DL + RL =
Deep Reinforcement Learning

(Slides by Svetlana Lazebnik, B Ravindran, David Silver)

Function approximation

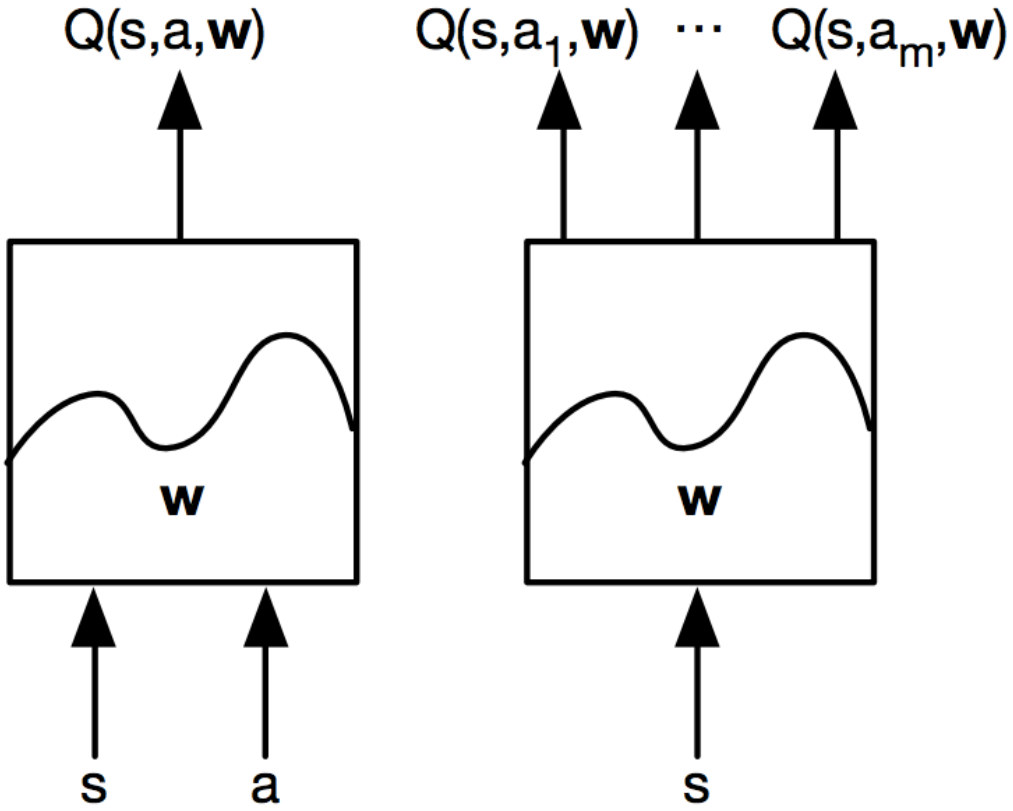
- So far, we've assumed a *lookup table* representation for utility function U(s) or action-utility function Q(s,a)
- This does not work if the state space is really large or continuous
- Alternative idea: approximate the utilities or Q values using parametric functions and automatically learn the parameters:

$$V(s) \approx \hat{V}(s;w)$$

$$Q(s,a) \approx \hat{Q}(s,a;w)$$

Deep Q learning

- Train a deep neural network to output Q values:



Source: D. Silver

Deep Q learning

- Regular TD update: “nudge” Q(s,a) towards the target

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left(R(s) + \gamma \max_{a'} Q(s',a') - Q(s,a)\right)$$

- Deep Q learning: encourage estimate to match the target by minimizing squared error:

$$L(w) = \left(R(s) + \gamma \max_{a'} Q(s',a';w) - Q(s,a;w)\right)^2$$

target estimate

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target estimate

- Compare to supervised learning:

$$L(w) = \left(y - f(x;w)\right)^2$$

  - Key difference: the target in Q learning is also moving!

