Carnegie Mellon
School of Computer Science

Deep Reinforcement Learning and Control

Deep Q Learning

CMU 10-403

Katerina Fragkiadaki

Used Materials

- **Disclaimer**: Much of the material and slides for this lecture were borrowed from Russ Salakhutdinov, Rich Sutton's class and David Silver's class on Reinforcement Learning.

Optimal Value Function

- An optimal value function is the maximum achievable value

$$Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a) = Q^{\pi^*}(s,a)$$

- Once we have Q^*, the agent can act optimally

$$\pi^*(s) = \operatorname*{argmax}_{a} Q^*(s,a)$$

- Formally, optimal values decompose into a Bellman equation

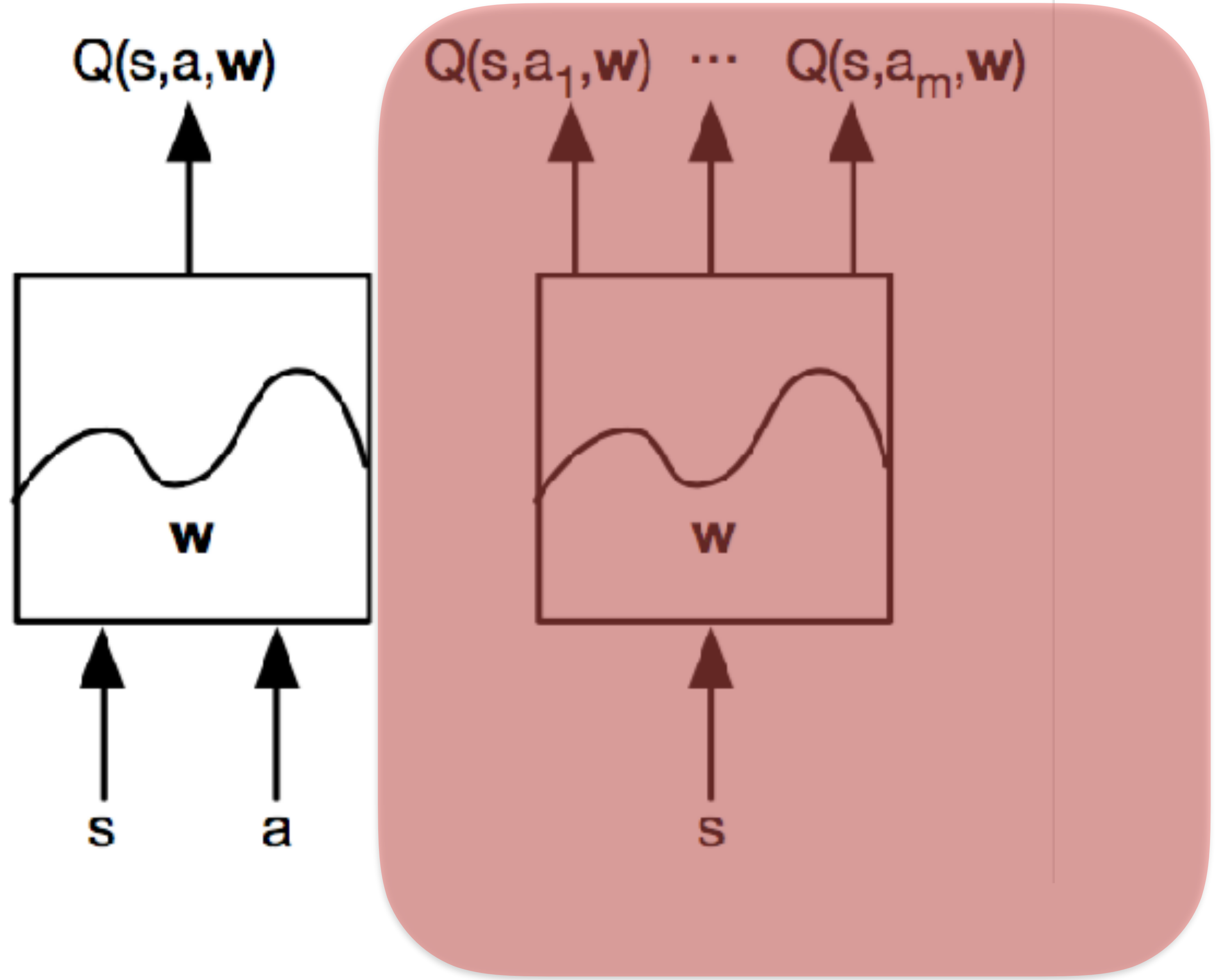
$$Q^*(s,a) = \mathbb{E}_{s'}\left[r + \gamma \max_{a'} Q^*(s',a') \mid s,a\right]$$

Deep Q-Networks (DQNs)

- Represent action-state value function by Q-network with weights w

$$Q(s, a, \mathbf{w}) \approx Q^*(s, a)$$

When would this be preferred?



Q-Learning with FA

- 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 $r + \gamma \max_{a'} Q(s',a',\mathbf{w})$ as a target

- Minimize MSE loss by stochastic gradient descent

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

- Remember VFA lecture: Minimize mean-squared error between the true action-value function $q_\pi(S,A)$ and the approximate Q function:

$$J(\mathbf{w}) = \mathbb{E}_\pi\left[(q_\pi(S,A) - \hat{q}(S,A,\mathbf{w}))^2\right]$$

Q-Learning with FA

- Minimize MSE loss by stochastic gradient descent

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

Q-Learning: Off-Policy TD Control

- One-step Q-learning:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\Big[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)\Big]$$

Initialize $Q(s, a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
    Initialize S
    Repeat (for each step of episode):
        Choose A from S using policy derived from Q (e.g., ε-greedy)
        Take action A, observe R, S'
        $Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma \max_a Q(S', a) - Q(S, A)]$
        $S \leftarrow S'$;
    until S is terminal

Q-Learning with FA

- Minimize MSE loss by stochastic gradient descent

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

Q-Learning

- Minimize MSE loss by stochastic gradient descent

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- But diverges using neural networks due to:
  1. Correlations between samples
  2. Non-stationary targets

Solution to both problems in DQN:

Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih Koray Kavukcuoglu David Silver Alex Graves Ioannis Antonoglou

Daan Wierstra Martin Riedmiller

DeepMind Technologies

DQN

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

s_1, a_1, r_2, s_2
s_2, a_2, r_3, s_3
s_3, a_3, r_4, s_4
...
$s_t, a_t, r_{t+1}, s_{t+1}$

$$\rightarrow \quad s, a, r, s'$$

- Sample experiences from data-set and apply update

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

- To deal with non-stationarity, target parameters w− are held fixed

Experience Replay

- Given experience consisting of ⟨state, value⟩, or <state, action/value> pairs

$$\mathcal{D} = \{\langle s_1, v_1^\pi \rangle, \langle s_2, v_2^\pi \rangle, \ldots, \langle s_T, v_T^\pi \rangle\}$$

- Repeat
  - Sample state, value from experience

$$\langle s, v^\pi \rangle \sim \mathcal{D}$$

  - Apply stochastic gradient descent update

$$\Delta \mathbf{w} = \alpha(v^\pi - \hat{v}(s, \mathbf{w}))\nabla_{\mathbf{w}} \hat{v}(s, \mathbf{w})$$

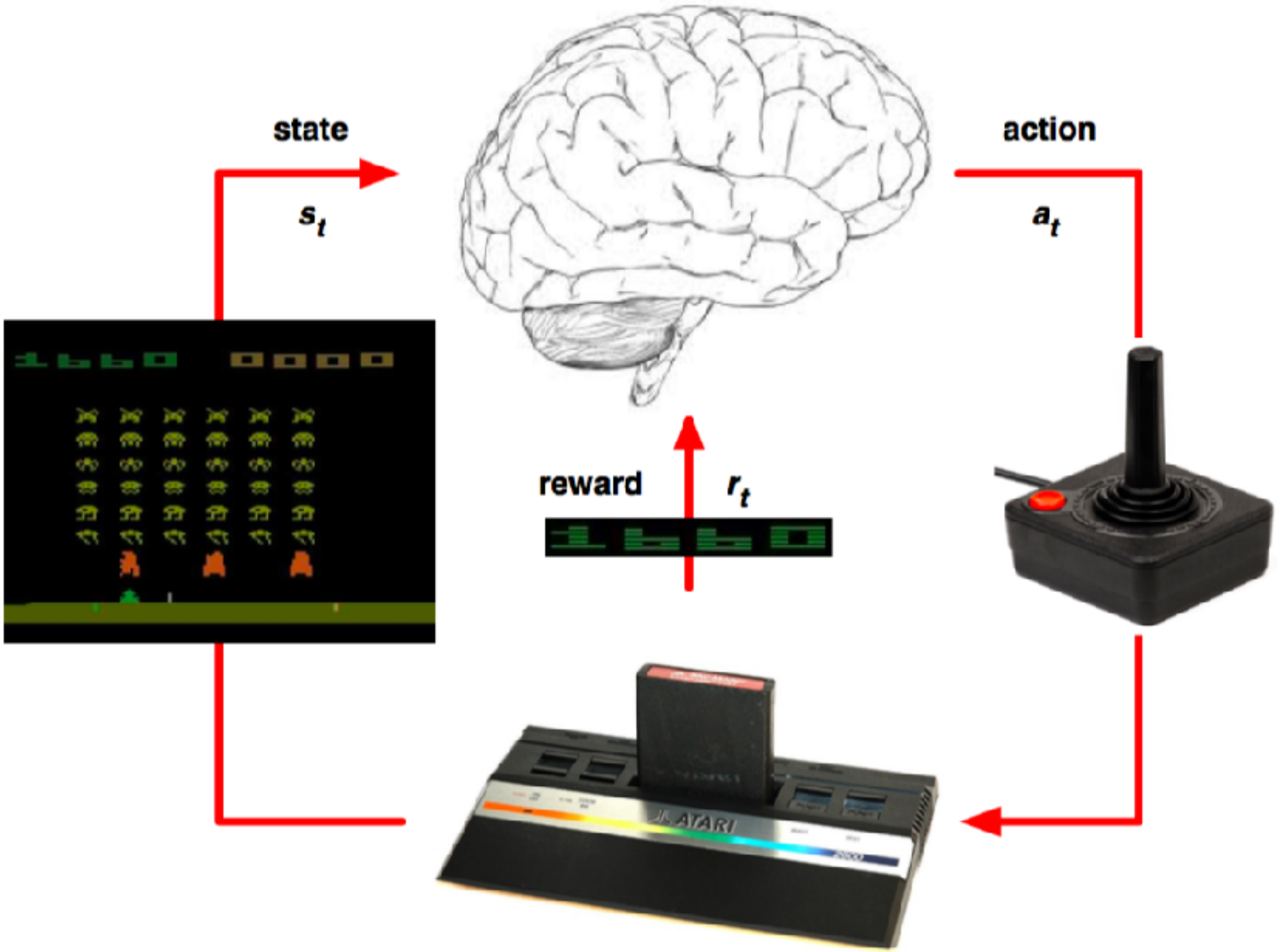
DQNs: Experience Replay

- DQN uses experience replay and fixed Q-targets
- Store transition $(s_t, a_t, r_{t+1}, s_{t+1})$ in replay memory D
- Sample random mini-batch of transitions (s,a,r,s′) from D
- Compute Q-learning targets w.r.t. old, fixed parameters w−
- Optimize MSE between Q-network and Q-learning targets

$$\mathcal{L}_i(w_i) = \mathbb{E}_{s,a,r,s' \sim \mathcal{D}_i}\left[\left(\underbrace{r + \gamma \max_{a'} Q(s', a'; w_i^-)}_{\text{Q-learning target}} - \underbrace{Q(s, a; w_i)}_{\text{Q-network}}\right)^2\right]$$

