Reinforcement learning

Episode 3

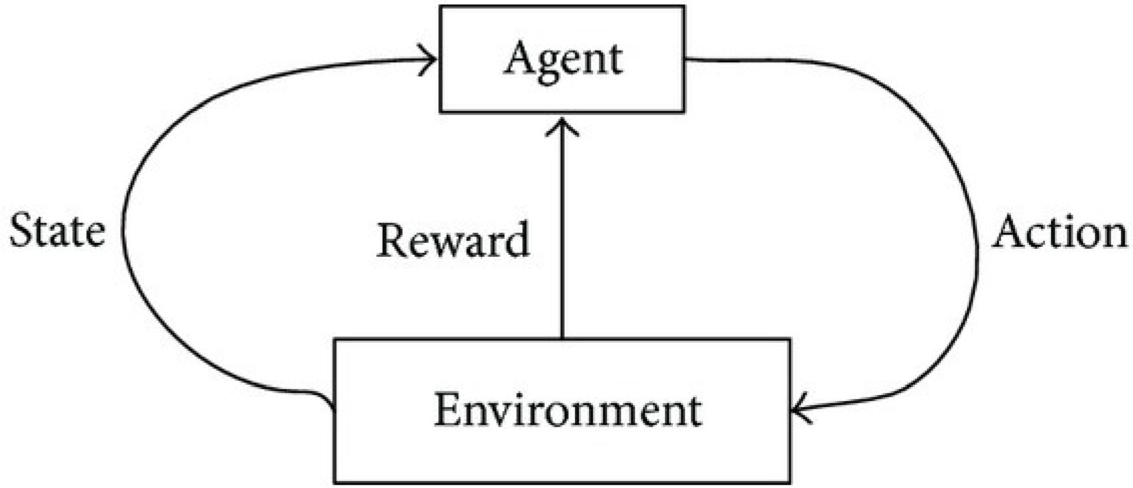
Approximate & deep RL

Yandex Data Factory

LAMBDA

British Hedgehog Preservation Society

Recap: MDP



Classic MDP(Markov Decision Process)

Agent interacts with environment

- Environment states: $s \in S$
- Agent actions: $a \in A$
- State transition: $P(s_{t+1} | s_t, a_t)$
- Reward: $r_t = r(s_t, a_t)$

Recap: total reward

Objective:
Total reward

$$R_t = r_t + \gamma \cdot r_{t+1} + \gamma^2 \cdot r_{t+2} + ... + \gamma^n \cdot r_{t+n}$$

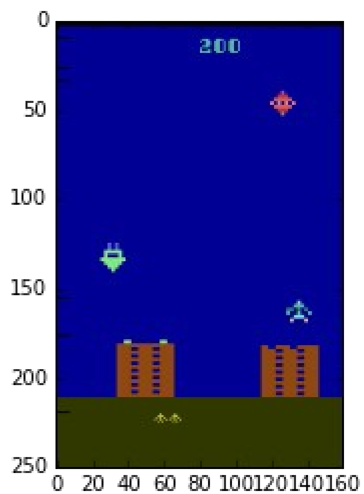
$$\gamma \in (0,1)\, const$$

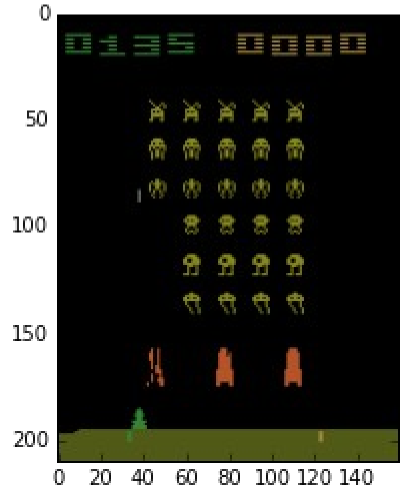
γ ~ patience

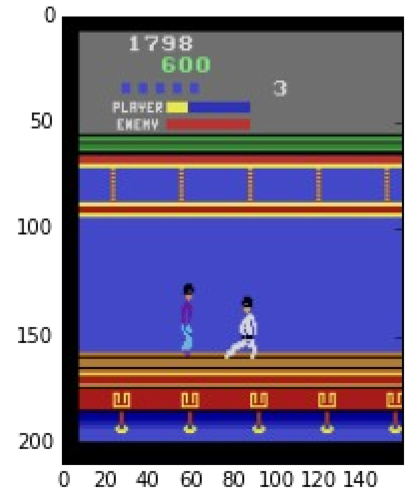
Reinforcement learning:
- Find policy that maximizes the expected reward

$$\pi = P(a|s) : E[R] \rightarrow max$$

~~Reality~~ check: videogames

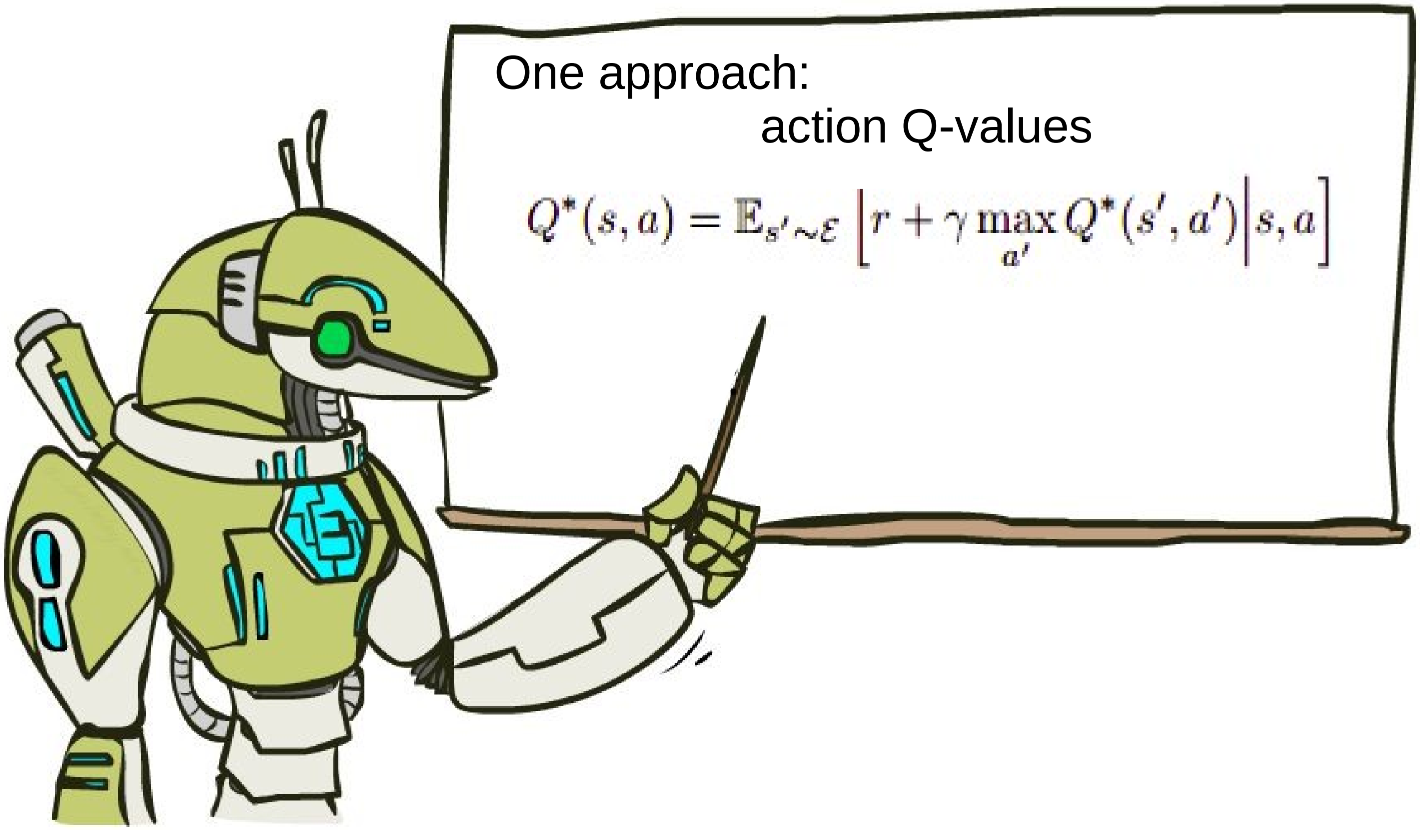






- **Trivia:** What are the states and actions?