Online Q learning algorithm

- Observe experience (s,a,s', r)
- Compute target $y = \quad r \quad + \gamma \max_{a'} Q(s', a'; w)$
- Update weights to reduce the error

$$L = \left(y - Q(s, a; w)\right)^2$$

- Gradient: $\nabla_w L = \left(Q(s, a; w) - y\right) \nabla_w Q(s, a; w)$

- Weight update: $w \leftarrow w - \alpha \nabla_w L$

- This is called *stochastic gradient descent* (SGD)

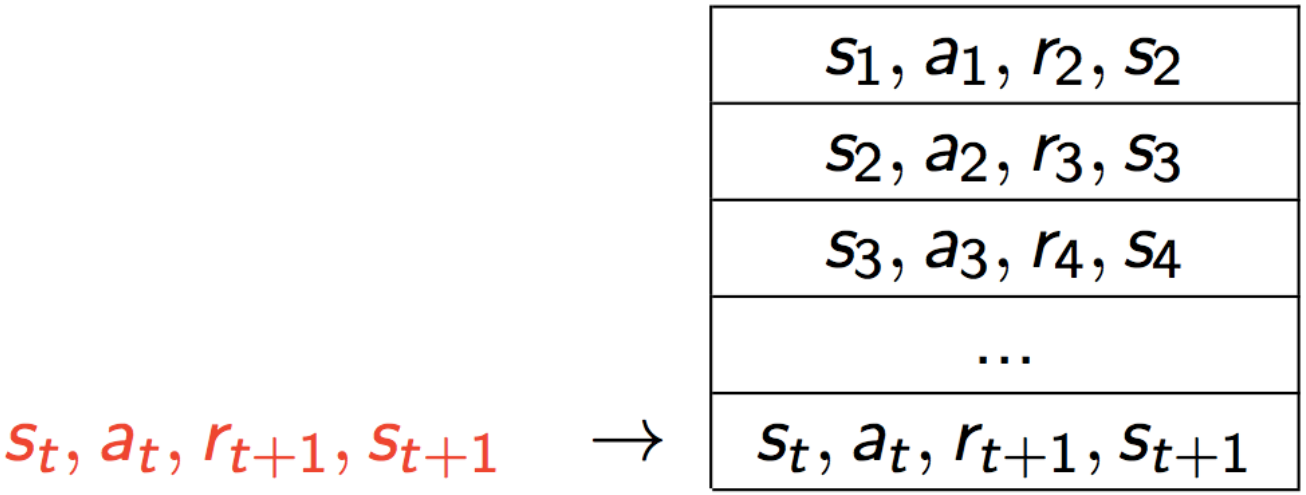
Dealing with training instability

- Challenges
  - Target values are not fixed
  - Successive experiences are correlated and dependent on the policy
  - Policy may change rapidly with slight changes to parameters, leading to drastic change in data distribution
- Solutions
  - Freeze target Q network
  - Use *experience replay*

Mnih et al. Human-level control through deep reinforcement learning, *Nature* 2015

Experience replay

- At each time step:
  - Take action a_t according to epsilon-greedy policy
  - Store experience (s_t, a_t, r_{t+1}, s_{t+1}) in *replay memory buffer*
  - Randomly sample *mini-batch* of experiences from the buffer



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  - Randomly sample *mini-batch* of experiences from the buffer
  - Perform update to reduce objective function

$$\mathbf{E}_{s,a,s'}\left[\left(R(s)+\gamma\max_{a'}Q(s',a';w^{-})-Q(s,a;w)\right)^2\right]$$