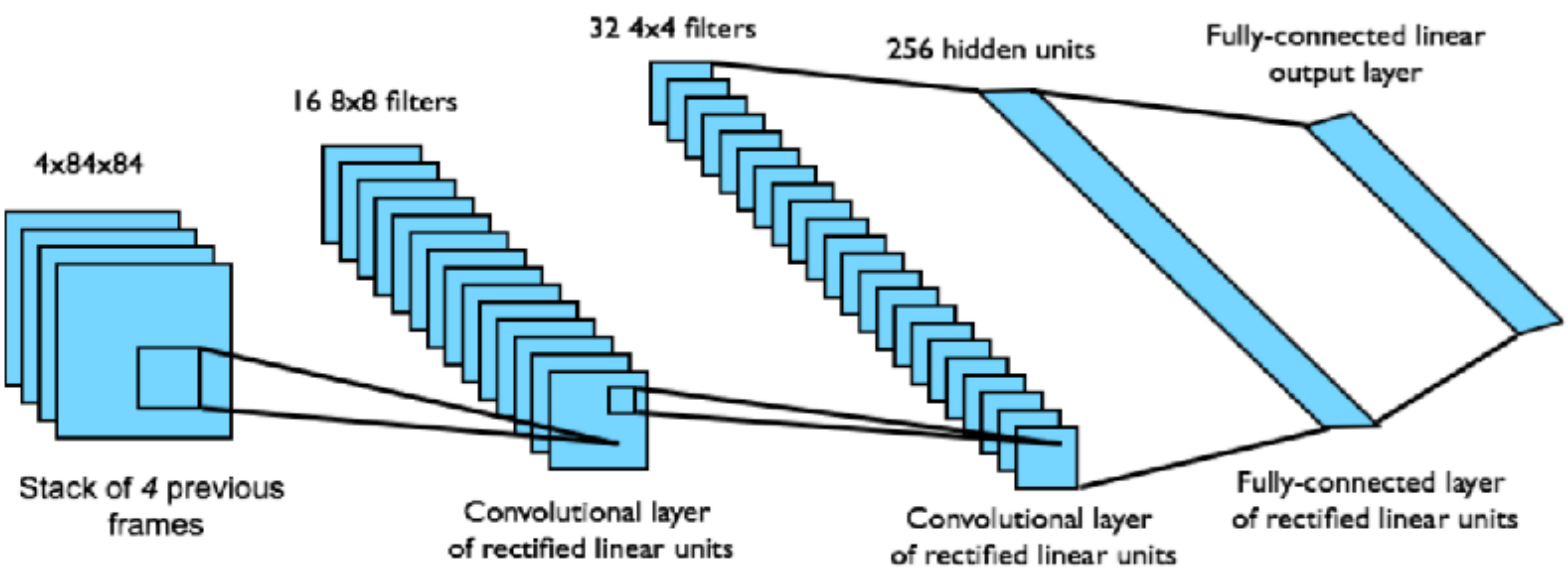
- Use stochastic gradient descent

DQNs in Atari



DQNs in Atari

- End-to-end learning of values Q(s,a) from pixels
- Input observation 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

Mnih et.al., Nature, 2014

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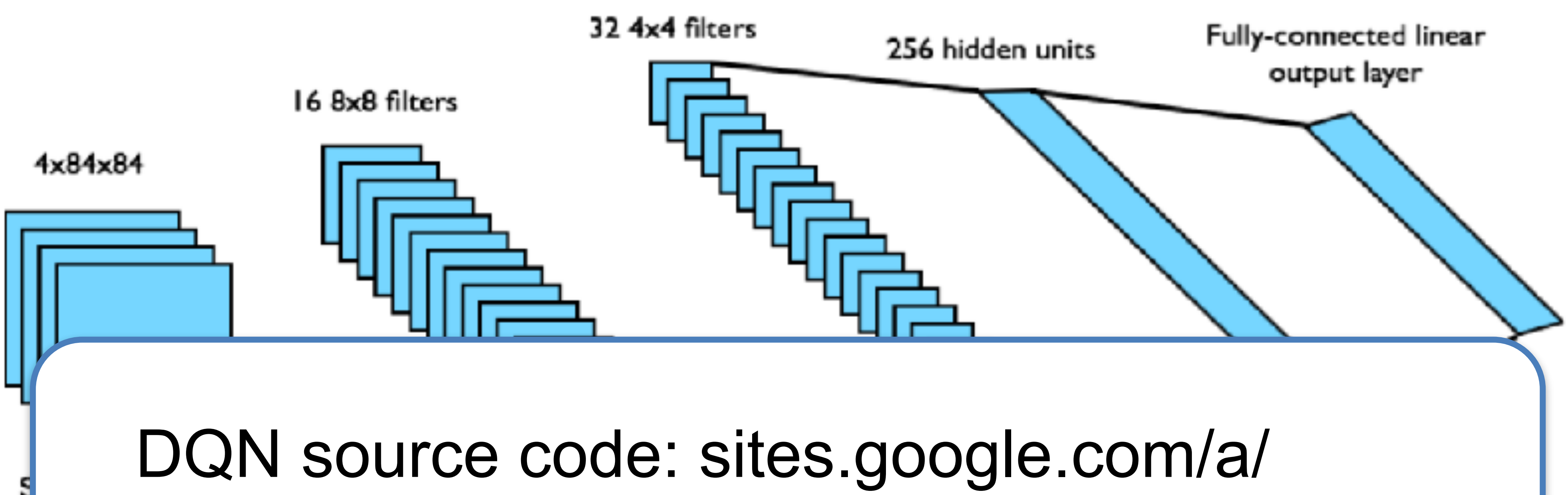


DQN source code: sites.google.com/a/deepmind.com/dqn/

- Netw[illegible]s

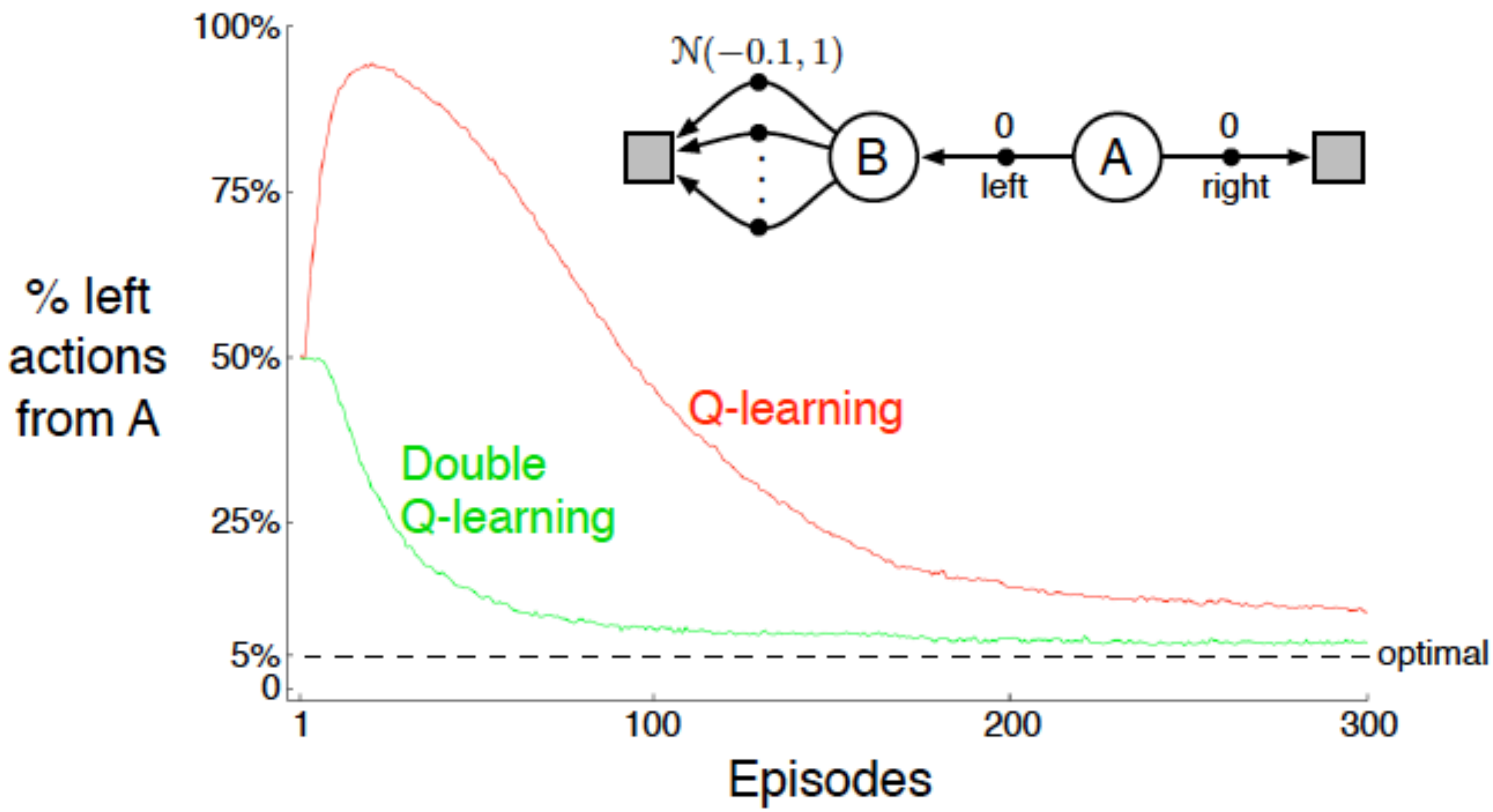
Mnih et.al., Nature, 2014

Extensions

- Double Q-learning for fighting maximization bias
- Prioritized experience replay
- Dueling Q networks
- Multistep returns
- Value distribution
- Stochastic nets for explorations instead of \epsilon-greedy

Maximization Bias

- We often need to maximize over our value estimates. The estimated maxima suffer from maximization bias
- Consider a state for which all ground-truth q(s,a)=0. Our estimates Q(s,a) are uncertain, some are positive and some negative. Q(s,argmax_a(Q(s,a)) is positive while q(s,argmax_a(q(s,a))=0.



