Human-level control through deep reinforcement learning

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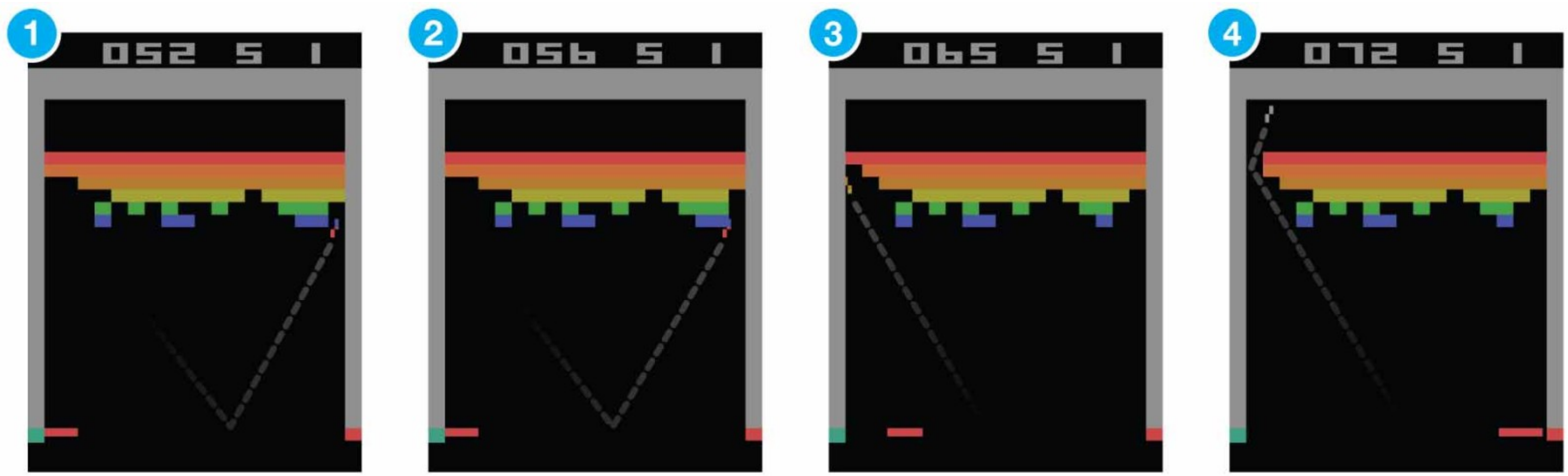
Agenda

- Problem
- Action-value function Q
- Paper’s additions to Q learning
- Training details
- Algorithm
- Results
- Summary and discussion

Problem

- Create an agent that would perform different, varied and challenging tasks
- Tasks: 49 games in the Atari 2600 platform



Agent and emulator

- Agent selects action a_t from $\{a_1, \ldots, a_K\}$ possible game actions
- Emulator executes action and returns:
  - Image for the current screen x_t
  - Game score → Δ game score for reward r_t
- Agent's goal: maximize future rewards $R_t = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}$
  - Discounted by γ = 0.99