Keep parameters of *target network* fixed, update every once in a while

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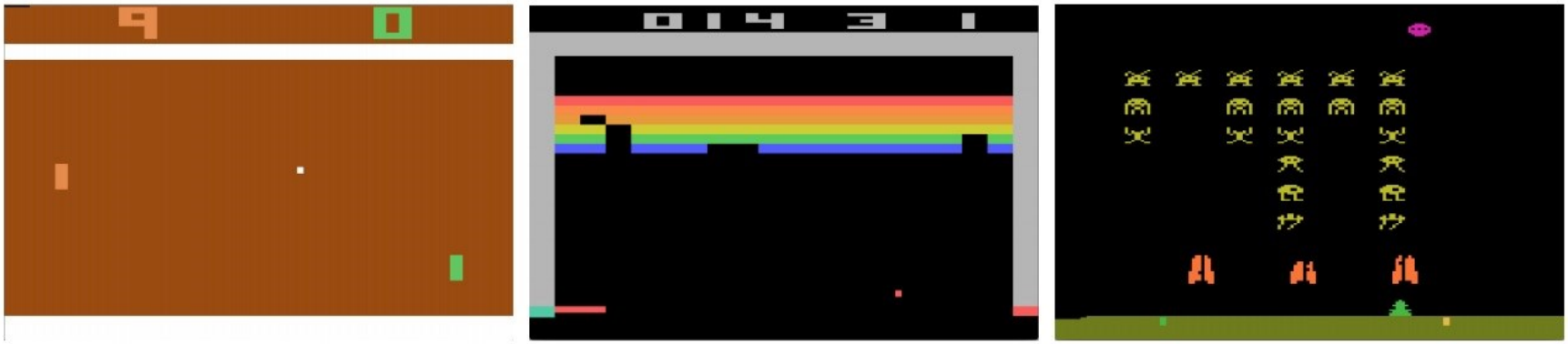
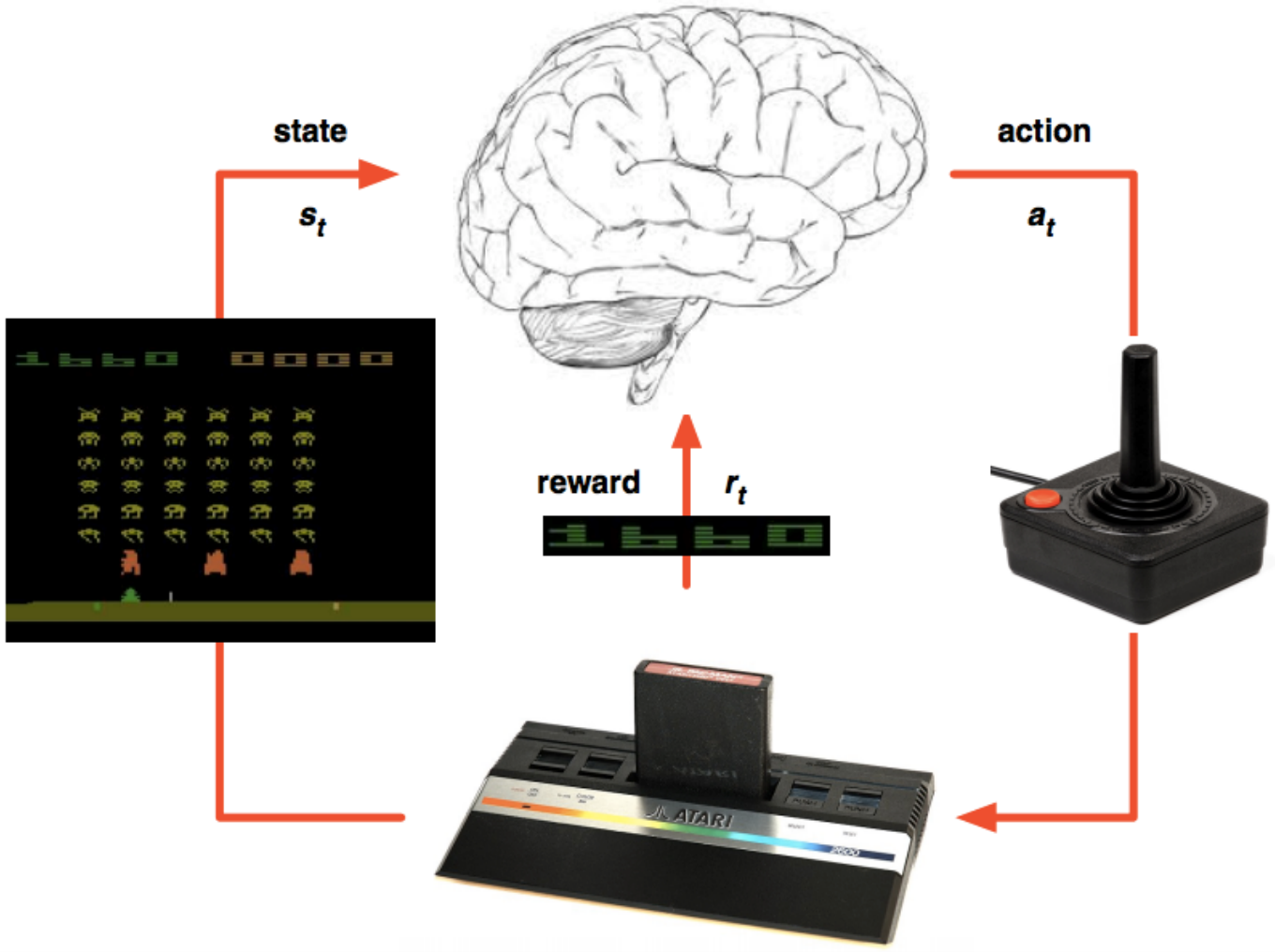
Atari