Double Q-Learning

- Train 2 action-value functions, Q_1 and Q_2
- Do Q-learning on both, but
  - never on the same time steps (Q_1 and Q_2 are independent)
  - pick Q_1 or Q_2 at random to be updated on each step

- If updating Q_1, use Q_2 for the value of the next state:

$$Q_1(S_t, A_t) \leftarrow Q_1(S_t, A_t) + \\ + \alpha\Big(R_{t+1} + Q_2\big(S_{t+1}, \arg\max_a Q_1(S_{t+1}, a)\big) - Q_1(S_t, A_t)\Big)$$

- Action selections are ε-greedy with respect to the sum of Q_1 and Q_2

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Double Tabular Q-Learning

Initialize $Q_1(s,a)$ and $Q_2(s,a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily
Initialize $Q_1(\textit{terminal-state}, \cdot) = Q_2(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
    Initialize S
    Repeat (for each step of episode):
        Choose A from S using policy derived from Q_1 and Q_2 (e.g., ε-greedy in $Q_1 + Q_2$)
        Take action A, observe R, S'
        With 0.5 probabilility:
$$Q_1(S,A) \leftarrow Q_1(S,A) + \alpha\Big(R + \gamma Q_2\big(S', \arg\max_a Q_1(S',a)\big) - Q_1(S,A)\Big)$$
        else:
$$Q_2(S,A) \leftarrow Q_2(S,A) + \alpha\Big(R + \gamma Q_1\big(S', \arg\max_a Q_2(S',a)\big) - Q_2(S,A)\Big)$$
        $S \leftarrow S'$;
    until S is terminal

Hado van Hasselt 2010

Double Deep Q-Learning

- Current Q-network w is used to select actions
- Older Q-network w− is used to evaluate actions

$$I = \Bigg(r + \gamma \overbrace{Q(s', \underbrace{\operatorname*{argmax}_{a'} Q(s', a', \mathbf{w})}_{\text{Action selection: w}}, \mathbf{w}^-)}^{\text{Action evaluation: w−}} - Q(s, a, \mathbf{w})\Bigg)^2$$

van Hasselt, Guez, Silver, 2015

Prioritized Replay

- Weight experience according to ``surprise" (or error)
- Store experience in priority queue according to DQN error

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

- Stochastic Prioritization

$$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$$

p_i is proportional to DQN error

- α determines how much prioritization is used, with α = 0 corresponding to the uniform case.

Schaul, Quan, Antonoglou, Silver, ICLR 2016

Multistep Returns

- Truncated n-step return from a state s_t: $$R_t^{(n)} = \sum_{k=0}^{n-1} \gamma_t^{(k)} R_{t+k+1}$$

- Multistep Q-learning update rule:

$$I = \left(R_t^{(n)} + \gamma_t^{(n)} \max_{a'} Q(S_{t+n}, a', \mathbf{w}) - Q(s, a, \mathbf{w})\right)^2$$

- Singlestep Q-learning update rule:

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

Rainbow: Combining Improvements in Deep Reinforcement Learning

Matteo Hessel DeepMind

Joseph Modayil DeepMind

Hado van Hasselt DeepMind

Tom Schaul DeepMind

Georg Ostrovski DeepMind

Will Dabney DeepMind

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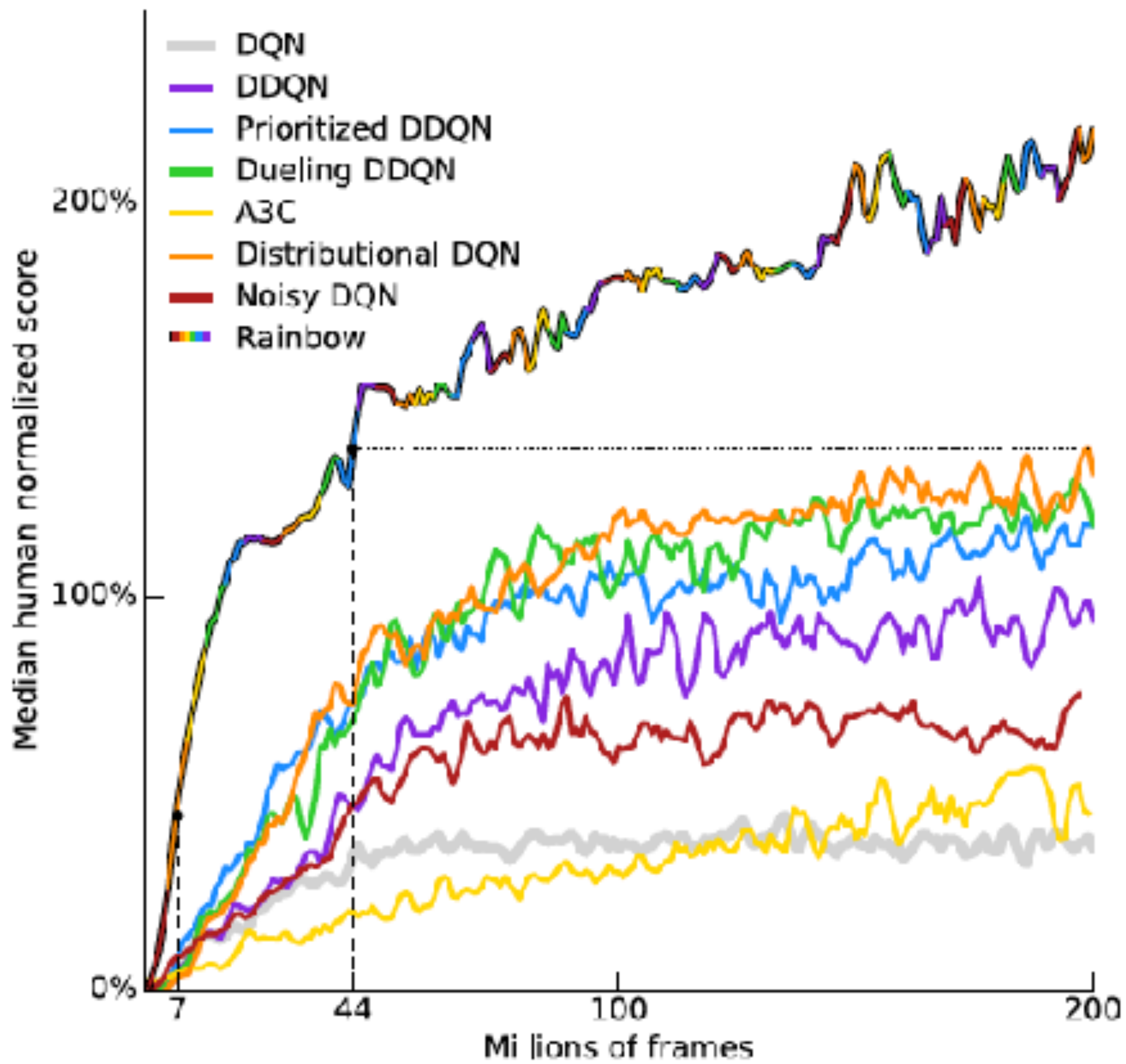

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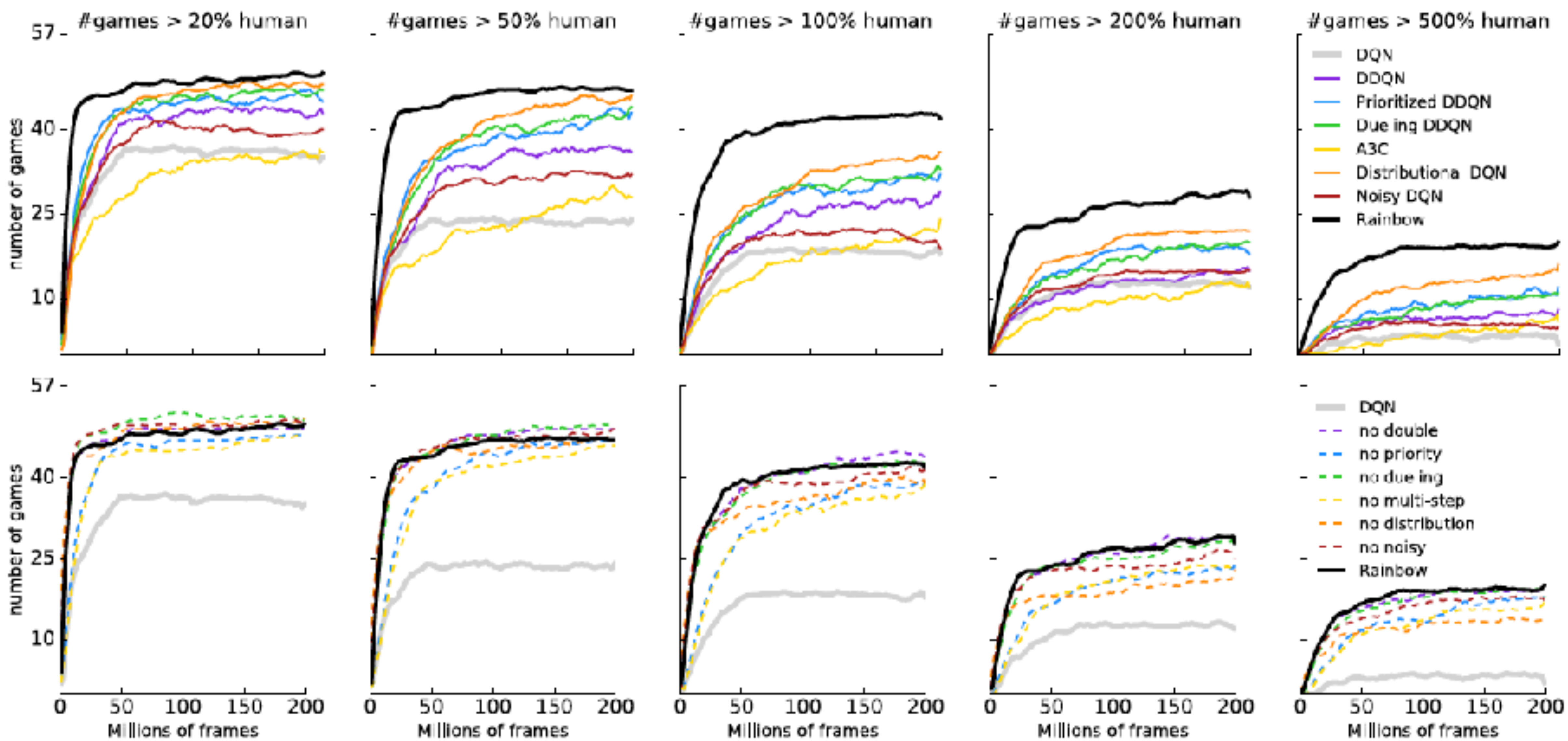