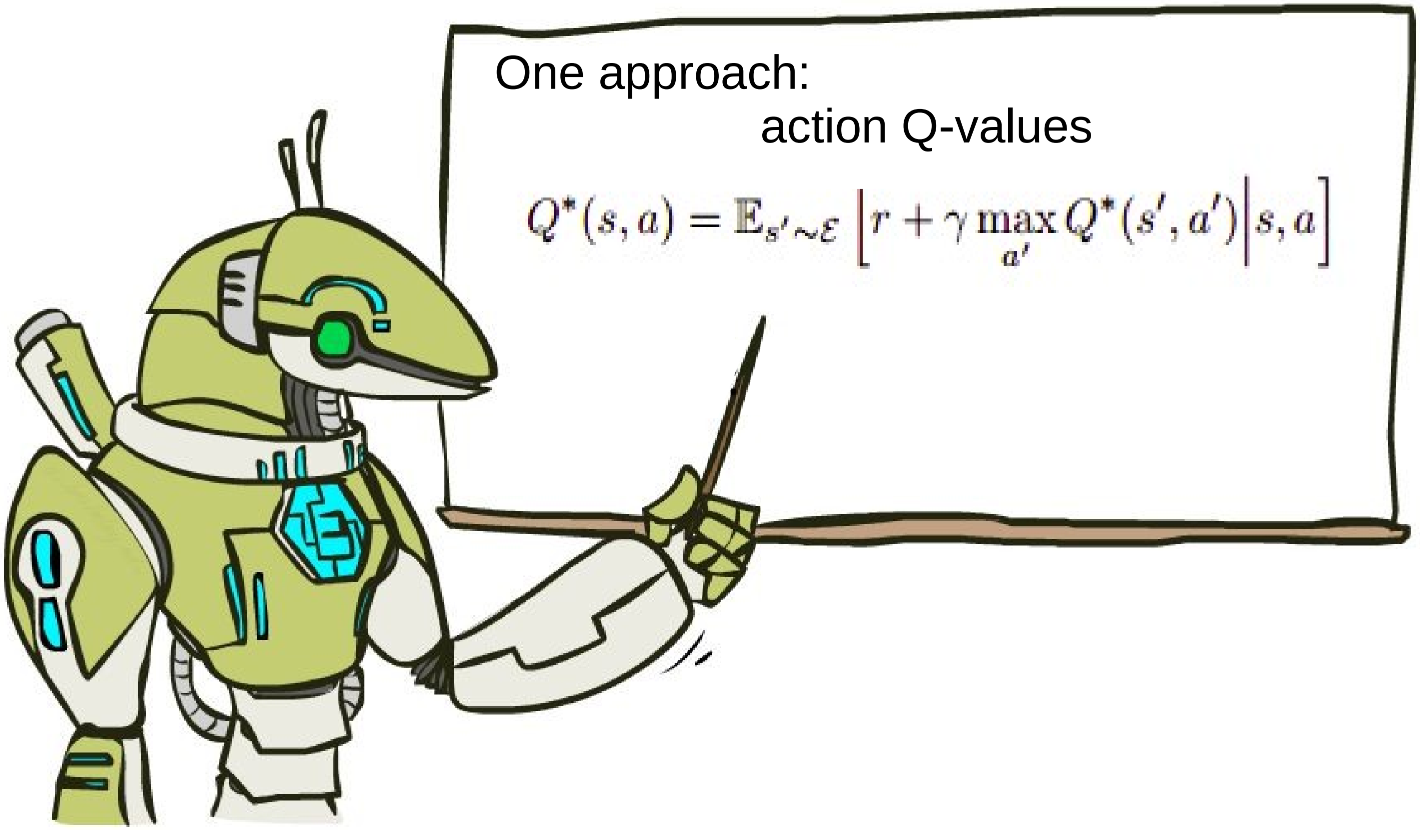
Recap: Q-learning



Definition: Q(s,a) is an expected total reward **R** that can be obtained starting from state **s** by taking action **a** and following optimal policy since next state.