- Learnt to play from video input
  - from scratch
- Used a complex *neural network!*
  - Considered one of the hardest learning problems solved by a computer.
- More importantly *reproducible!!*

Deep Q learning in Atari



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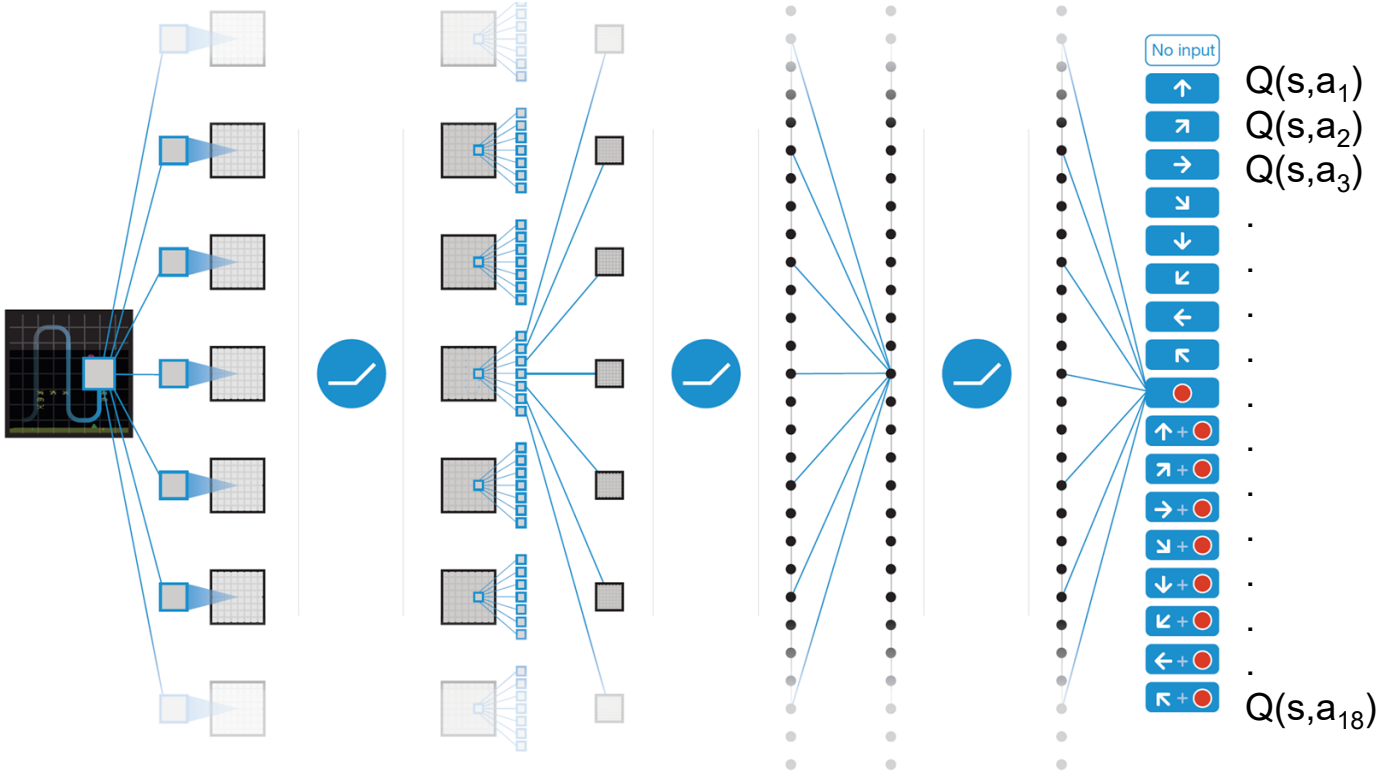
Deep Q learning in Atari