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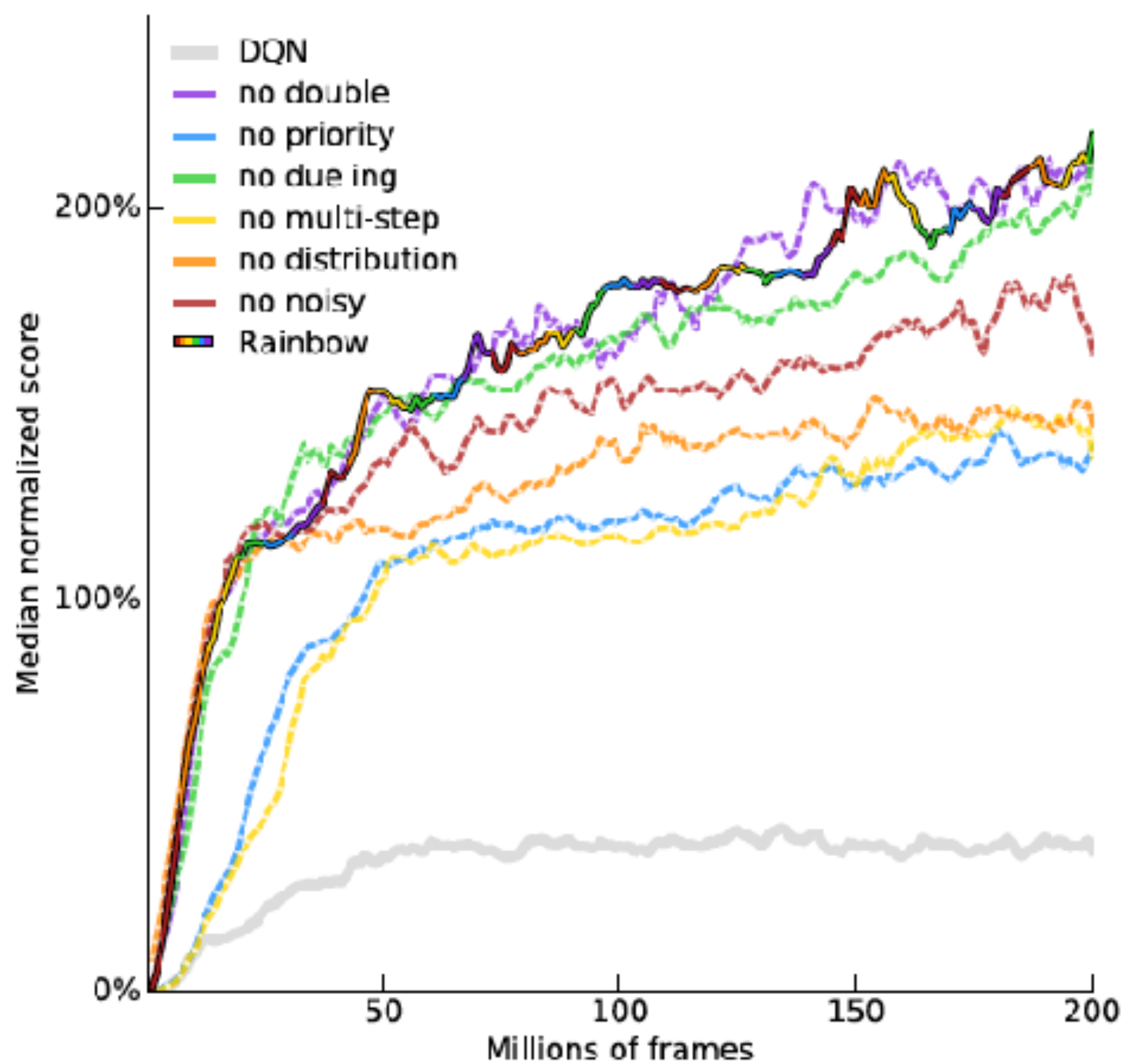

Question

- Imagine we have access to the internal state of the Atari simulator. Would online planning (e.g., using MCTS), outperform the trained DQN policy?

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- Imagine we have access to the internal state of the Atari simulator. Would online planning (e.g., using MCTS), outperform the trained DQN policy?
    - With enough resources, yes.
    - Resources = number of simulations (rollouts) and maximum allowed depth of those rollouts.
    - There is always an amount of resources when a vanilla MCTS (not assisted by any deep nets) will outperform the learned with RL policy.

Question

- Then why we do not use MCTS with online planning to play Atari instead of learning a policy?

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- Then why we do not use MCTS with online planning to play Atari instead of learning a policy?

  - Because using vanilla (not assisted by any deep nets) MCTS is very very slow, definitely very far away from real time game playing that humans are capable of.

Question

- If we used MCTS during training time to suggest actions using online planning, and we would try to mimic the output of the planner, would we do better than DQN that learns a policy without using any model while playing in real time?

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- If we used MCTS during training time to suggest actions using online planning, and we would try to mimic the output of the planner, would we do better than DQN that learns a policy without using any model while playing in real time?

    - That would be a very sensible approach!

Deep Learning for Real-Time Atari Game Play Using Offline Monte-Carlo Tree Search Planning

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Offline MCTS to train online fast reactive policies

- **AlphaGo**: train policy and value networks at training time, combine them with MCTS at test time
- **AlphaGoZero**: train policy and value networks with MCTS in the training loop and at test time (same method used at train and test time)
- **Offline MCTS**: train policy and value networks with MCTS in the training loop, but at test time use the (reactive) policy network, without any lookahead planning.
  - Where does the benefit come from?

Revision: Monte-Carlo Tree Search

1. **Selection**
   - Used for nodes we have seen before
   - Pick according to UCB
2. **Expansion**
   - Used when we reach the frontier
   - Add one node per playout
3. **Simulation**
   - Used beyond the search frontier
   - Don't bother with UCB, just play randomly
4. **Backpropagation**
   - After reaching a terminal node
   - Update value and visits for states expanded in selection and expansion

Bandit based Monte-Carlo Planning, Kocsis and Szepesvari, 2006

Upper-Confidence Bound

Sample actions according to the following score:

$$\underbrace{v_i}_{\text{value estimate}} + \underbrace{C}_{\text{tunable parameter}} \times \sqrt{\frac{\ln(\overbrace{N}^{\text{parent node visits}})}{\underbrace{n_i}_{\text{number of visits}}}}$$

- score is decreasing in the number of visits (explore)
- score is increasing in a node's value (exploit)
- always tries every option once

Finite-time Analysis of the Multiarmed Bandit Problem, Auer, Cesa-Bianchi, Fischer, 2002