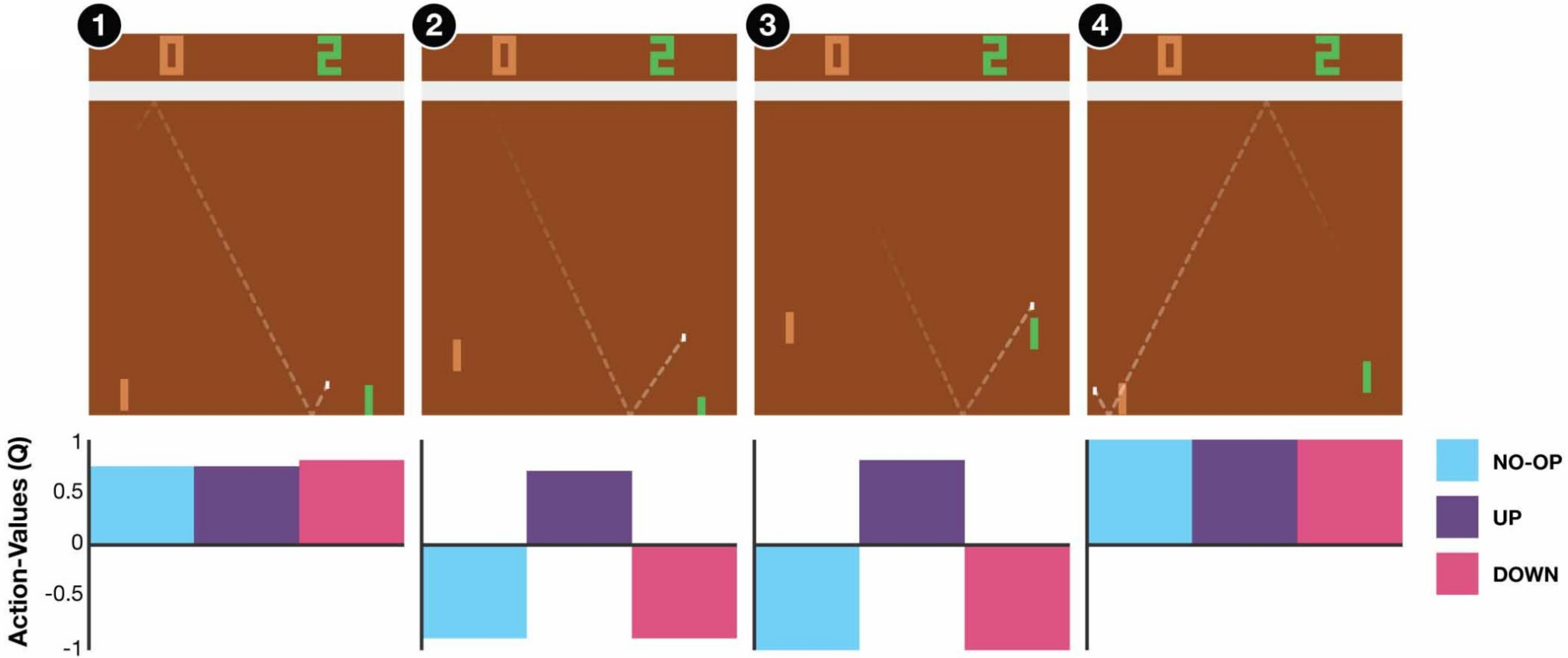
Action-value function *Q*

- Optimal action-value function

$$Q^*(s,a) = \max_{\pi} \mathbb{E}\left[R_t \mid s_t = s, a_t = a, \pi\right]$$

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

- Observed states: *s* this step, *s*' next step
- Action taken: *a* this step, *a*' next step
- π: policy mapping states to actions


1
2
3
4
0
2
Action-Values (Q)
1
0.5
0
-0.5
-1
NO-OP
UP
DOWN

Q-network: approximator for Q^*

- Instead of optimal target values

$$r + \gamma \max_{a'} Q^*(s', a')$$

use approximate target values

$$r + \gamma \max_{a'} Q(s', a'; \theta_i^-)$$

- θ_i^-: parameters from some previous iteration
- Q-network: neural network function approximator with weights θ

Loss function

For iteration *i*

$$L_i(\theta_i) = \mathbb{E}_{s,a,r,s'}\left[\left(r + \gamma \max_{a'} Q(s',a';\theta_i^-) - Q(s,a;\theta_i)\right)^2\right]$$

$$\nabla_{\theta_i} L(\theta_i) \quad = \mathbb{E}_{s,a,r,s'}\left[\left(r + \gamma \max_{a'} Q\left(s',a';\theta_i^-\right) - Q(s,a;\theta_i)\right)\nabla_{\theta_i} Q(s,a;\theta_i)\right]$$