$$\pi(s): argmax_a Q(s,a)$$

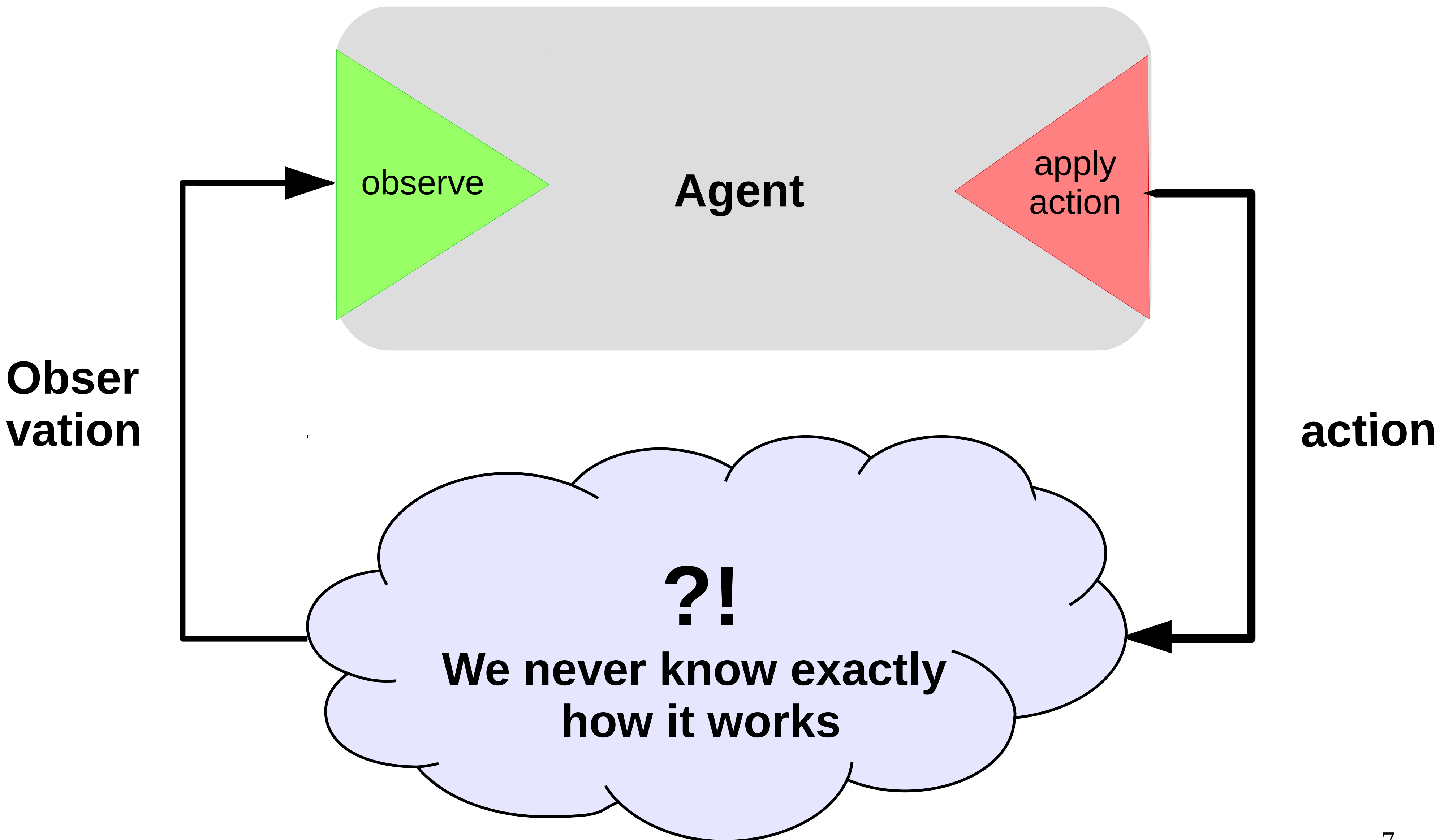
Recap: Q-learning



- Initialize with zeros/random
- Iteratively minimize

$$argmin_{Q(s_t,a_t)} \left(Q(s_t, a_t) - [r_t + \gamma \cdot max_{a'} Q(s_{t+1}, a')] \right)^2$$

Real world


observe
Agent
apply
action
Obser
vation
action
?!
We never know exactly
how it works

Problem:

State space is usually large,

sometimes continuous.

And so is action space;

However, states do have a structure, similar states have similar action outcomes.

From tables to approximations

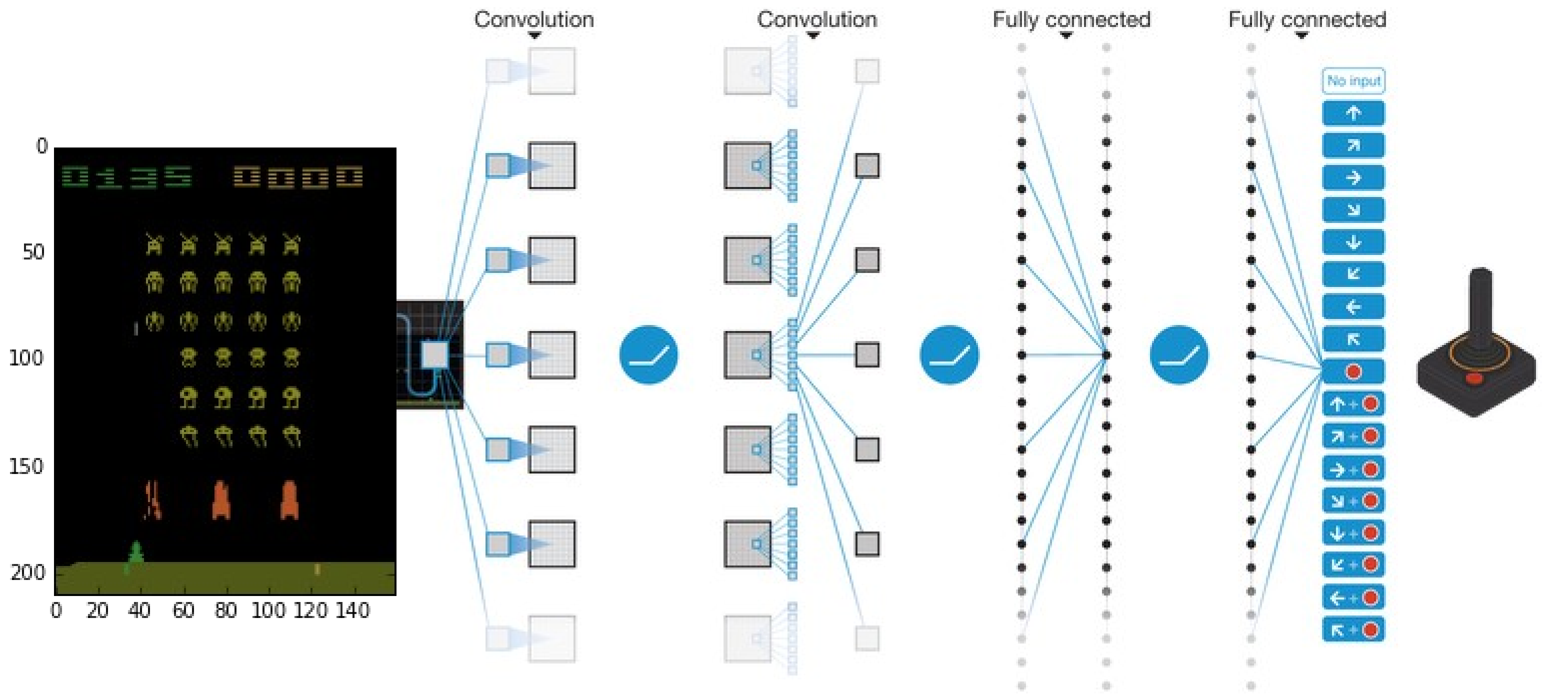
- Before:
  - For all states, for all actions, remember Q(s,a)

- Now:
  - Approximate Q(s,a) with some function
  - e.g. linear model over state features