Basic MCTS pseudocode

```
function MCTS_sample(state)
    state.visits++
    if all children of state expanded:
        next_state = UCB_sample(state)
        winner = MCTS_sample(next_state)
    else:
        if some children of state expanded:
            next_state = expand(random unexpanded child)
        else:
            next_state = state
        winner = random_playout(next_state)
    update_value(state, winner)
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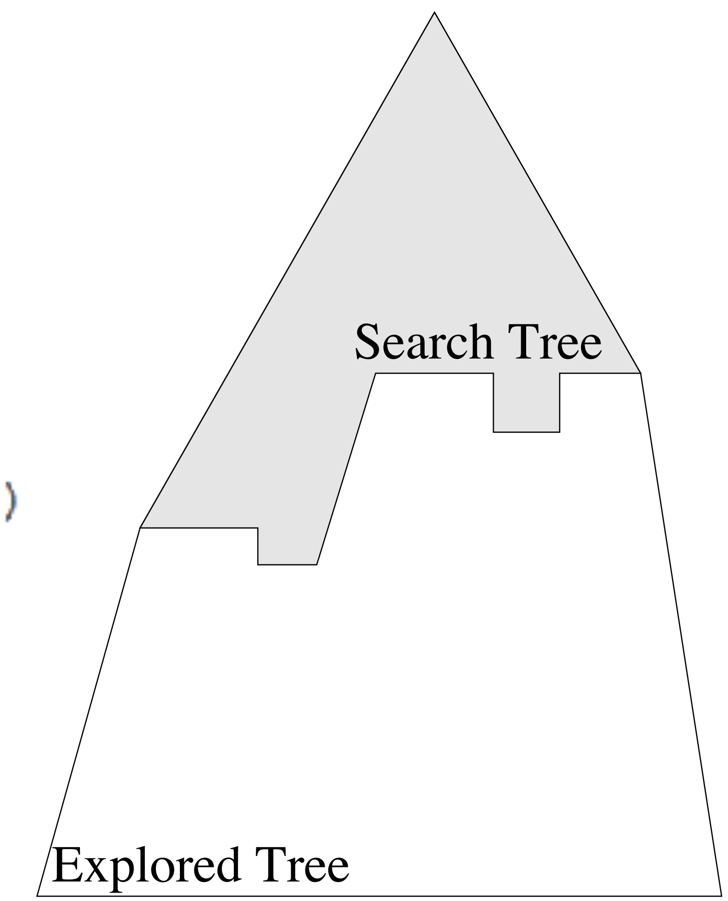

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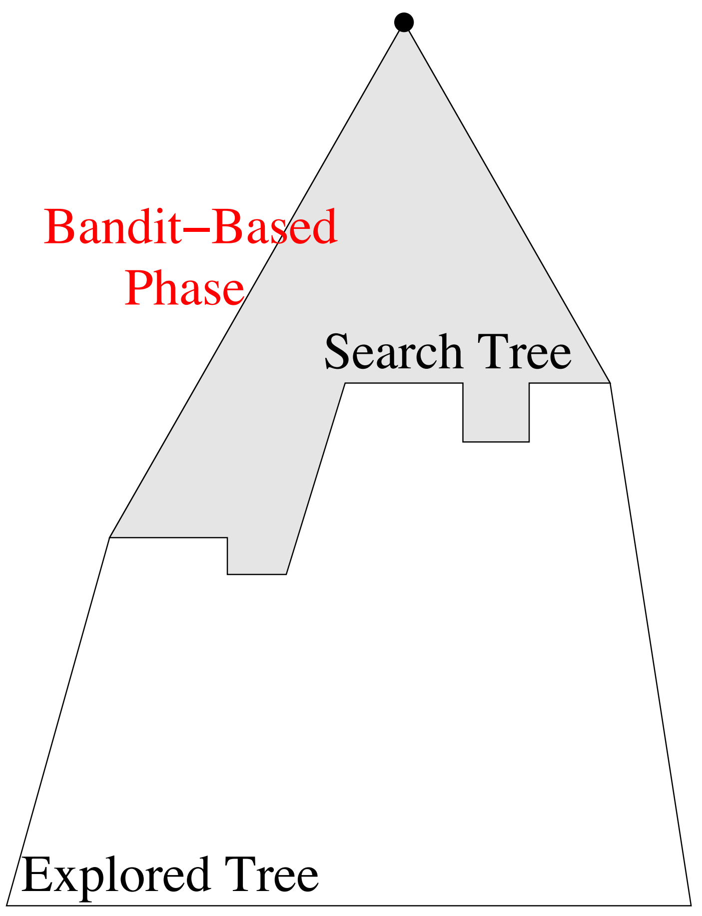

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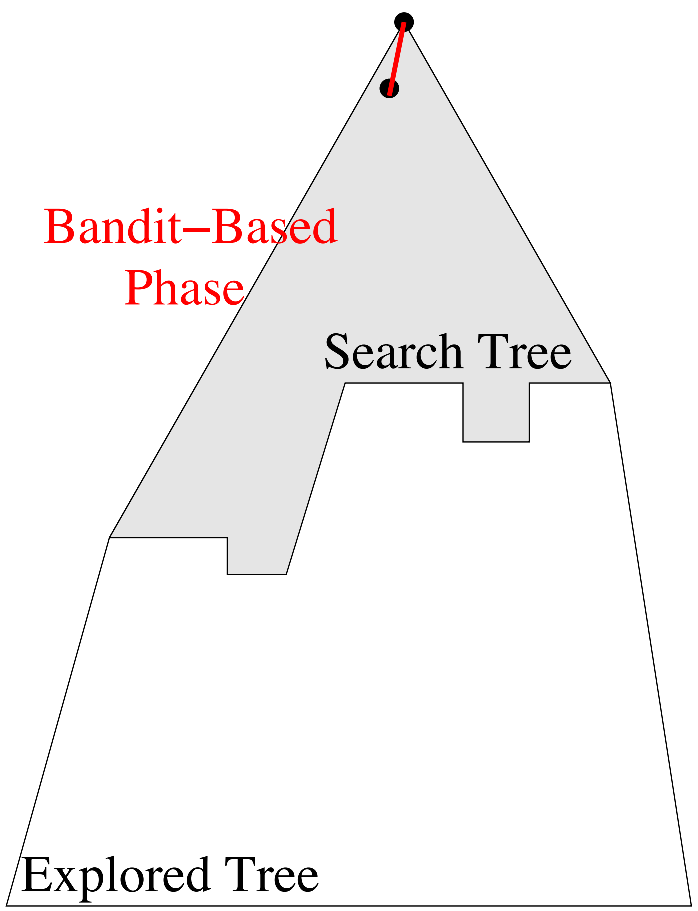