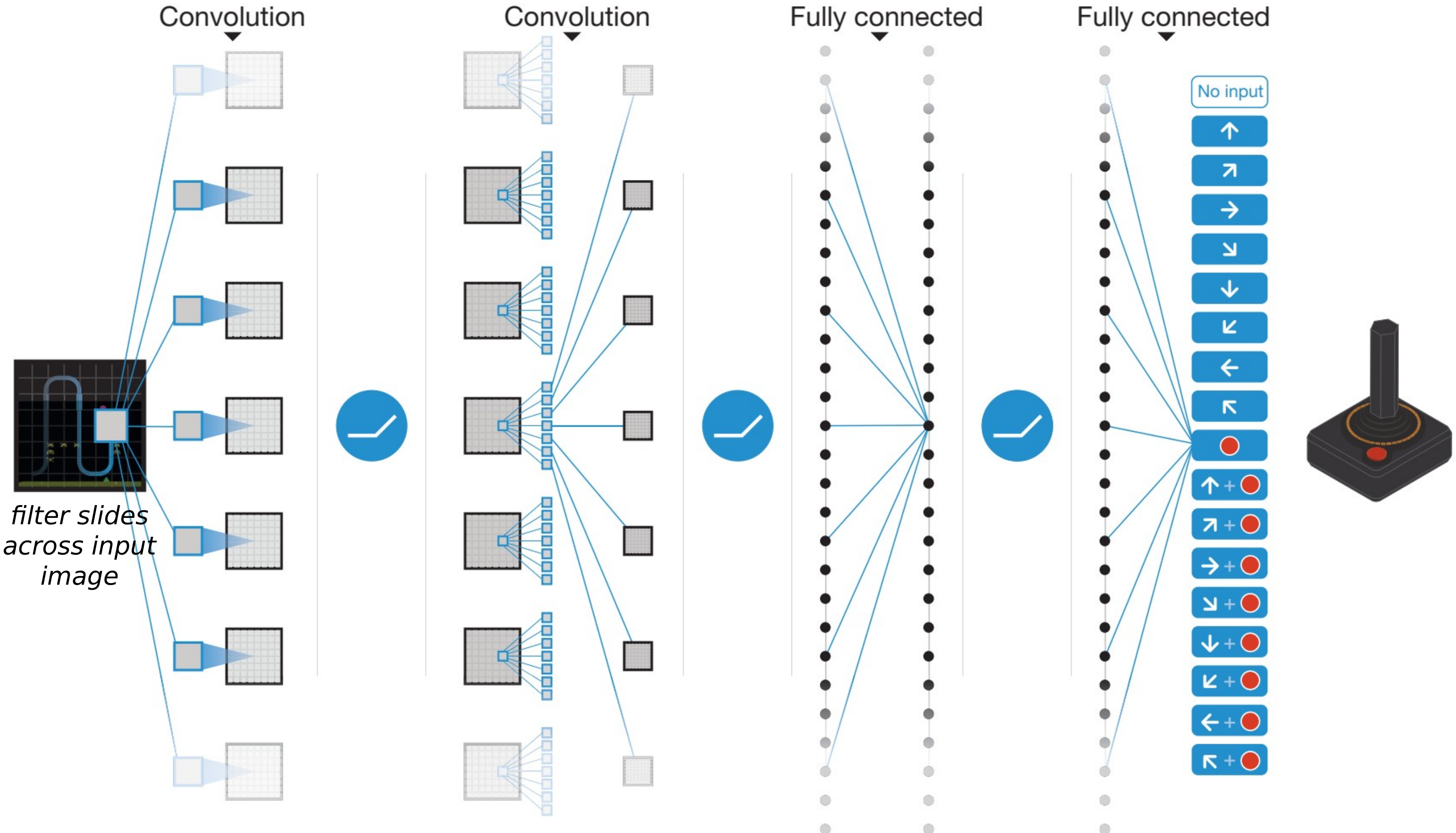
Paper’s additions to Q-learning

1. Convolutional network

2. Experience replay

3. Second target network

Input
84 × 84 pixels
× 4 frames
preprocessed image

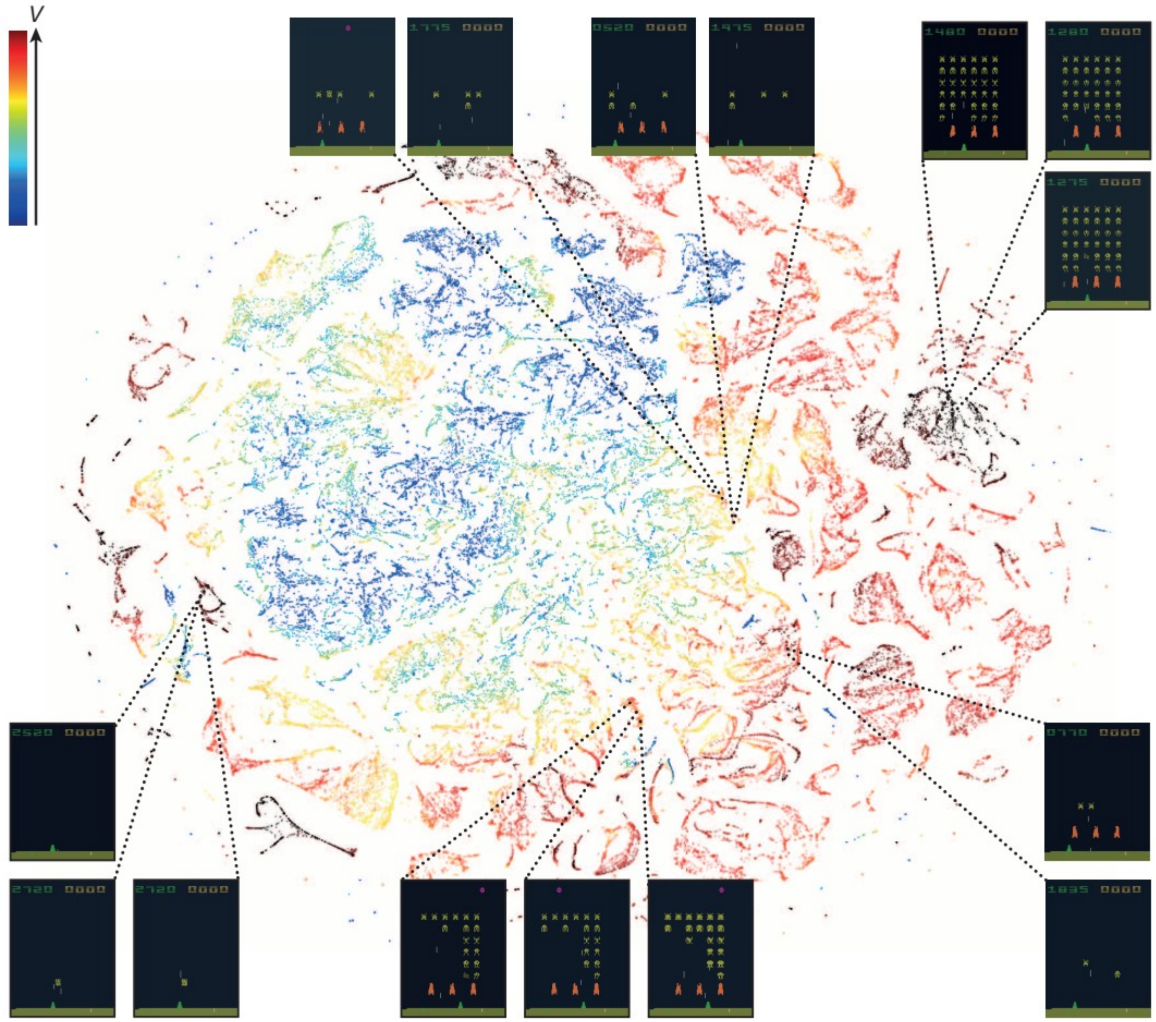


32 8 × 8 filters, stride 4

64 4 × 4 filters, stride 2

512 units

# of units = # of game actions



- Values of game states in the last hidden layer
- t-SNE
- After 2 hours of play
- Nearby points = perceptively similar states