- End-to-end learning of Q(s,a) from pixels s
- Output is Q(s,a) for 18 joystick/button configurations
- Reward is change in score for that step



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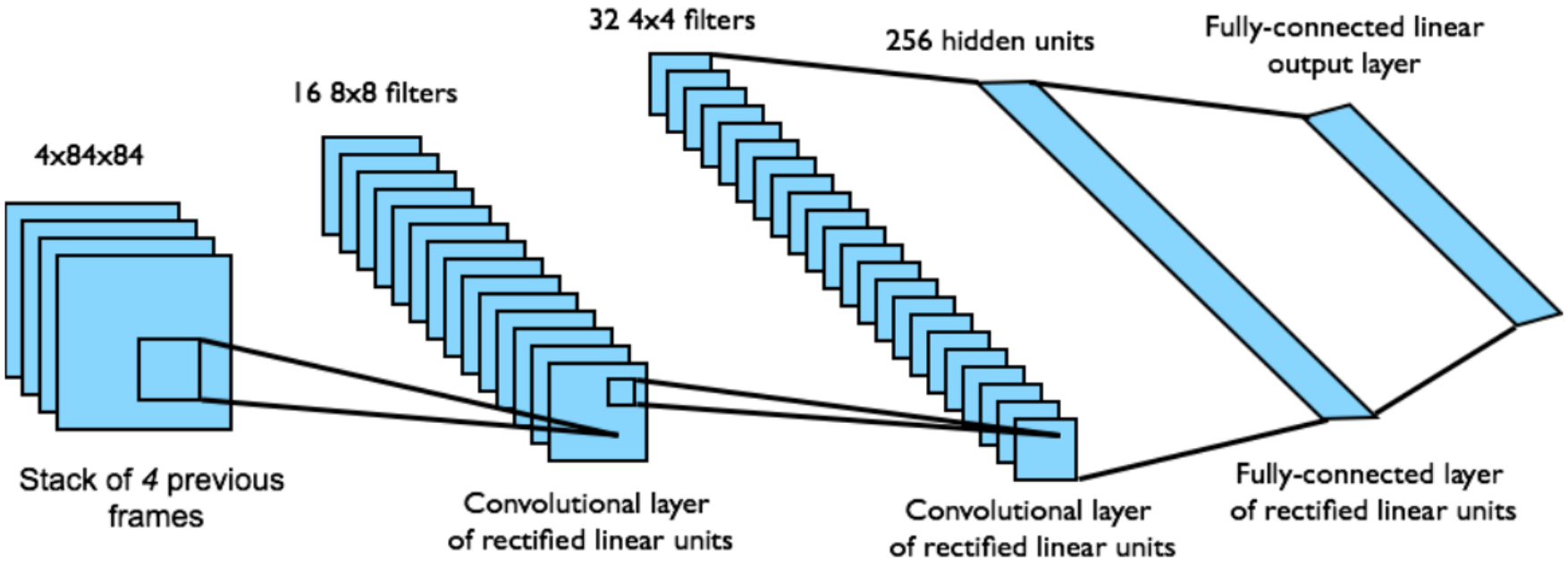
Deep Q learning in Atari

- Input state s is stack of raw pixels from last 4 frames
- Network architecture and hyperparameters fixed for all games