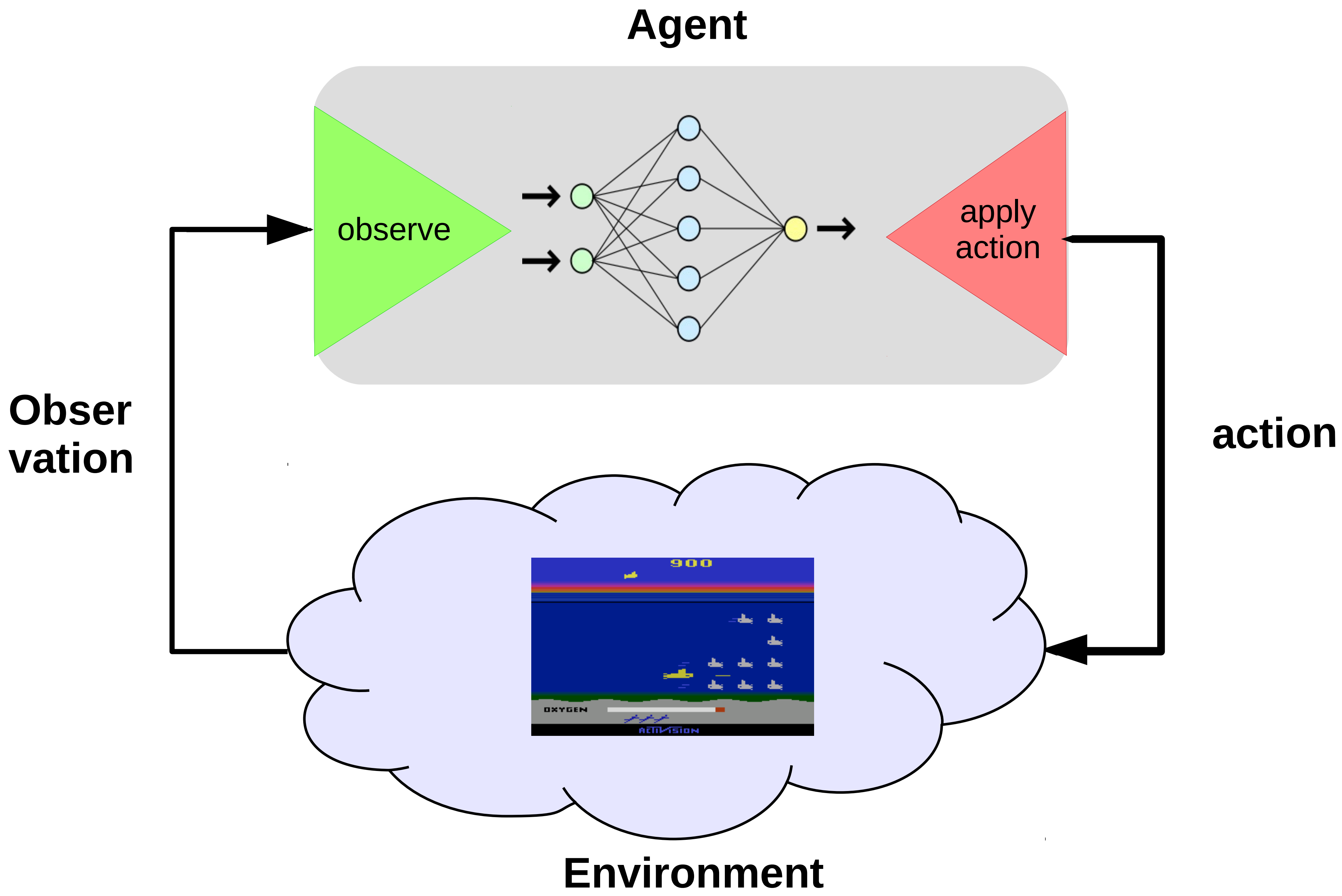
$$argmin_{w,b}\left(Q(s_t,a_t)-[r_t+\gamma\cdot max_{a'}Q(s_{t+1},a')]\right)^2$$

Trivia: should we use linear regression or logistic regression?

Deep learning approach: DQN



MDP again


Agent
observe
apply
action
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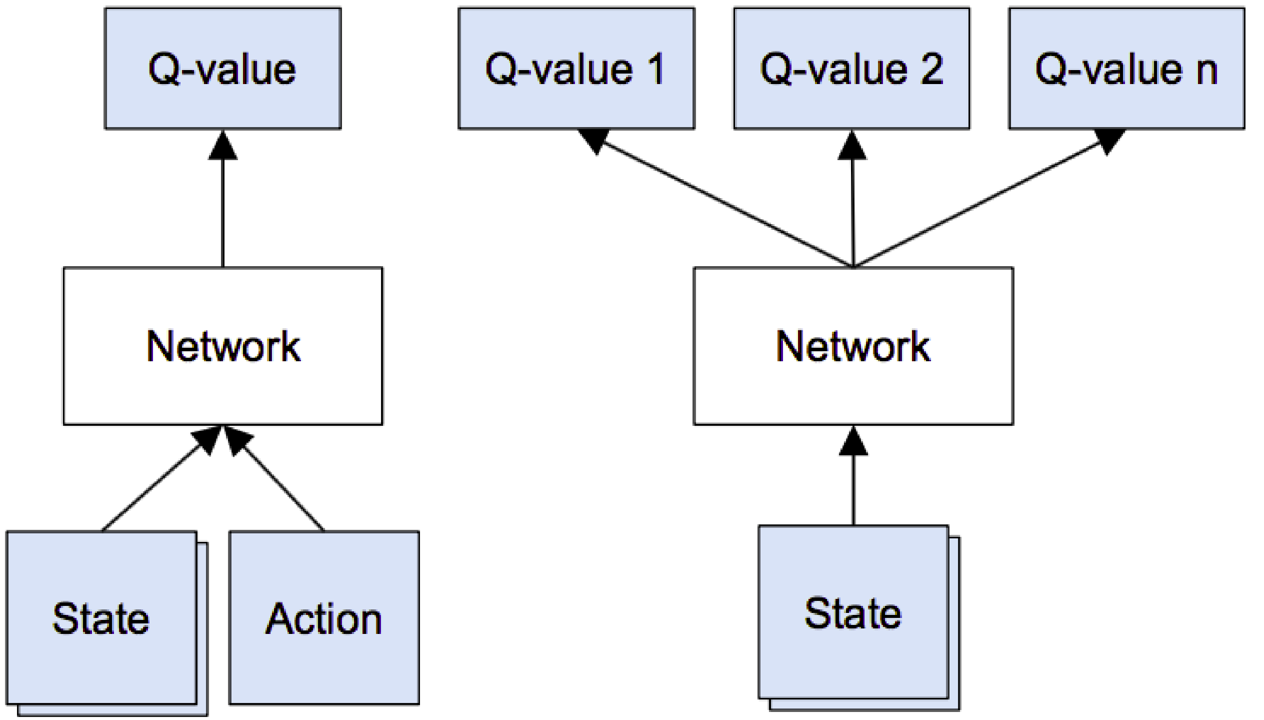
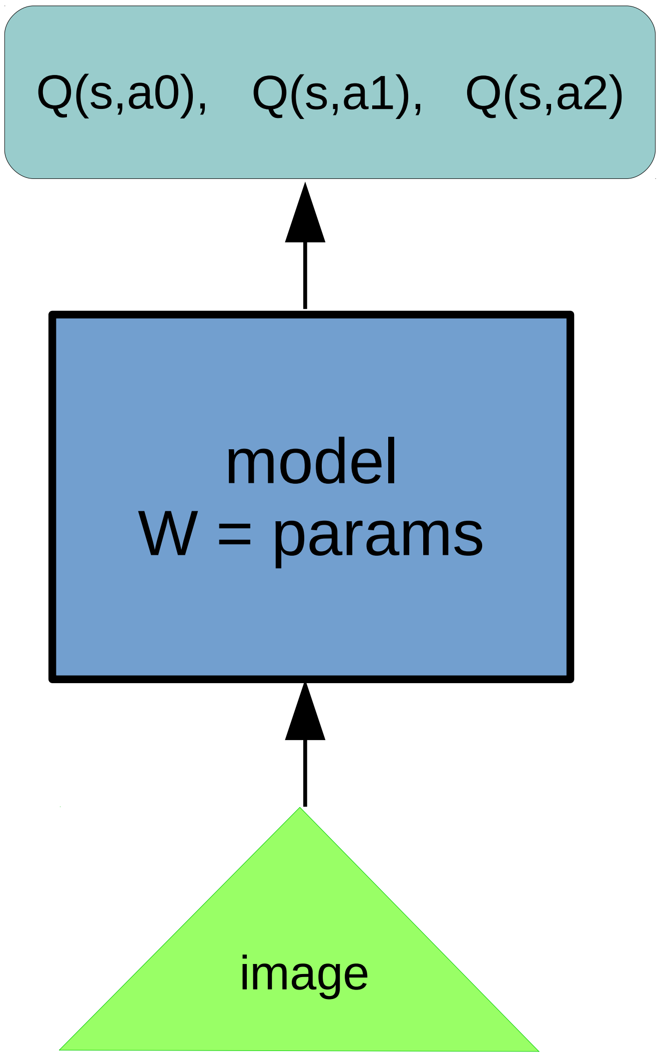
OXYGEN
Environment