2. Experience replay

- Store a history of 1 mln most recent (*s*, *a*, *r*, *s*') in replay memory
- Draw random minibatch of samples during training
- Stabilizes learning: prevents the agent from learning from only recent experiences
  – Which are highly correlated with current state
- Start populating after 50,000 initial random moves

3. Second target network $\hat{Q}$

- Use $\hat{Q}$ to generate targets y_j on each update
  - Instead of the main network Q
- Periodically set $\hat{Q} = Q$
- Stabilizes learning: makes divergence less likely
  - An update that increases $Q(s_t, a_t)$ often also increases $Q(s_{t+1}, a)\ \forall\, a$
  - So increases $y_j \rightarrow$ possible divergence

Effect of experience replay and target network

Game	With replay, with target Q	With replay, without target Q	Without replay, with target Q	Without replay, without target Q
Breakout	316.8	240.7	10.2	3.2
Enduro	1006.3	831.4	141.9	29.1
River Raid	7446.6	4102.8	2867.7	1453.0
Seaquest	2894.4	822.6	1003.0	275.8
Space Invaders	1088.9	826.3	373.2	302.0

Training

- RMSProp, minibatch size 32
- ε-greedy policy
  - ε annealed from 1 to 0.1 in the first 1 mln frames
  - $\varepsilon = 0.1$ afterwards
- Trained for 50 million frames (≈38 days of playing)

Preprocess input

- Atari 2600 frames are 210 × 160 color images
- Preprocess:
  1. Max of each pixel color value over frame at t and $t - 1$ to remove flickering
  2. Rescale to 84 × 84 and convert to grayscale
  3. Stack 4 most recent frames

Other training elements

- Both rewards and errors clipped at [-1; 1]
- Select action on every 4^{th} frame, instead of every frame
  - Selected action repeated on skipped frames
  - Less expensive to run the emulator for one step than to have the agent select an action
  - The fastest a human can press the “fire” button is every 6^{th} frame
- Hyperparameters selected in “informal search” (not e.g. grid search)

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

    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

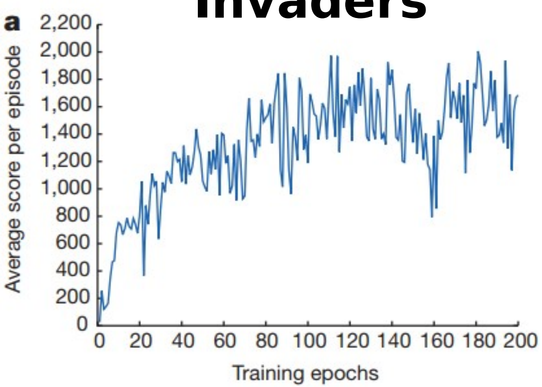
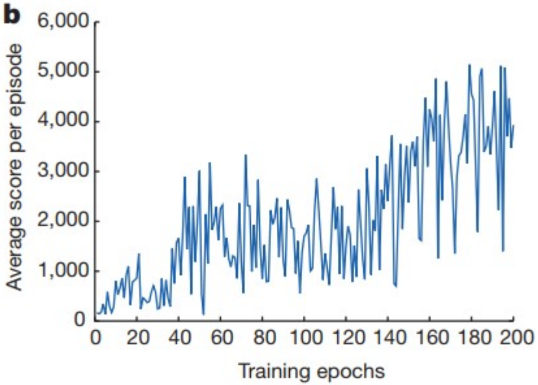
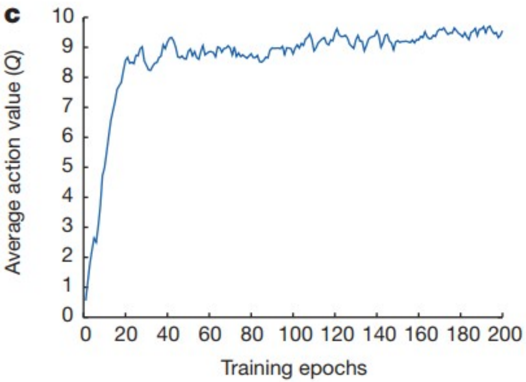
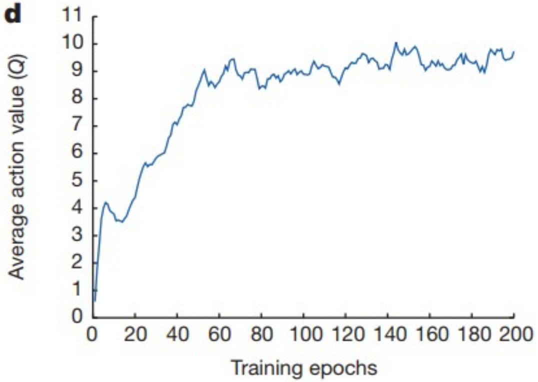
    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}\left(\phi_{j+1}, a'; \theta^{-}\right) & \text{otherwise} \end{cases}$