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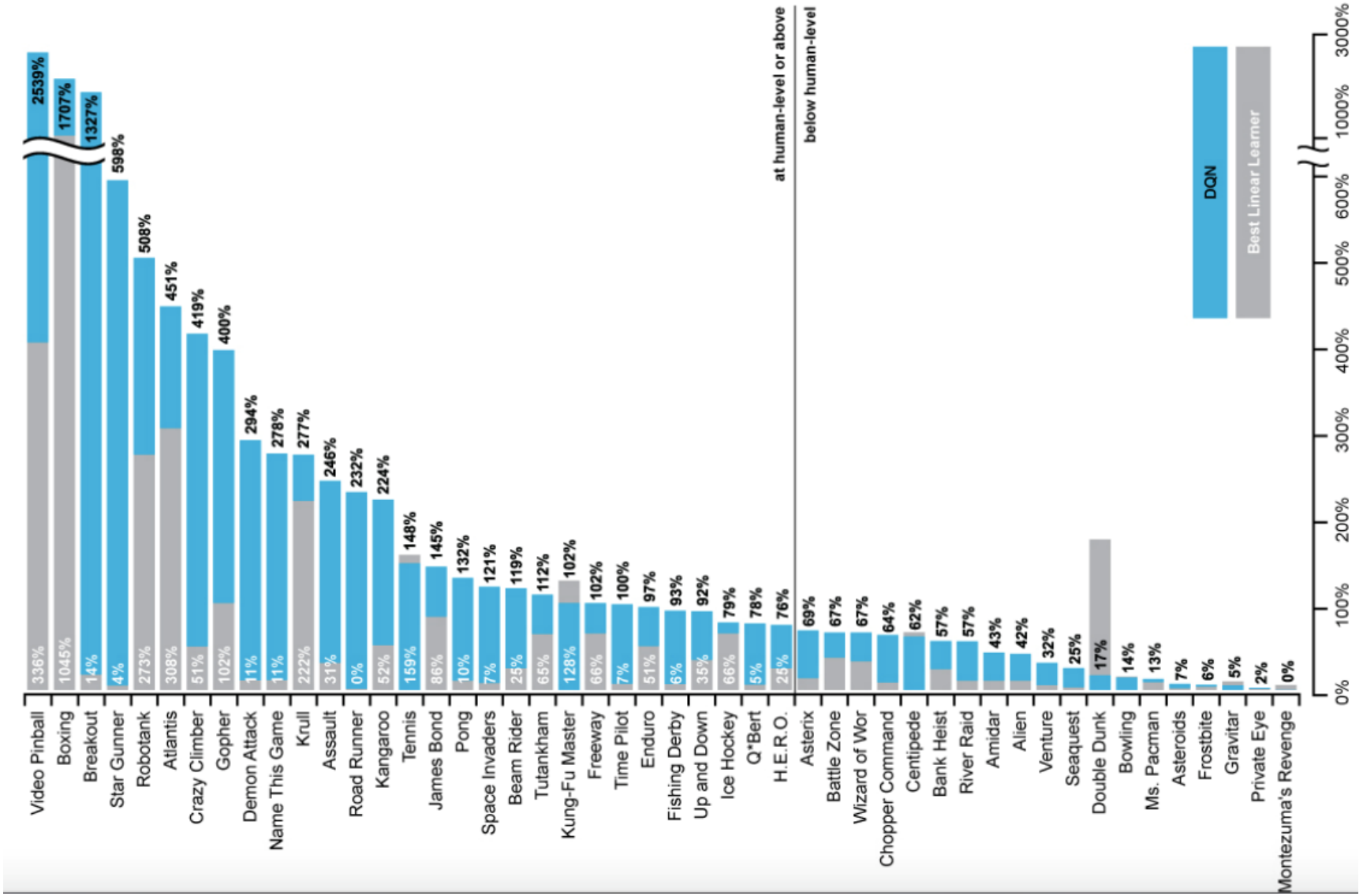
Deep Q learning in Atari



