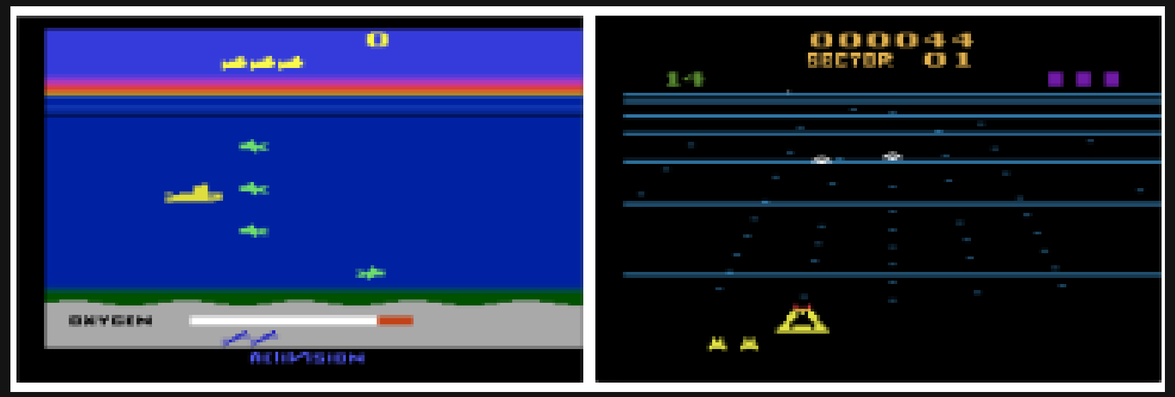
Playing Atari with Deep Reinforcement Learning

YUSUF EMRE BAYAT

Abstract

We present the first deep learning model to successfully learn control policies directly from high-dimensional sensory input using reinforcement learning. The model is a convolutional neural network, trained with a variant of Q-learning, whose input is raw pixels and whose output is a value function estimating future rewards. We apply our method to seven Atari 2600 games from the Arcade Learning Environment, with no adjustment of the architecture or learning algorithm. We find that it outperforms all previous approaches on six of the games and surpasses a human expert on three of them.

Arcade Learning Environment



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

Deep Reinforcement Learning

$$R_t = \sum_{t'=t}^{T} \gamma^{t'-t} r_t$$

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

$$L_i(\theta_i) = \mathbb{E}_{s,a \sim \rho(\cdot)} \left[(y_i - Q(s,a;\theta_i))^2 \right],$$

$$\nabla_{\theta_i} L_i(\theta_i) = \mathbb{E}_{s,a \sim \rho(\cdot); s' \sim \mathcal{E}} \left[\left(r + \gamma \max_{a'} Q(s',a';\theta_{i-1}) - Q(s,a;\theta_i) \right) \nabla_{\theta_i} Q(s,a;\theta_i) \right]$$

Algorithm

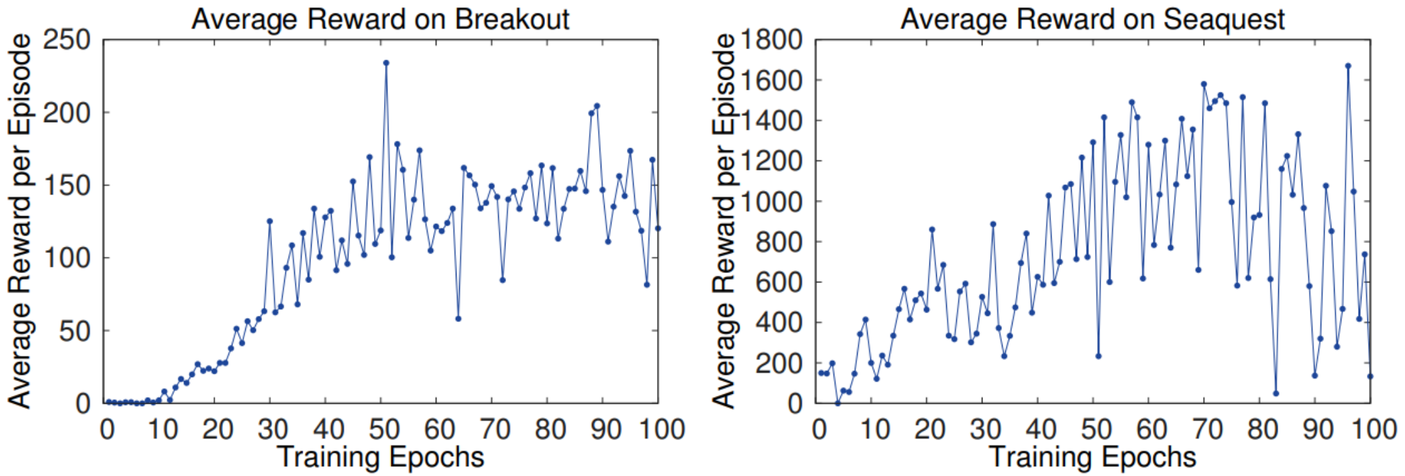
Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
    Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
    for $t = 1, T$ **do**
        With probability ϵ select a random action a_t
        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 3
    end for
end for