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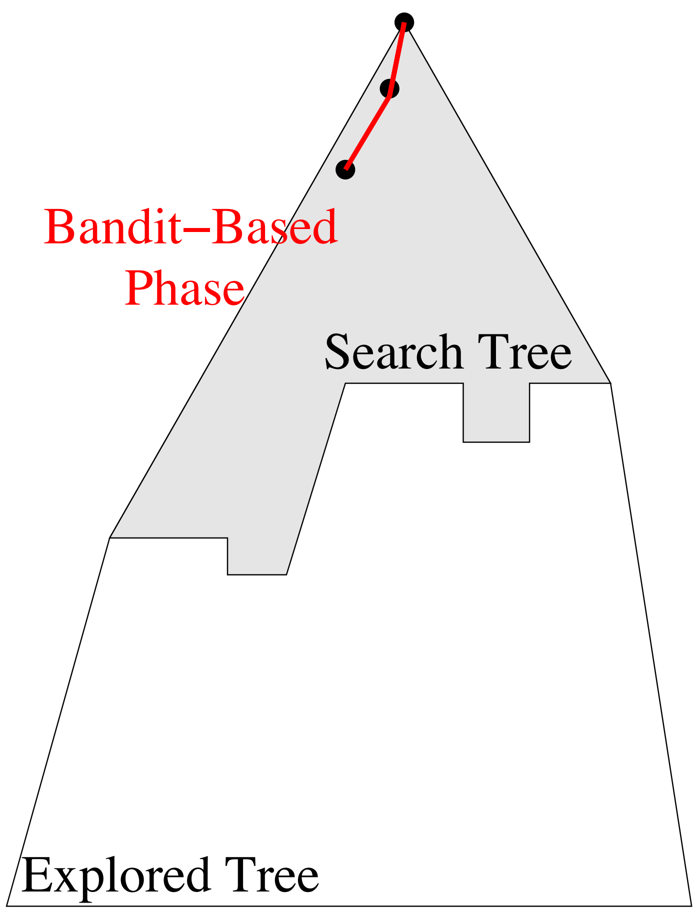

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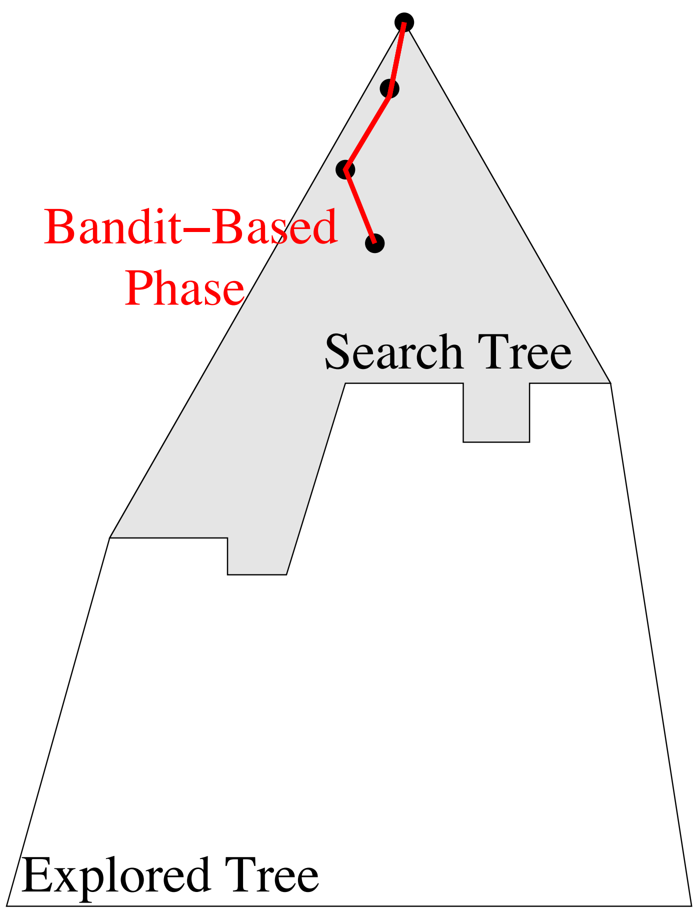

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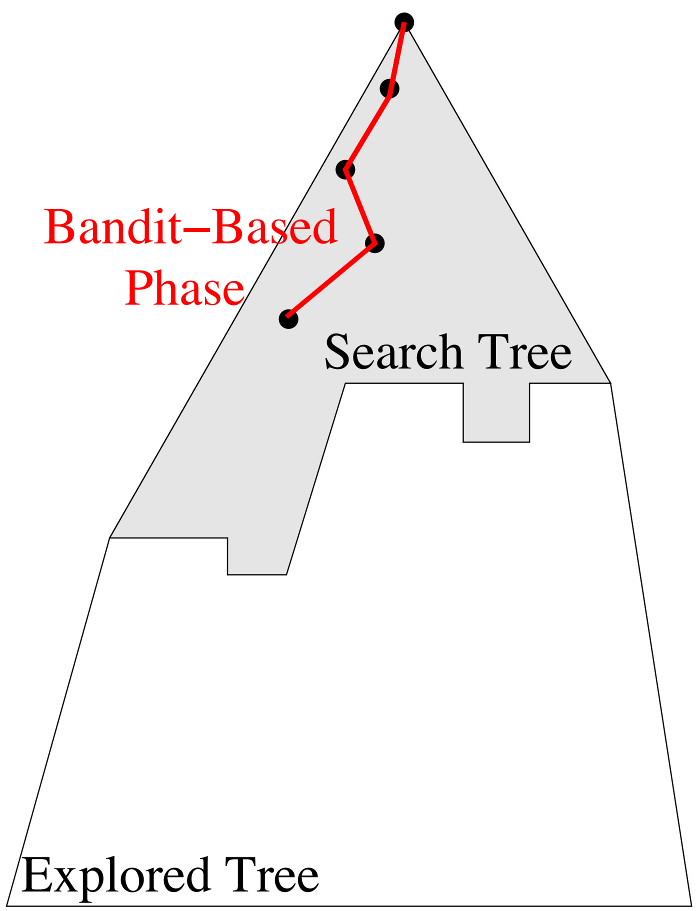

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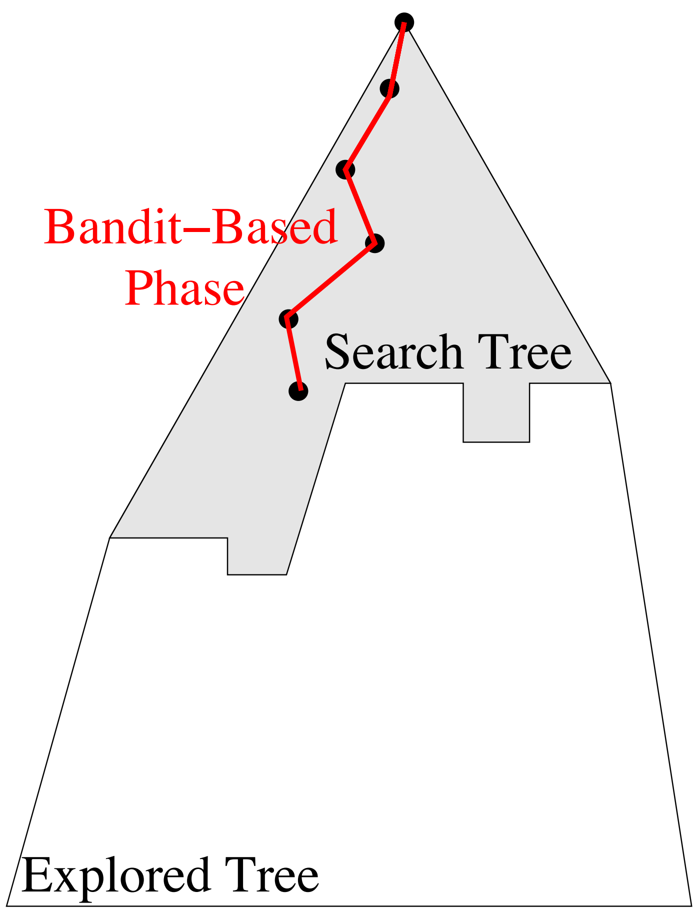

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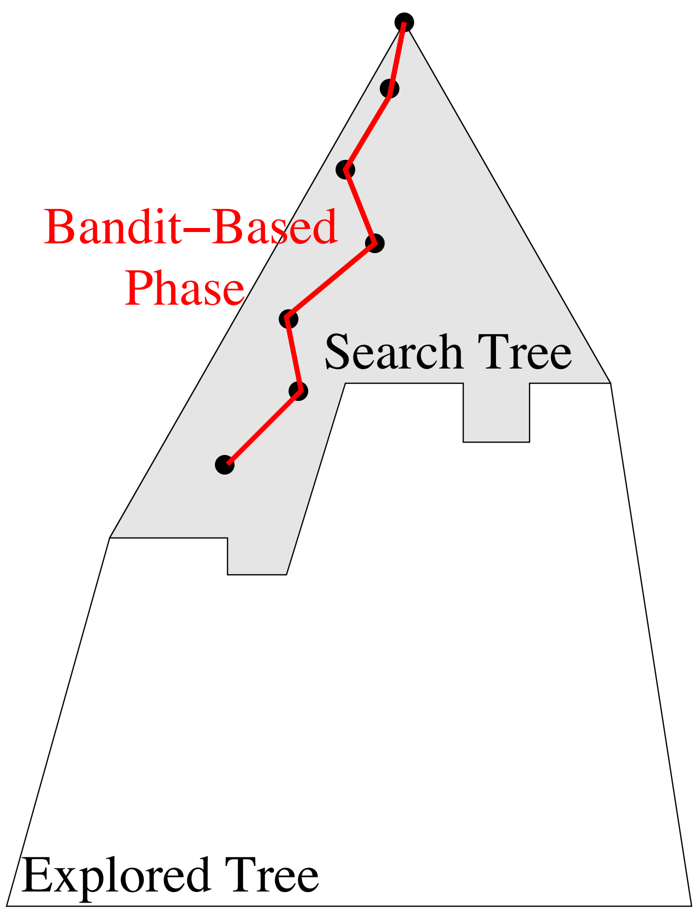

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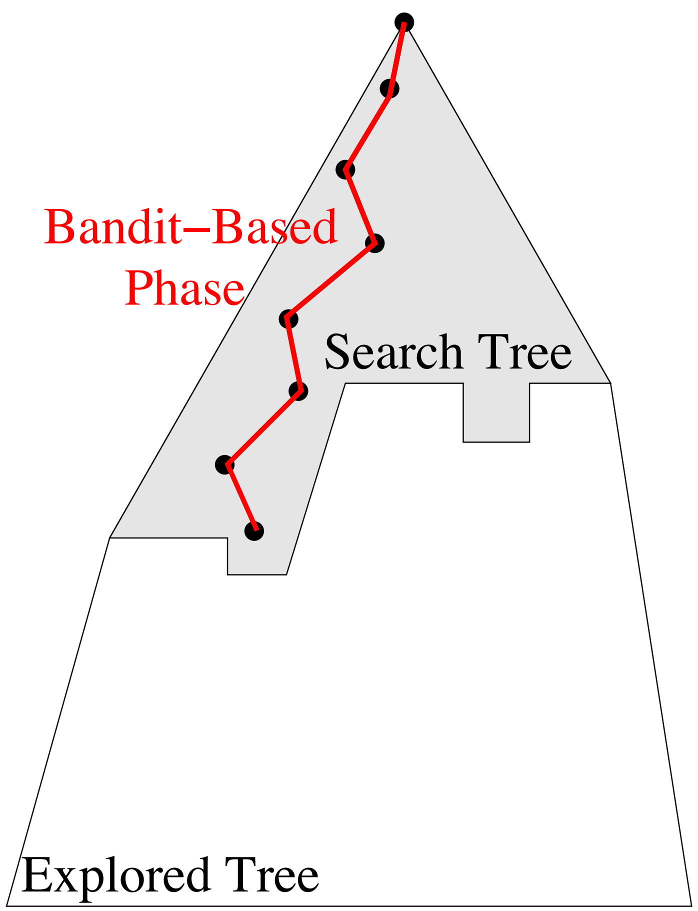

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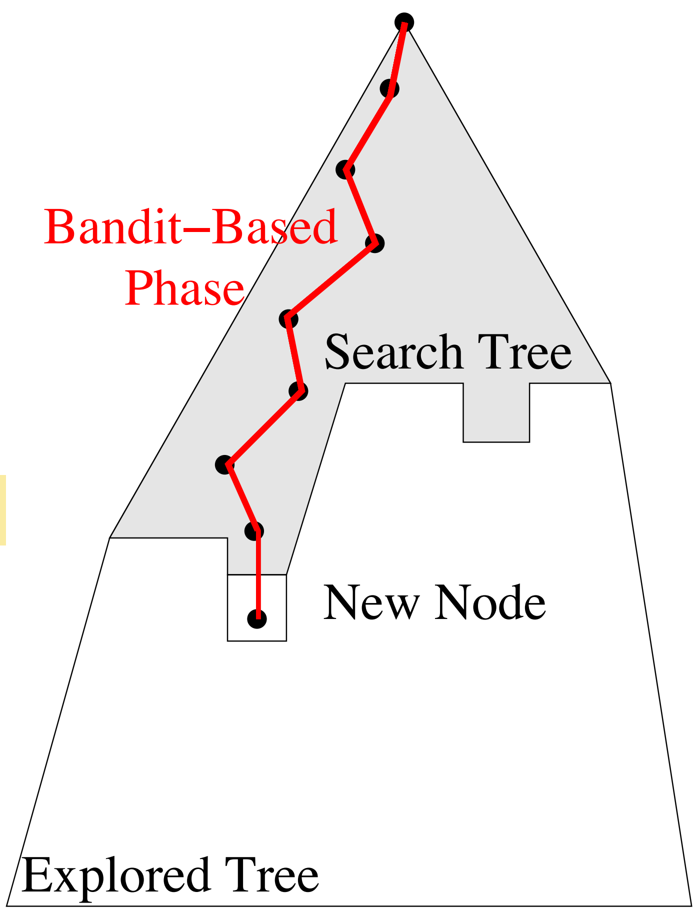

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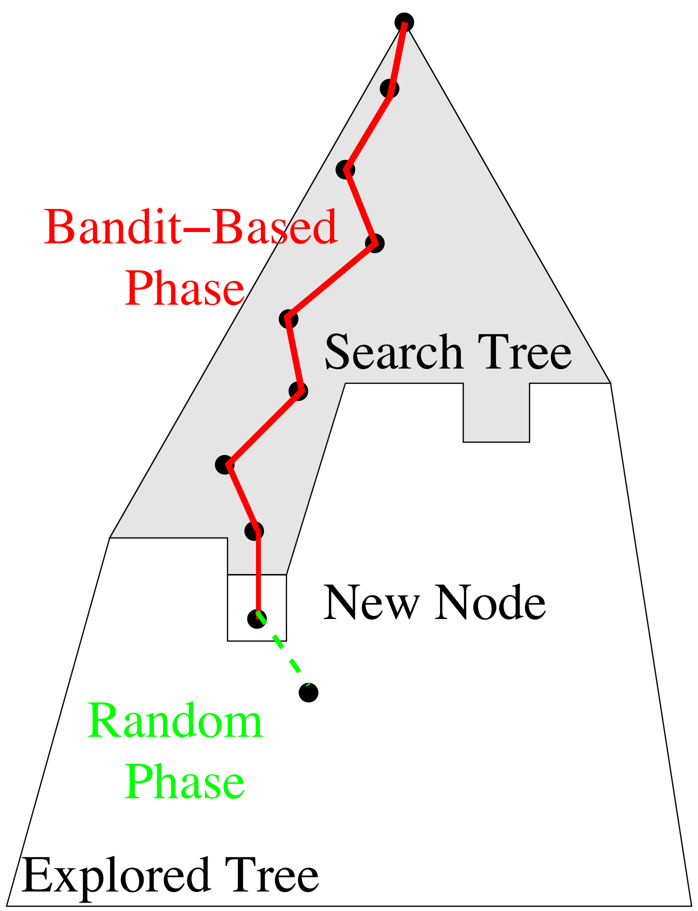