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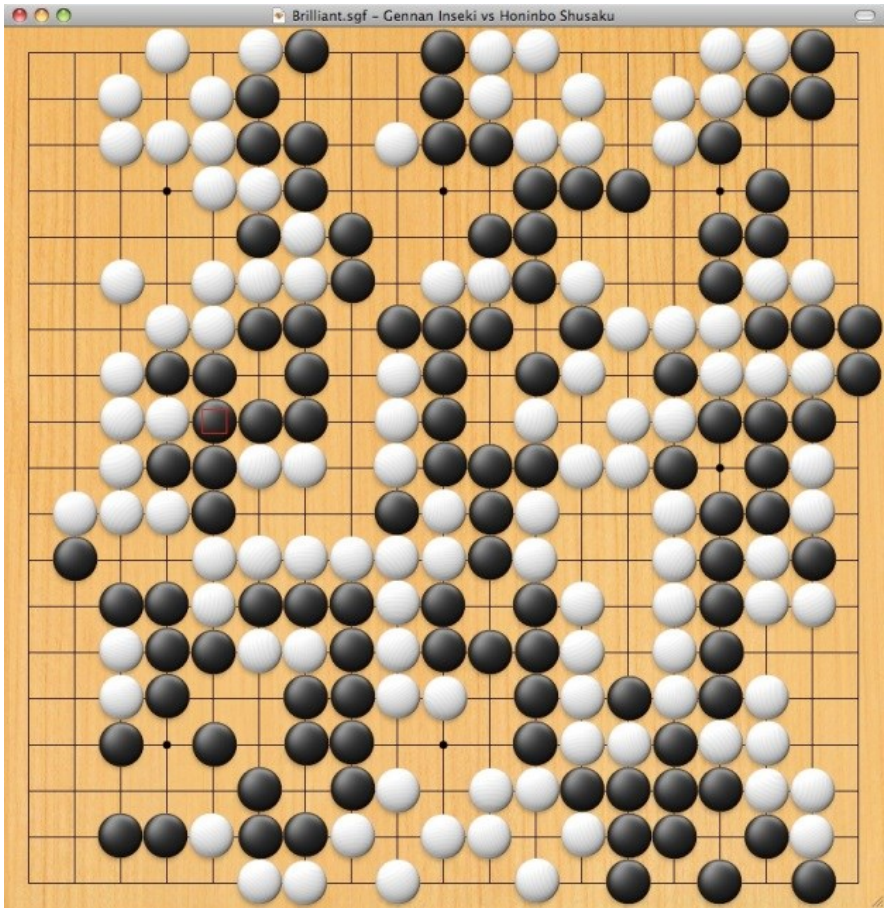
Breakout demo

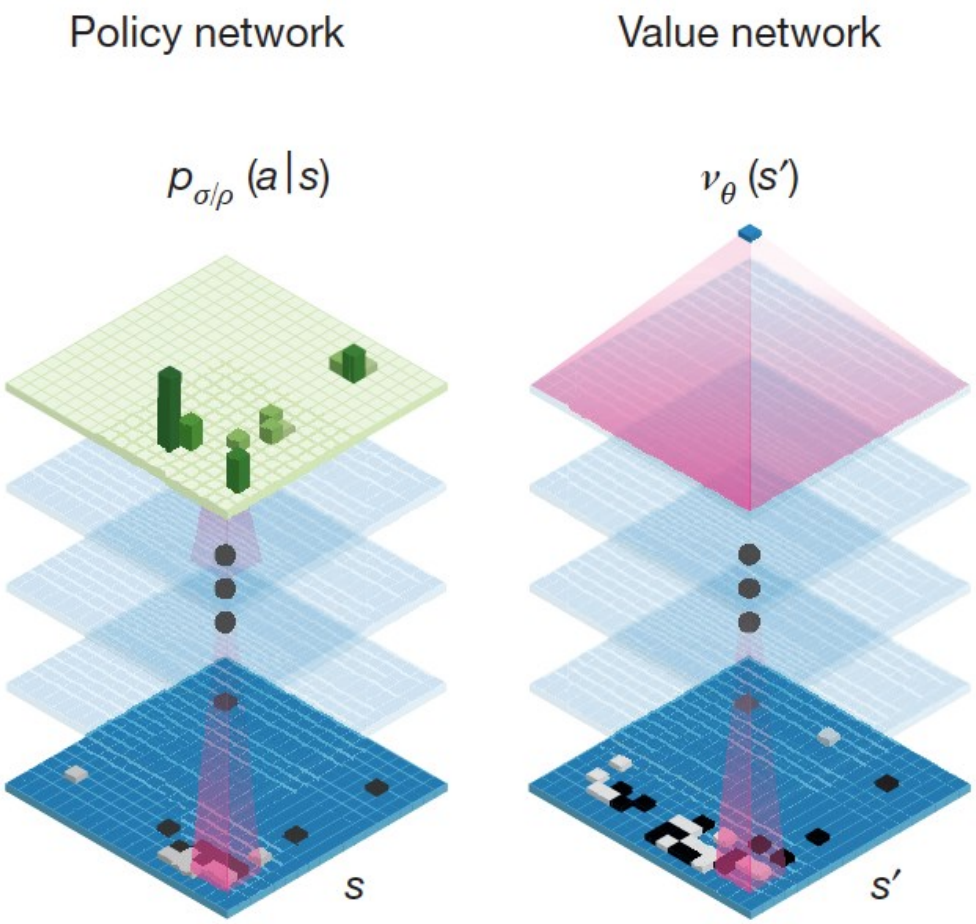
https://www.youtube.com/watch?v=TmPfTpjtdgg