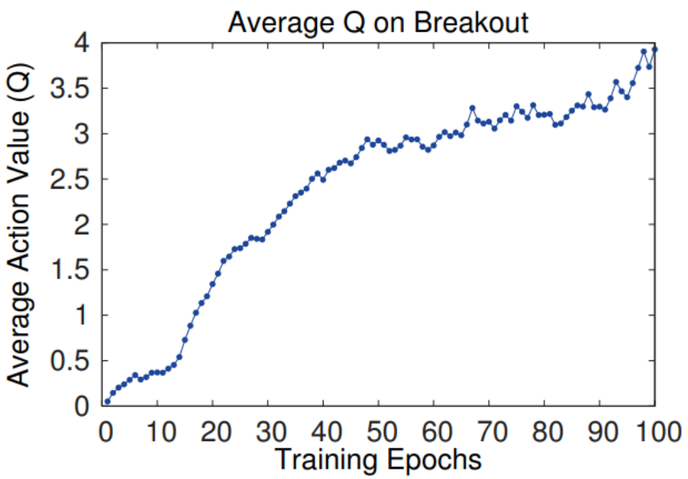
4.1 Preprocessing and Model Architecture

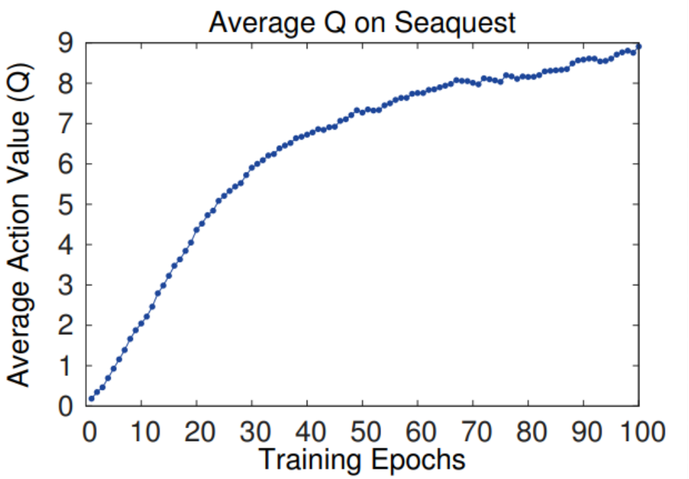
Working directly with raw Atari frames, which are 210×160 pixel images with a 128 color palette, can be computationally demanding, so we apply a basic preprocessing step aimed at reducing the input dimensionality. The raw frames are preprocessed by first converting their RGB representation to gray-scale and down-sampling it to a 110×84 image. The final input representation is obtained by cropping an 84×84 region of the image that roughly captures the playing area. The final cropping stage is only required because we use the GPU implementation of 2D convolutions from [11], which expects square inputs. For the experiments in this paper, the function ϕ from algorithm 1 applies this preprocessing to the last 4 frames of a history and stacks them to produce the input to the Q-function.

network consists is an $84 \times 84 \times 4$ image produced by ϕ. The first hidden layer convolves 16 8×8 filters with stride 4 with the input image and applies a rectifier nonlinearity [10, 18]. The second hidden layer convolves 32 4×4 filters with stride 2, again followed by a rectifier nonlinearity. The final hidden layer is fully-connected and consists of 256 rectifier units. The output layer is a fully-connected linear layer with a single output for each valid action. The number of valid actions varied between 4 and 18 on the games we considered. We refer to convolutional networks trained with our approach as Deep Q-Networks (DQN).

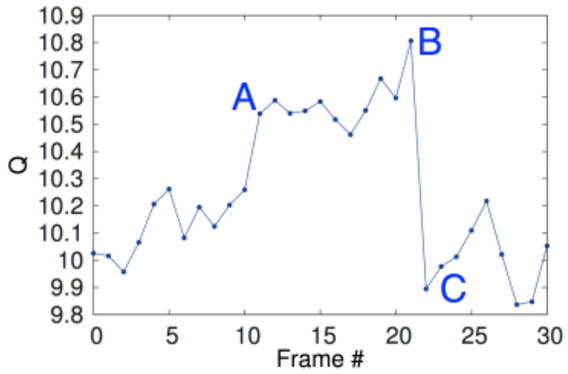
Experiments







Exploratory Experiment



Comparison With Other Methods

	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

Conclusion

This paper introduced a new deep learning model for reinforcement learning, and demonstrated its ability to master difficult control policies for Atari 2600 computer games, using only raw pixels as input. We also presented a variant of online Q-learning that combines stochastic minibatch updates with experience replay memory to ease the training of deep networks for RL. Our approach gave state-of-the-art results in six of the seven games it was tested on, with no adjustment of the architecture or hyperparameters.