Deep learning approach: DQN



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

Approximate Q-learning



Q-values:

$$\hat{Q}(s_t, a_t) = r + \gamma \cdot argmax_{a'} \hat{Q}(s_{t+1}, a')$$

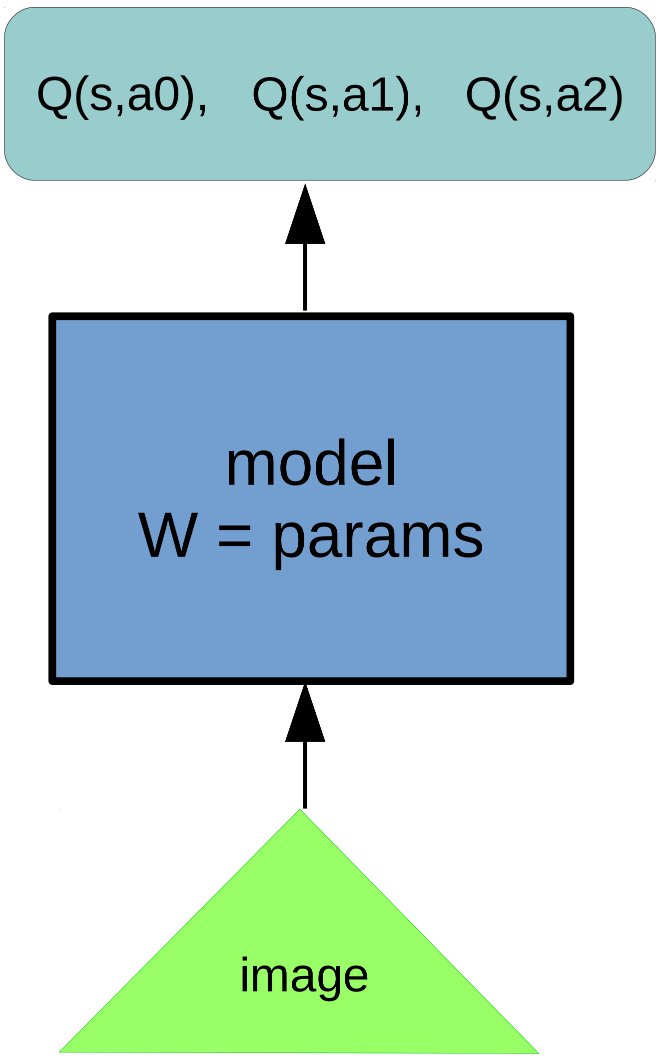
Objective:

$$L = (Q(s_t, a_t) - [r + \gamma \cdot argmax_{a'} Q(s_{t+1}, a')])^2$$

Gradient step:

$$w_{t+1} = w_t - \alpha \cdot \frac{\delta L}{\delta w}$$

Approximate Q-learning



Q-values:

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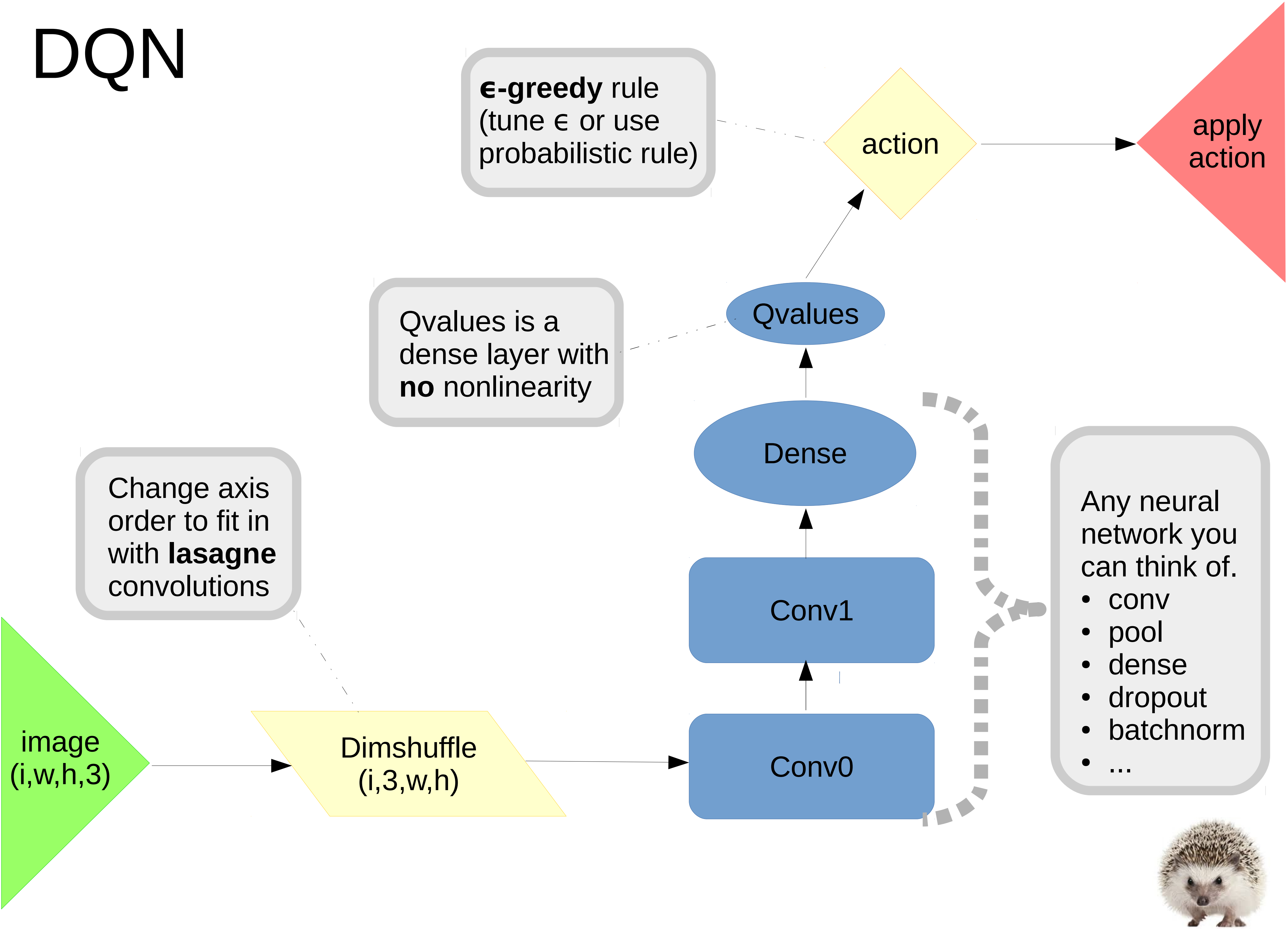
Objective:

$$L = \left(Q(s_t, a_t) - \left[r + \gamma \cdot \underbrace{argmax_{a'} Q(s_{t+1}, a')}_{\textbf{consider const}}\right]\right)^2$$

Gradient step:

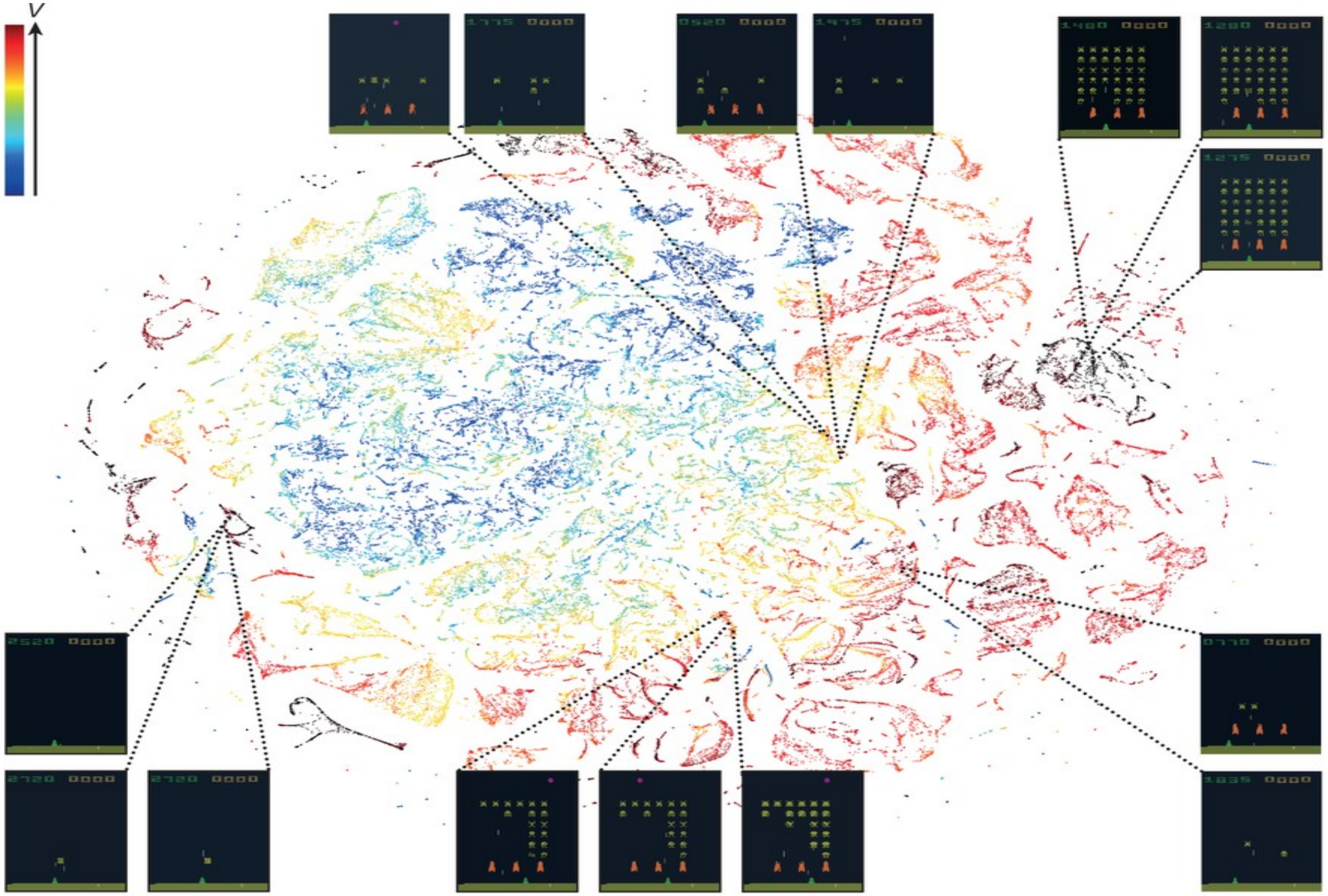
$$w_{t+1} = w_t - \alpha \cdot \frac{\delta L}{\delta w}$$

DQN

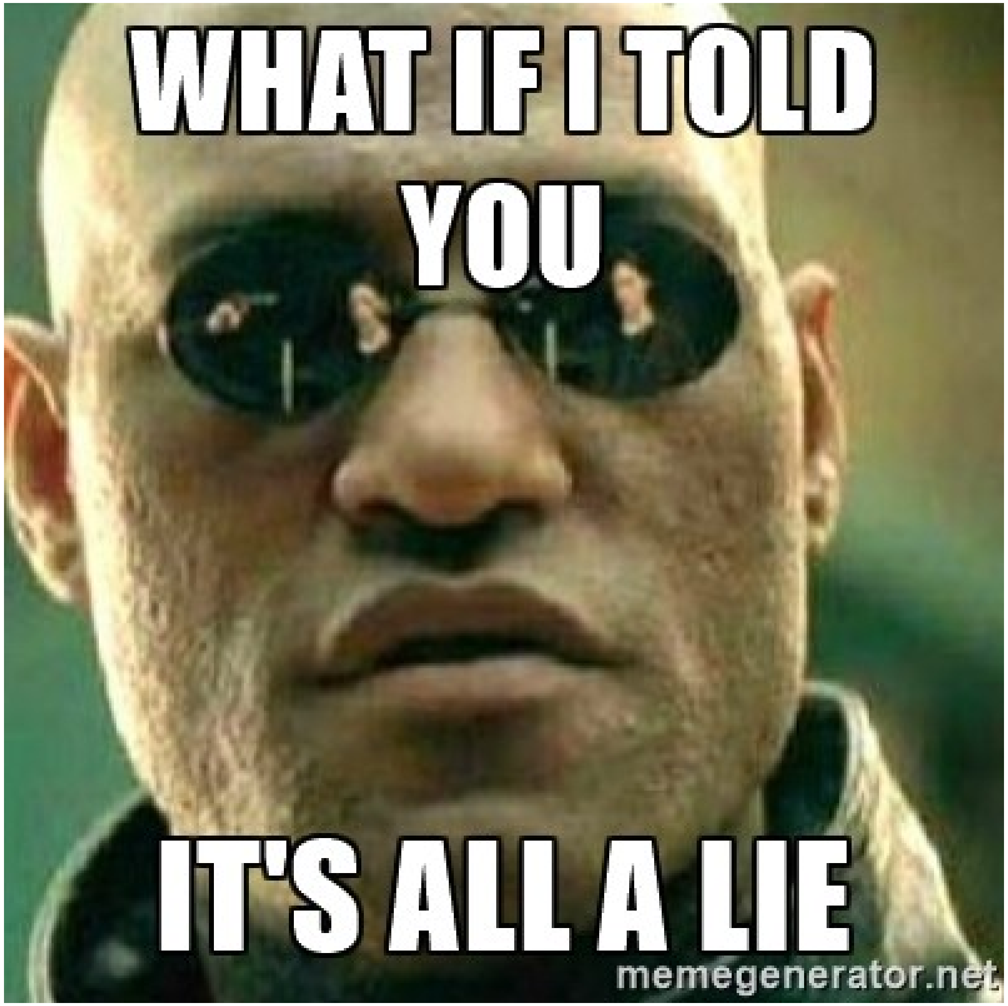


ϵ-greedy rule (tune ϵ or use probabilistic rule)
action
apply action
Qvalues is a dense layer with no nonlinearity
Qvalues
Dense
Change axis order to fit in with lasagne convolutions
Conv1
Any neural network you can think of.
• conv
• pool
• dense
• dropout
• batchnorm
• ...
image (i,w,h,3)
Dimshuffle (i,3,w,h)
Conv0