Playing Go



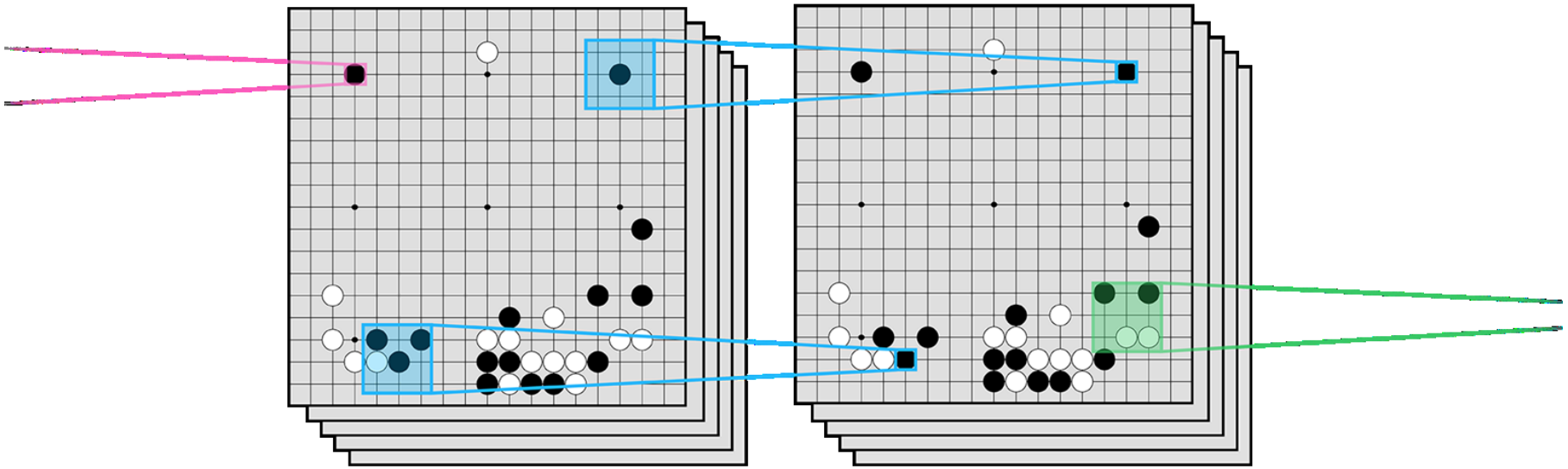
- Go is a known (and deterministic) environment
- Therefore, learning to play Go involves solving a known MDP
- Key challenges: huge state and action space, long sequences, sparse rewards

Review: AlphaGo



- **Policy network:** initialized by supervised training on large amount of human games
- **Value network:** trained to predict outcome of game based on self-play
- Networks are used to guide Monte Carlo tree search (MCTS)

D. Silver et al., Mastering the Game of Go with Deep Neural Networks and Tree Search, Nature 529, January 2016



Summary

- Deep Learning Strengths
  - universal approximators: learn non-trivial fns
  - compositional models ~similar to human brain
  - universal representation across modalities
  - discover features automagically
    - in a task-specific manner
    - features not limited by human creativity
- Deep Learning Weaknesses
  - resource hungry (data/compute)
  - Uninterpretable
- Deep RL: replace value/policy tables by deep nets
  - Great success in Go, Atari.