```
function random_playout(state):
    if is_terminal(state):
        return winner
    else: return random_playout(random_move(state))
```

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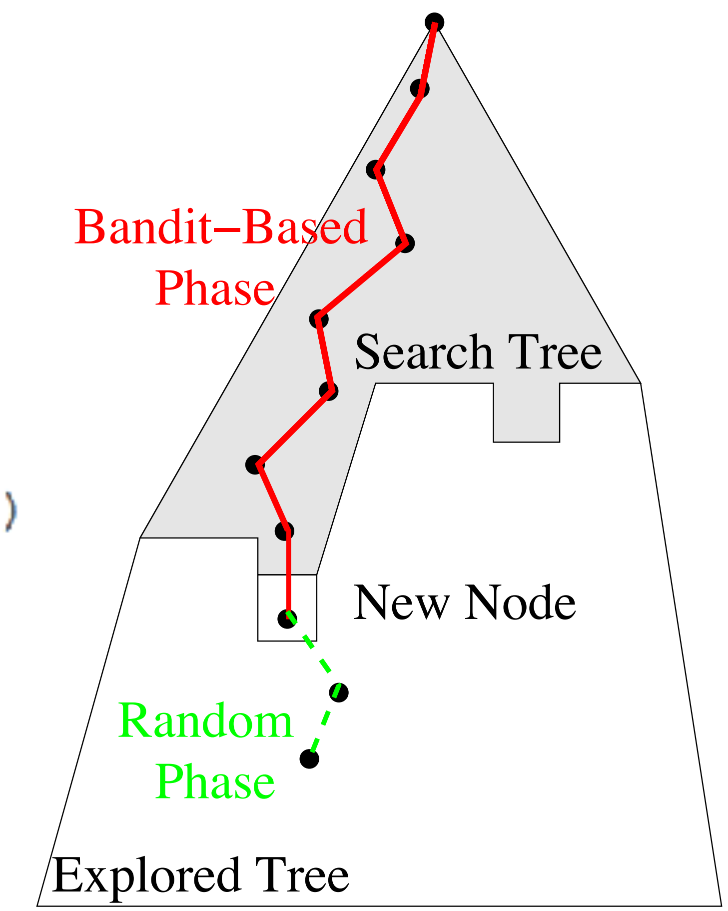
    update_value(state, winner)
```




```
function random_playout(state):
    if is_terminal(state):
        return winner
    else: return random_playout(random_move(state))
```

