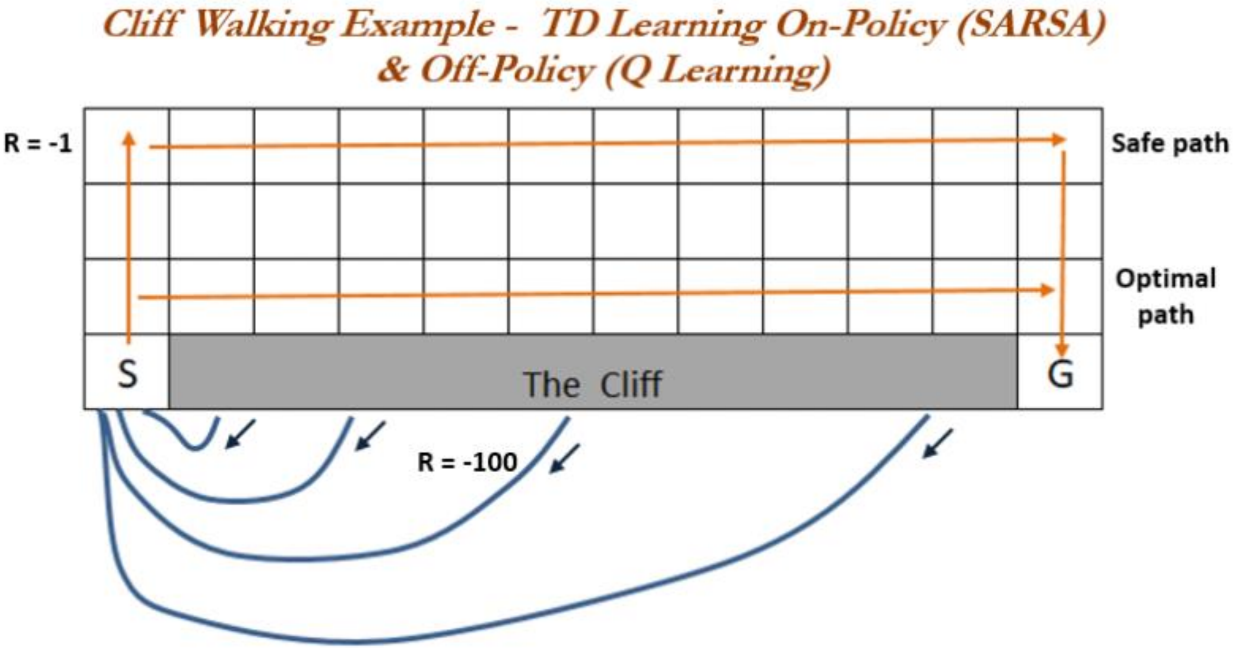


Q Learning



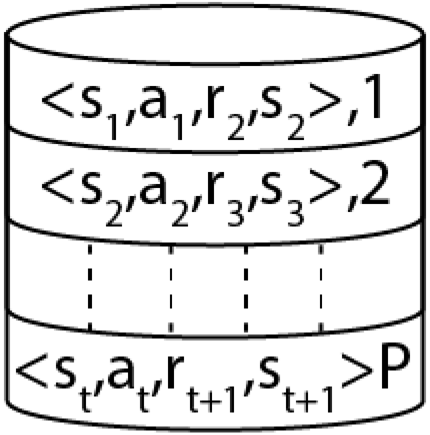
Deep Q Learning

SARSA vs Q-Learning



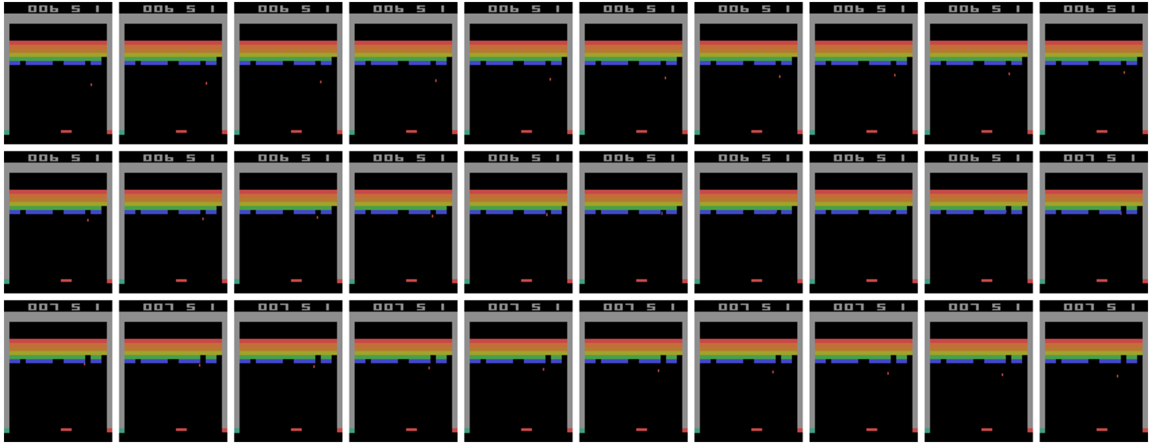
Experience Replay

- Save transitions in a replay Memory D
- Random sample previous transitions to update parameters