Because TSNE

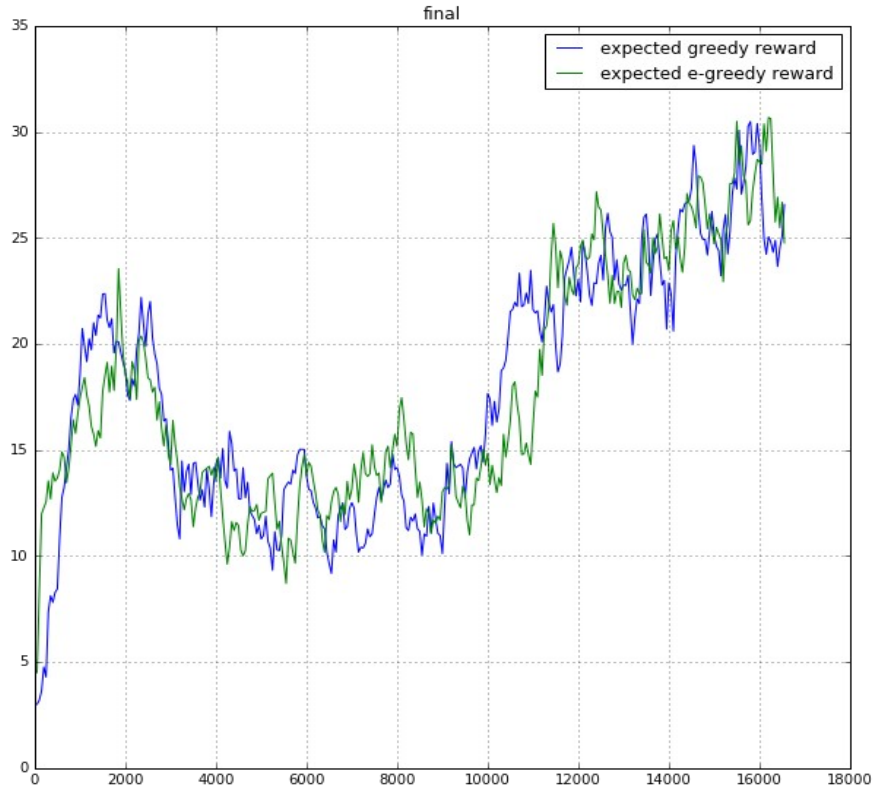


- Embedding of pre-last layer activations
- Color = state value = max_a Q(s,a)


WHAT IF I TOLD YOU
IT'S ALL A LIE
memegenerator.net

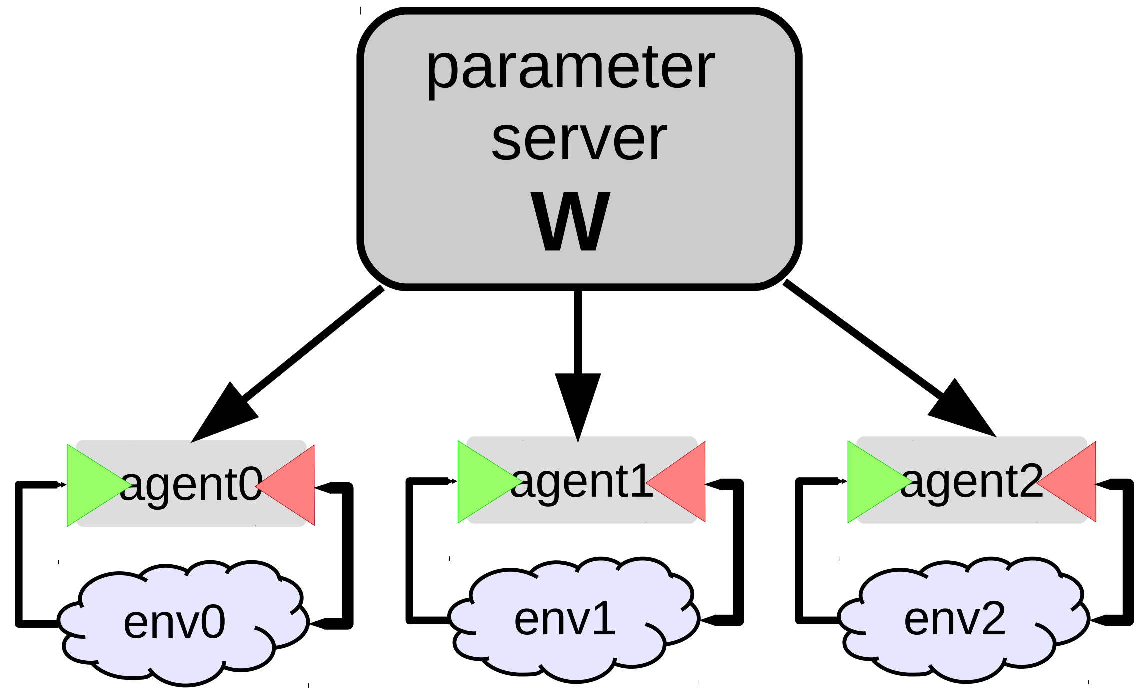
Problem

- Training samples are **not “i.i.d”**,
- Model forgets parts of environment it hasn't visited for some time
- Drops on learning curve
- **Any ideas?**



Multiple agent trick

Idea: Throw in several agents with shared **W**.



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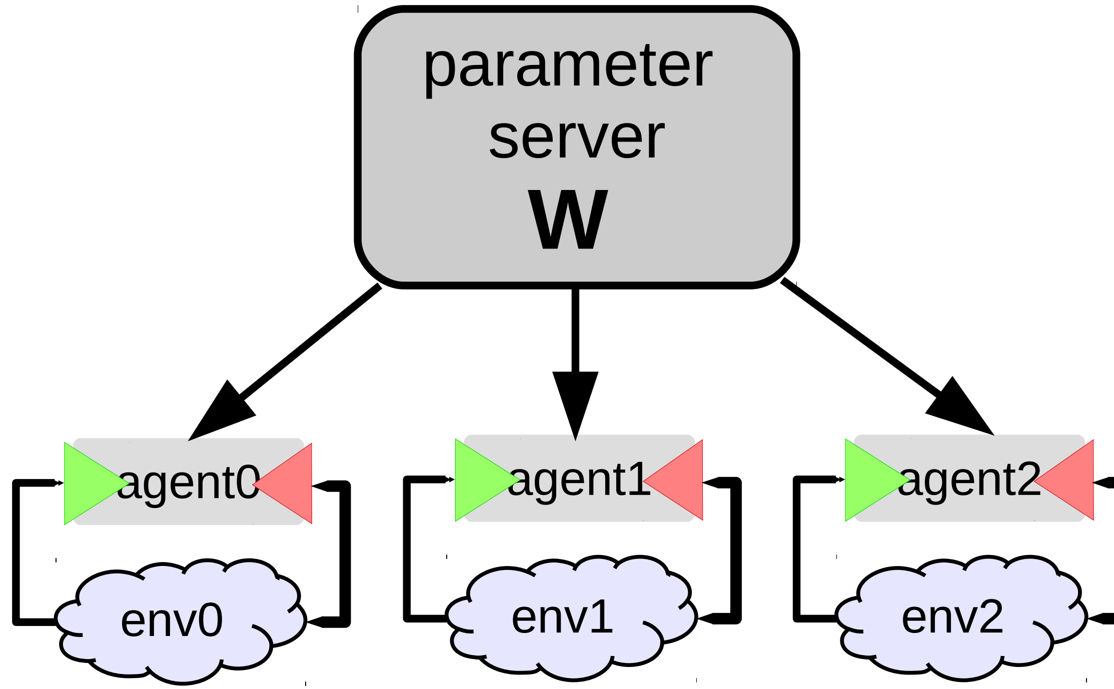


- Chances are, they will be exploring different parts of the environment,
- More stable training,
- Requires a lot of interaction,
- Alternative to experience replay.