    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

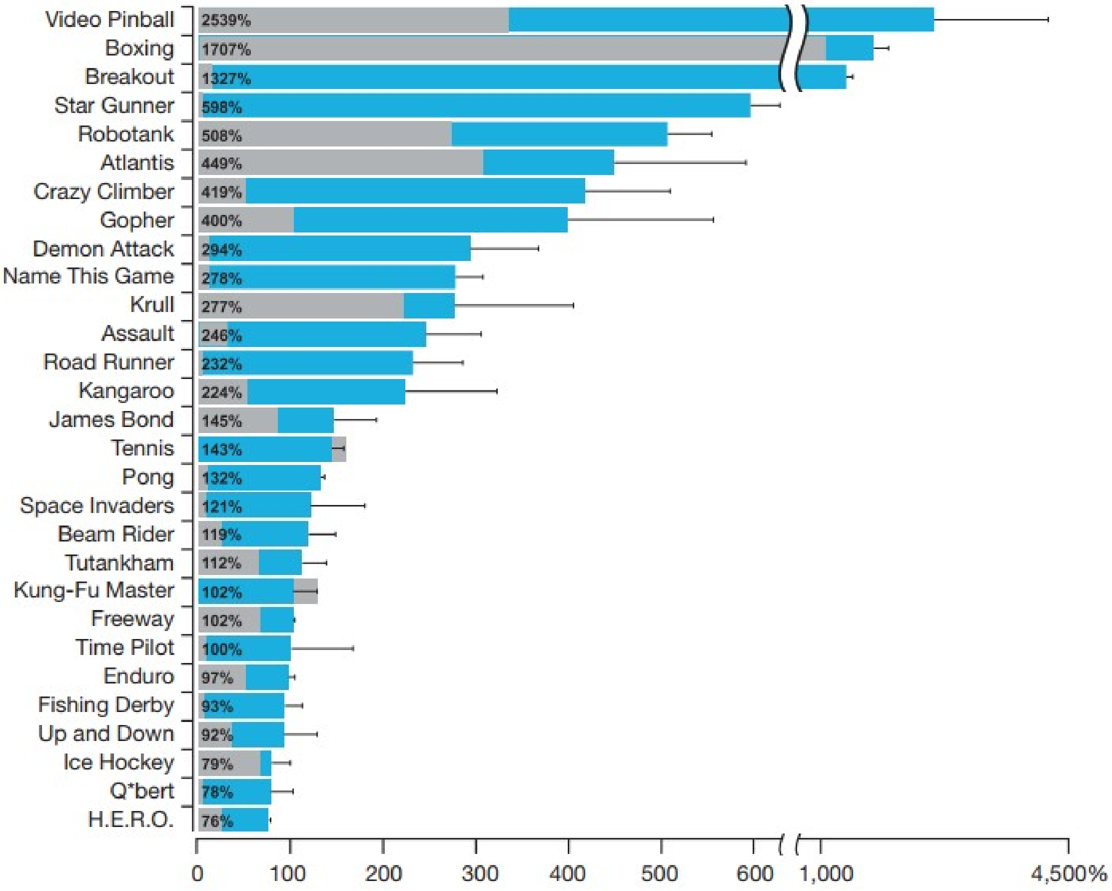
    Every C steps reset $\hat{Q} = Q$

  End For

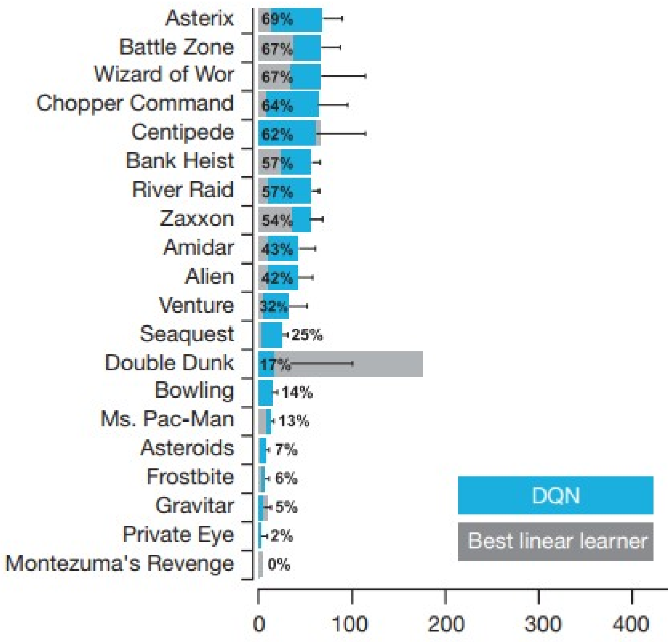
End For

	Space Invaders	**Seaquest**
Average score (ε=0.05, 520k frames)		
Average Q value (on holdout set of states)		
		

At human level or above



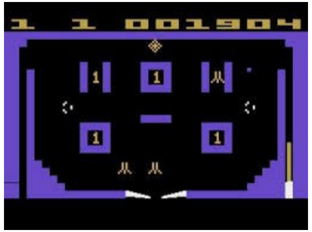
Below human level



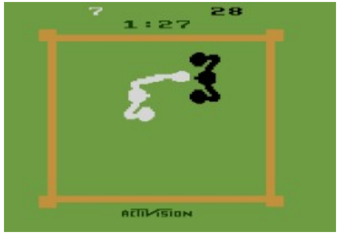
- 0%: random play
- 100%: professional human games tester
- Error bars: s.d. on 30 evaluation episodes
- Linear learner: single linear layer

Evaluation

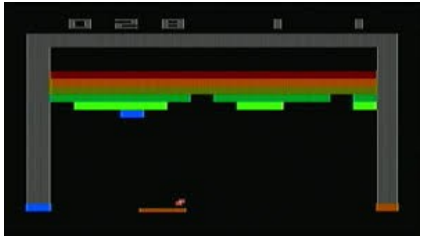
- Trained agents played each game 30 times for up to 5 mins each
  - Random number of initial "no-op"s up to 30



Pinball

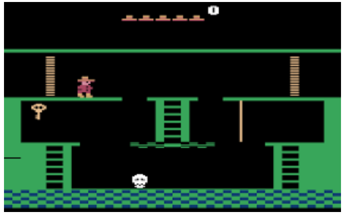


Boxing



Breakout

Star Gunner



Montezuma's Revenge

Private Eye

Gravitar

Ms. Pac-Man

Paper summary

- Combined Q-learning with a conv net
  - Able to use high-dimensional input
- Added techniques to stabilize learning:
  - Experience replay
  - Second network
- Result: generalizable agent
  - Learns in various different tasks (=Atari games)
  - Beats human performance in 29 of the 49 games

Discussion points

- Some games are more manageable for the agent than others. Why?
- What other tasks can this agent be applied to?
  - Anything in your line of work?
  - Would the architecture need to be tweaked?
- The agent starts with no clue about the environment it works in. How can this knowledge be used?
- Reward is highest game score. What other reward functions can be used here?
- 49 games = 49 trained agents. What can be done to generalize these agents?