Experience Replay Advantages

- Greater Data Efficiency
- Prevents frames to be highly correlated
- Average the behaviour distribution

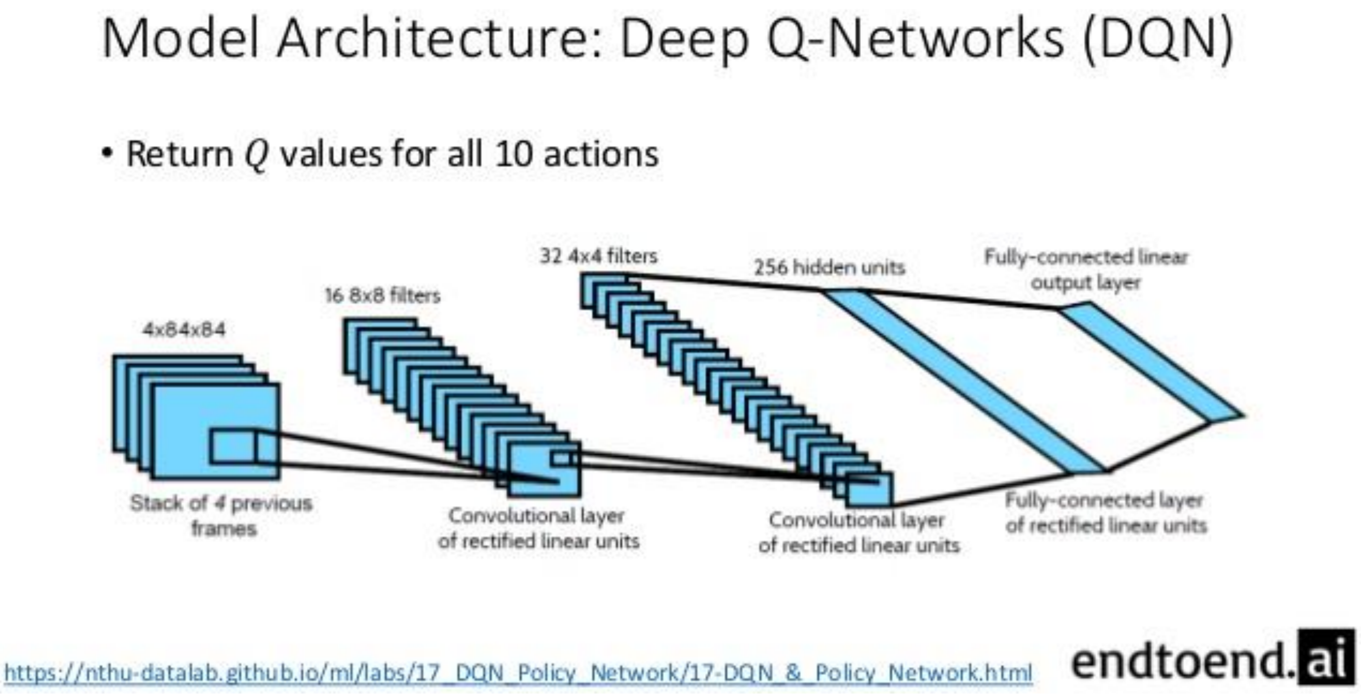


Preprocessing

- Originally 210 × 160 image with 128 color palette
- Gray-scale and downsampled to 110 × 84, cropped to 84 × 84
- Frame stacking
- Stack 4 preprocessed frames as input
- Need multiple frames for velocity, etc
- Frame Skipping

endtoend.ai

Model Architecture



Environment

- Same Algorithm implemented to 7 Atari Games
- Single Agent Problem
- Algorithm is model-free
  - No information to agents
  - No hand-crafted features
  - Same Neural Network structure and hyperparameters used in every game

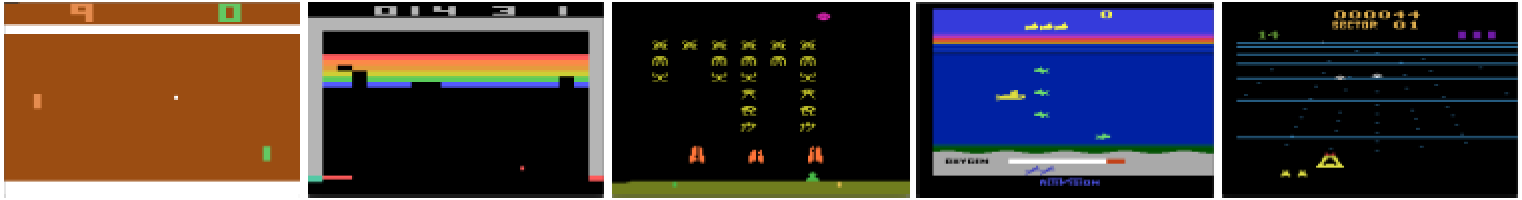


Figure 1: Screen shots from five Atari 2600 Games: (*Left-to-right*) Pong, Breakout, Space Invaders, Seaquest, Beam Rider