Basic MCTS pseudocode

```
function MCTS_sample(state)
    state.visits++
    if all children of state expanded:
        next_state = UCB_sample(state)
        winner = MCTS_sample(next_state)
    else:
        if some children of state expanded:
            next_state = expand(random unexpanded child)
        else:
            next_state = state
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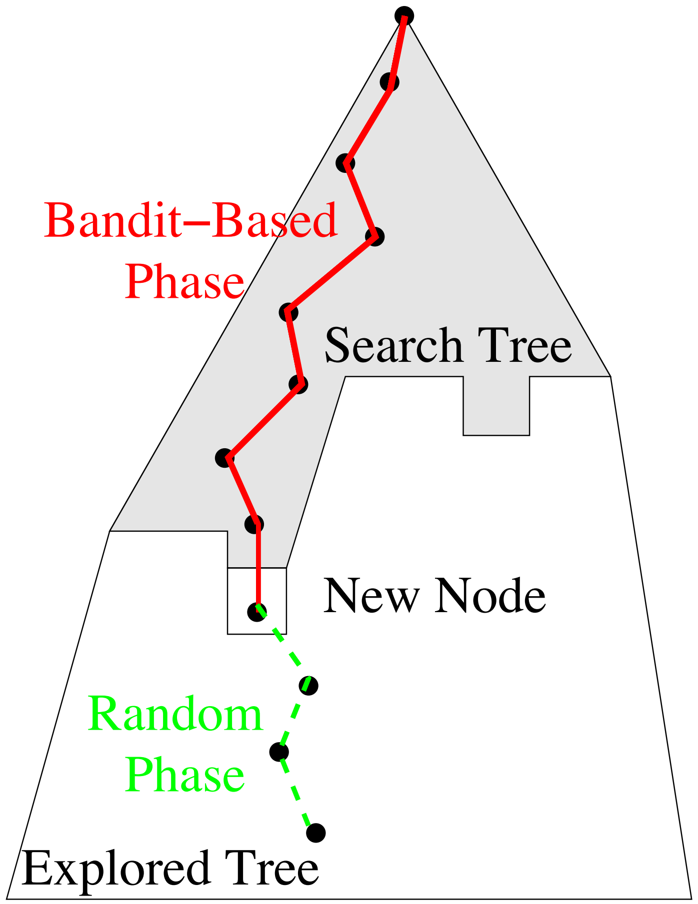


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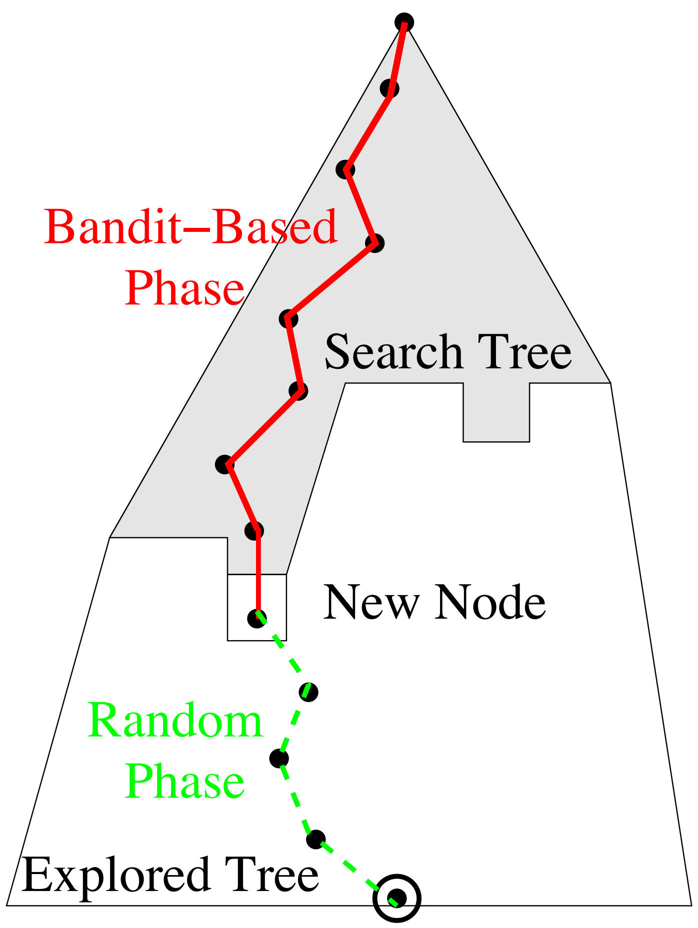

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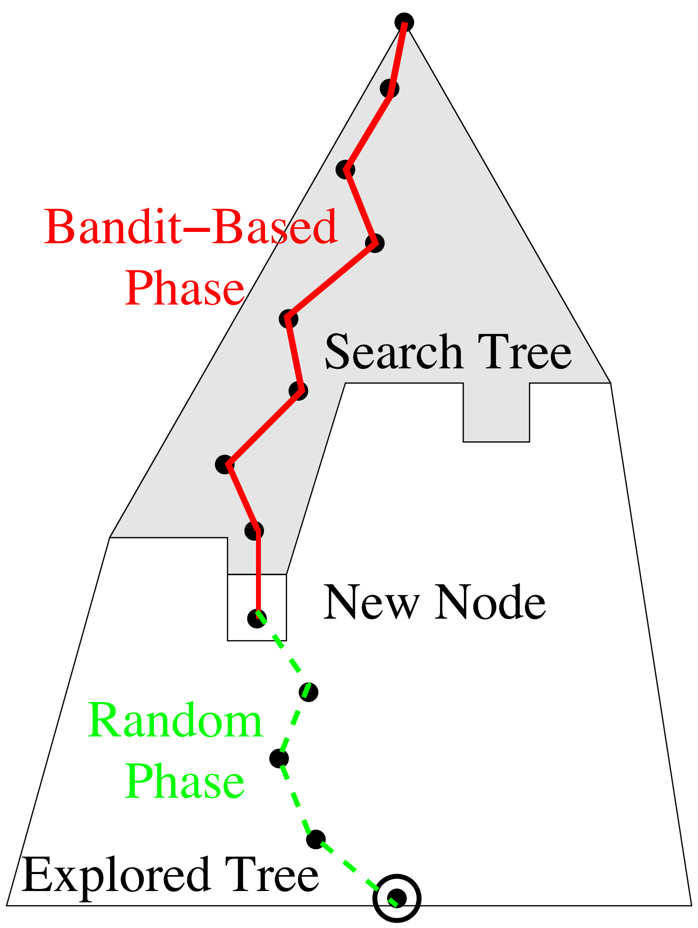

Learning from MCTS

- The MCTS agent plays against himself and generates (s, a, Q(s,a)) tuples. Use this data to train:
  - **UCTtoRegression:** A regression network, that given 4 frames regresses to Q(s,a,w) for all actions
  - **UCTtoClassification:** A classification network, that given 4 frames predicts the best action through multiclass classification
- The state distribution visited using actions of the MCTS planner will not match the state distribution obtained from the learned policy.
  - **UCTtoClassification-Interleaved:** Interleave UCTtoClassification with data collection: Start from 200 runs with MCTS as before, train UCTtoClassification, deploy it for 200 runs allowing 5% of the time a random action to be sampled, use MCTS to decide best action for those states, train UCTtoClassification and so on and so forth.

Results

Agent	*B.Rider*	*Breakout*	*Enduro*	*Pong*	*Q*bert*	*Seaquest*	*S.Invaders*
DQN	4092	168	470	20	1952	1705	581
-best	5184	225	661	21	4500	1740	1075
UCC	5342 (20)	175(5.63)	558(14)	19(0.3)	11574(44)	2273(23)	672(5.3)
-best	10514	351	942	21	29725	5100	1200
-greedy	5676	269	692	21	19890	2760	680
UCC-I	5388(4.6)	215(6.69)	601(11)	19(0.14)	13189(35.3)	2701(6.09)	670(4.24)
-best	10732	413	1026	21	29900	6100	910
-greedy	5702	380	741	21	20025	2995	692
UCR	2405(12)	143(6.7)	566(10.2)	19(0.3)	12755(40.7)	1024 (13.8)	441(8.1)

Table 2: Performance (game scores) of the off-line UCT game playing agent.

Agent	*B.Rider*	*Breakout*	*Enduro*	*Pong*	*Q*bert*	*Seaquest*	*S.Invaders*
UCT	7233	406	788	21	18850	3257	2354

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Online planning (without aided by any neural net!) outperforms DQN policy. It takes though ``a few days on a recent multicore computer to play for each game”.

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Classification is doing much better than regression! indeed, we are training for exactly what we care about.

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Interleaving is important to prevent mismatch between the training data and the data that the trained policy will see at test time.

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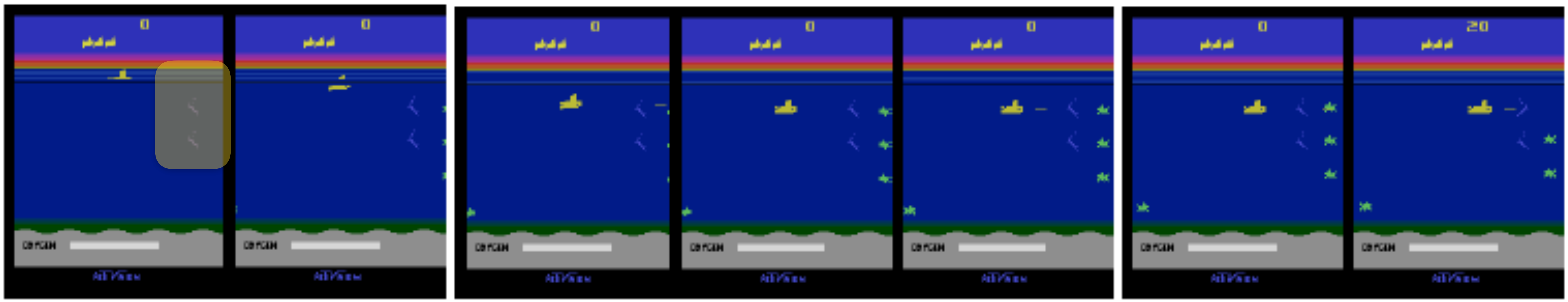
Results improve further if you allow MCTS planner to have more simulations and build more reliable Q estimates.

Problem



Step 69: FIRE Step 70: DOWN+FIRE Step 74:DOWN+FIRE Step 75:RIGHT+FIRE Step 76:RIGHT+FIRE Step 78: RIGHT+FIRE Step 79:DOWN+FIRE

We do not learn to save the divers. Saving 6 divers brings very high reward, but exceeds the depth of our MCTS planner, thus it is ignored.

Question

- Why don't we always use MCTS (or some other planner) as supervision for reactive policy learning?

  - Because in many domains we do not have access to the dynamics.

Neural Episodic Control

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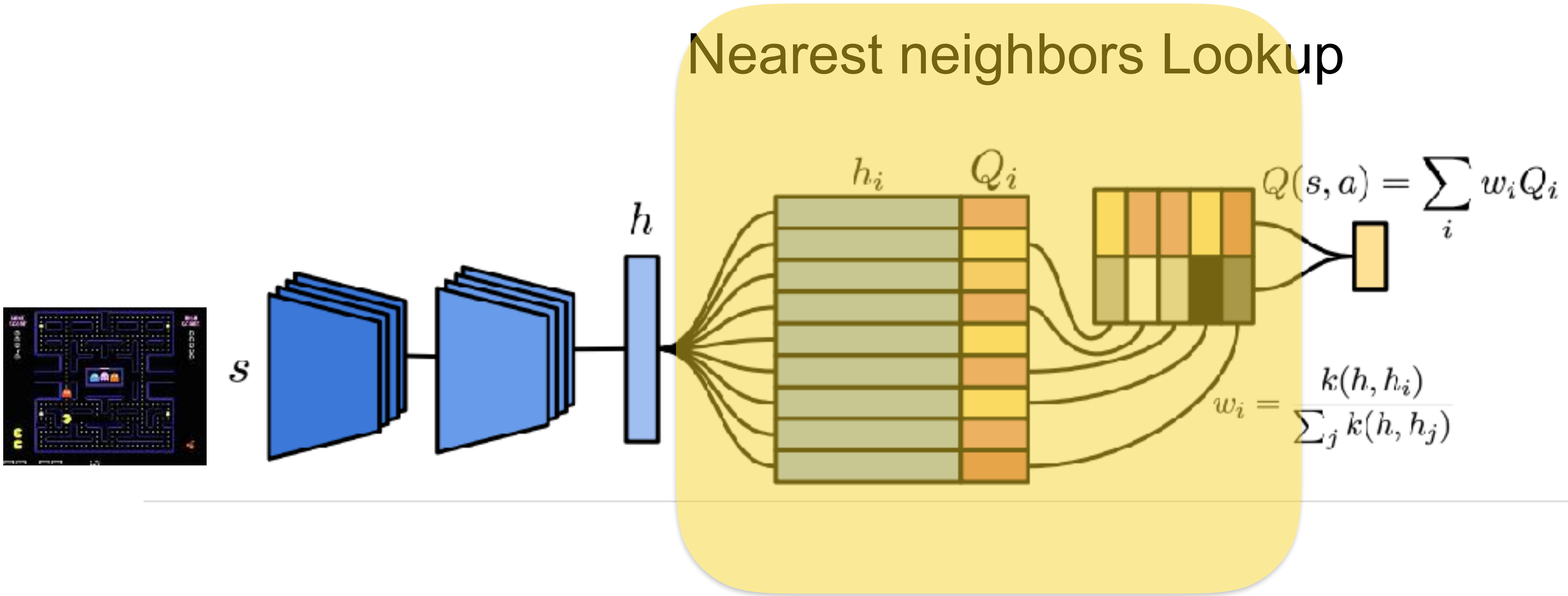
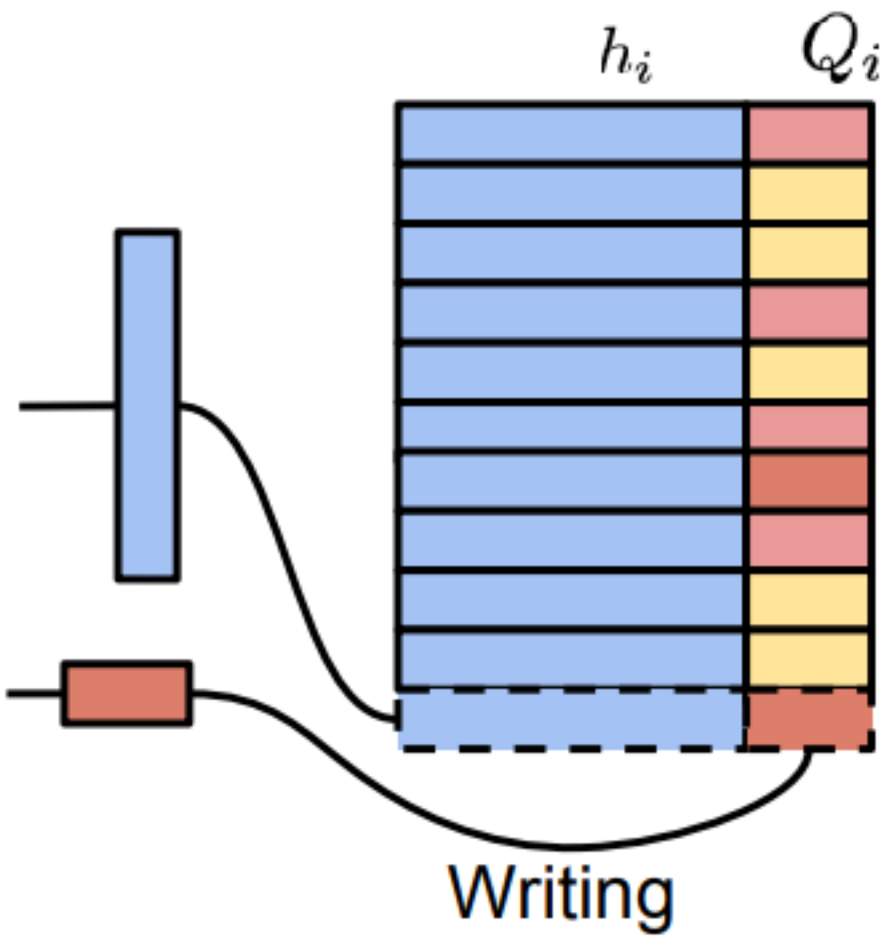


Nearest neighbors Lookup
s
h
h_i
Q_i
$Q(s,a) = \sum_i w_i Q_i$
$w_i = \frac{k(h, h_i)}{\sum_j k(h, h_j)}$

Writing in the memory

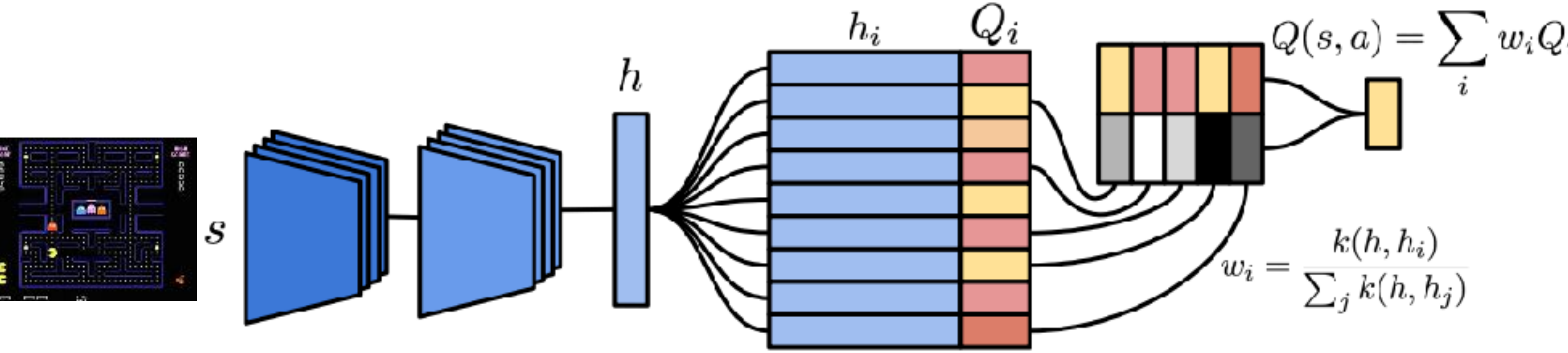


$$Q^{(N)}(s_t, a) = \sum_{j=0}^{N-1} \gamma^j r_{t+j} + \gamma^N \max_{a'} Q(s_{t+N}, a')$$

If identical key h present:

$$Q_i \leftarrow Q_i + \alpha(Q^{(N)}(s, a) - Q_i)$$

Else add row $(h, Q^N(s, a))$ to the memory



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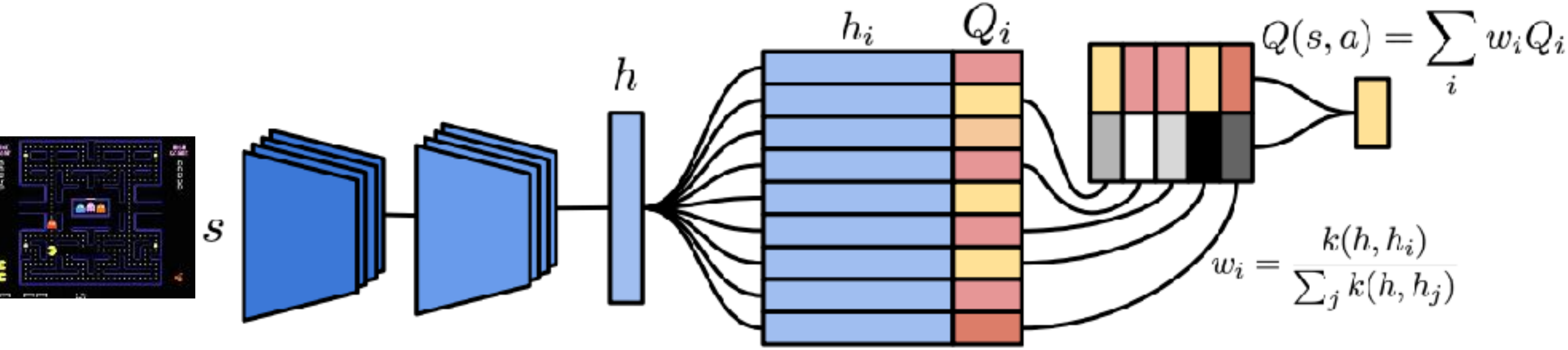
Algorithm 1 Neural Episodic Control

$\mathcal{D}$: replay memory.
M_a: a DND for each action a.
N: horizon for N-step Q estimate.
for each episode **do**
  for $t = 1, 2, \ldots, T$ **do**
    Receive observation s_t from environment with embedding h.
    Estimate $Q(s_t, a)$ for each action a via (1) from M_a
    $a_t \leftarrow \epsilon$-greedy policy based on $Q(s_t, a)$
    Take action a_t, receive reward r_{t+1}
    Append $(h, Q^{(N)}(s_t, a_t))$ to M_{a_t}.
    Append $(s_t, a_t, Q^{(N)}(s_t, a_t))$ to $\mathcal{D}$.
    Train on a random minibatch from $\mathcal{D}$.
  end for
end for



$$Q^{(N)}(s_t, a) = \sum_{j=0}^{N-1} \gamma^j r_{t+j} + \gamma^N \max_{a'} Q(s_{t+N}, a')$$

$$-\frac{1}{2}\nabla_{\mathbf{w}} J(\mathbf{w}) = (q_\pi(S,A) - \hat{q}(S,A,\mathbf{w}))\nabla_{\mathbf{w}}\hat{q}(S,A,\mathbf{w})$$

$$\Delta\mathbf{w} = \alpha(q_\pi(S,A) - \hat{q}(S,A,\mathbf{w}))\nabla_{\mathbf{w}}\hat{q}(S,A,\mathbf{w})$$

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