Pseudocode Algorithm

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    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 $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation $\boxed{3}$
  end for
end for

Evaluation Metric

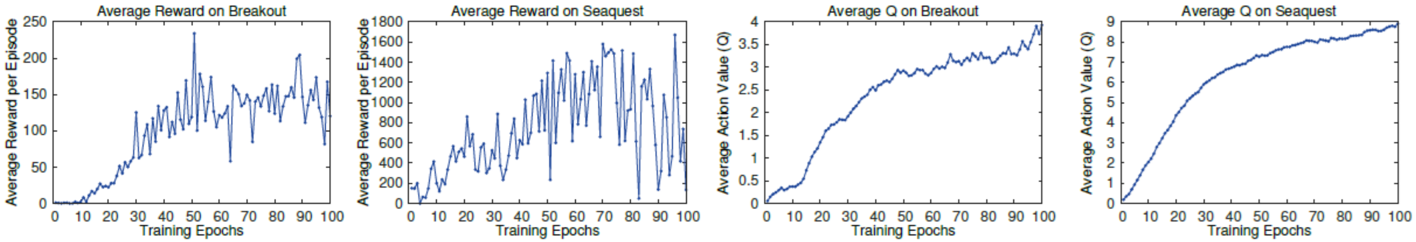


Figure 2: The two plots on the left show average reward per episode on Breakout and Seaquest respectively during training. The statistics were computed by running an ϵ-greedy policy with $\epsilon = 0.05$ for 10000 steps. The two plots on the right show the average maximum predicted action-value of a held out set of states on Breakout and Seaquest respectively. One epoch corresponds to 50000 minibatch weight updates or roughly 30 minutes of training time.

Experiments

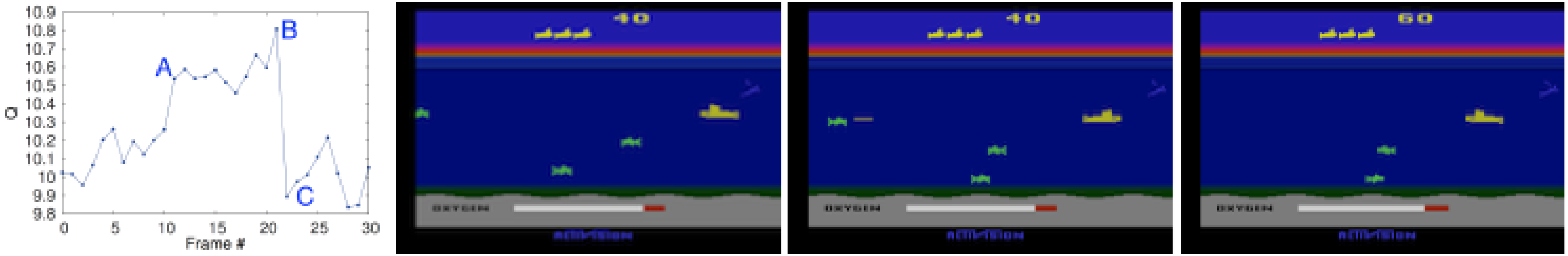
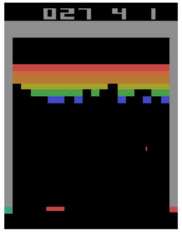


Figure 3: The leftmost plot shows the predicted value function for a 30 frame segment of the game Seaquest. The three screenshots correspond to the frames labeled by A, B, and C respectively.

Results



Breakout game

	B. Rider	Breakout	Enduro	Pong	Q*bert	Seaquest	S. Invaders
Random	354	1.2	0	−20.4	157	110	179
Sarsa [3]	996	5.2	129	−19	614	665	271
Contingency [4]	1743	6	159	−17	960	723	268
DQN	**4092**	**168**	**470**	**20**	**1952**	**1705**	**581**
Human	7456	31	368	−3	18900	28010	3690
HNeat Best [8]	3616	52	106	19	1800	920	**1720**
HNeat Pixel [8]	1332	4	91	−16	1325	800	1145
DQN Best	**5184**	**225**	**661**	**21**	**4500**	**1740**	1075

Table 1: The upper table compares average total reward for various learning methods by running an ϵ-greedy policy with $\epsilon = 0.05$ for a fixed number of steps. The lower table reports results of the single best performing episode for HNeat and DQN. HNeat produces deterministic policies that always get the same score while DQN used an ϵ-greedy policy with $\epsilon = 0.05$.