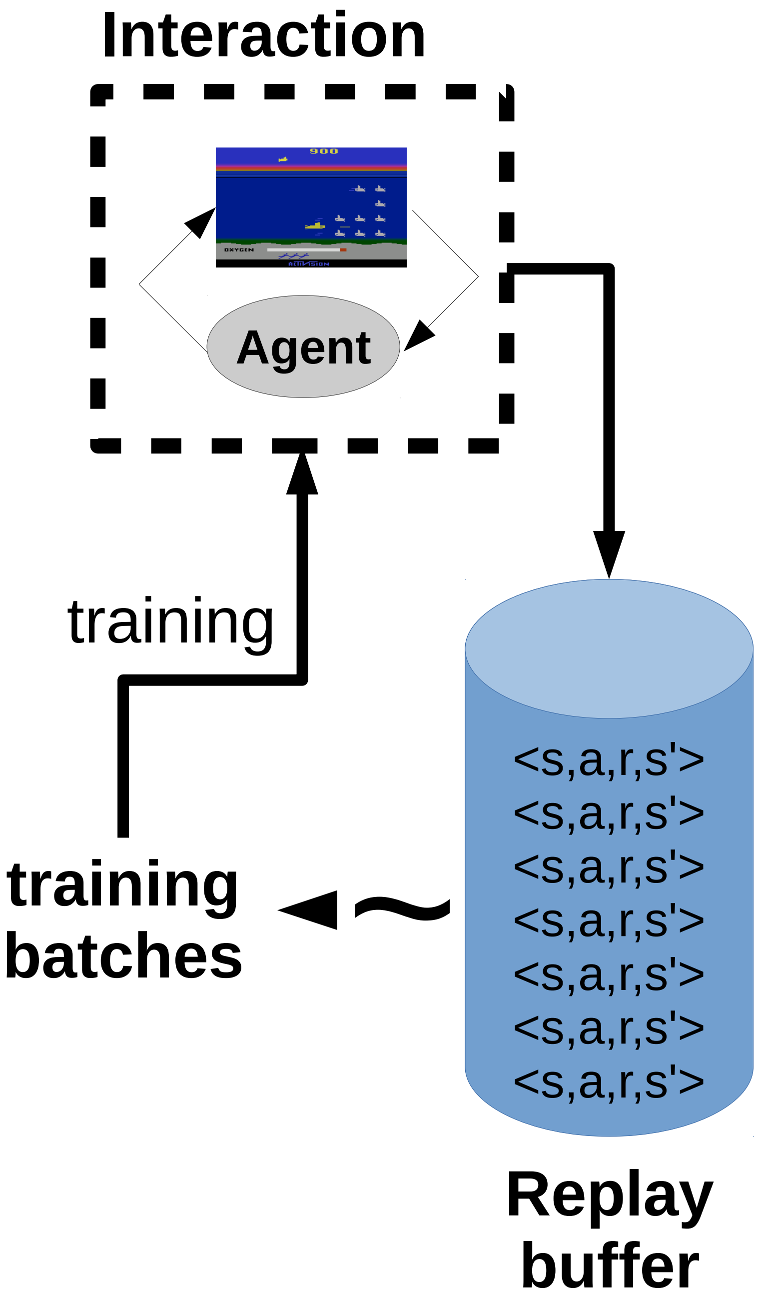
Experience replay

Idea: store several past interactions

<s,a,r,s'>

Train on random subsamples

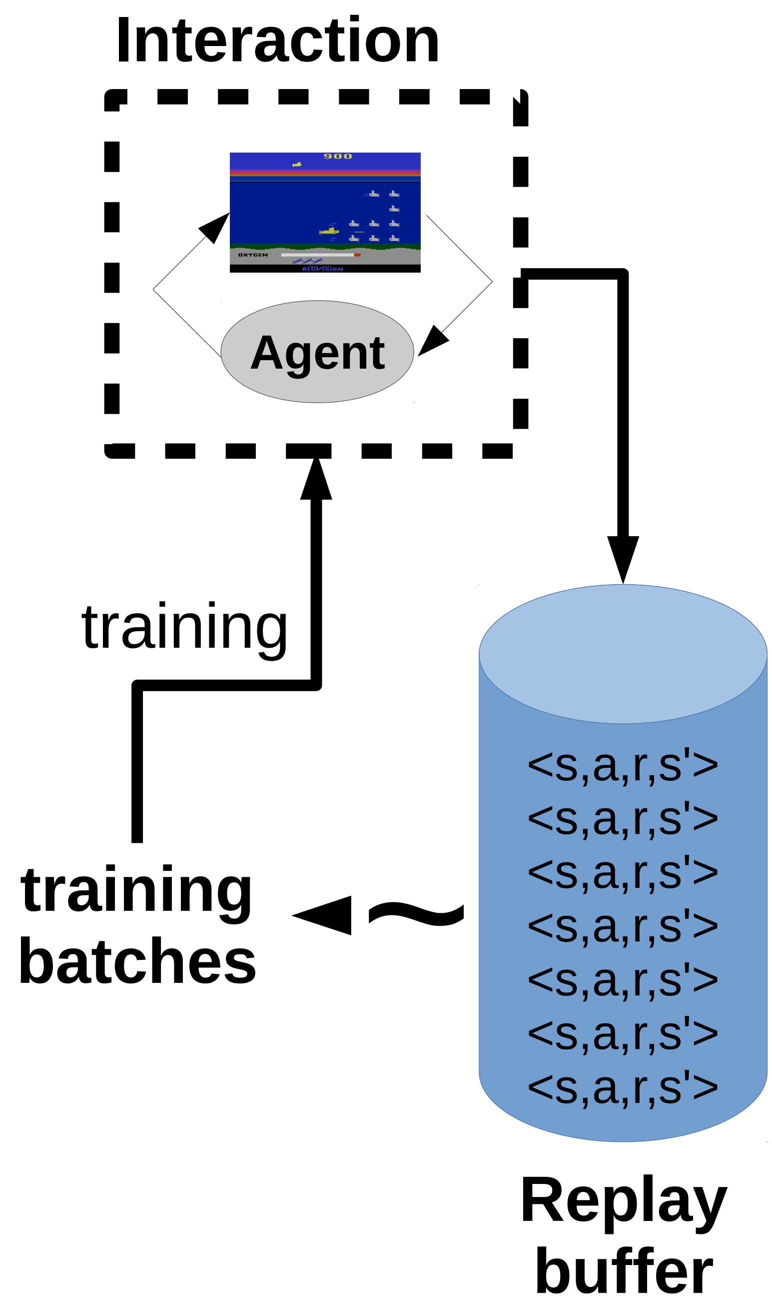
Any +/- ?



Experience replay

Idea: store several past interactions
<s,a,r,s'>
Train on random subsamples

- Atari DQN: >10^5 interactions
- Closer to i.i.d
  pool contains several sessions
- Older interactions were obtained
  under weaker policy
- Further development: prioritizing
  samples based on their importance.
  https://arxiv.org/abs/1511.05952



Autocorrelation

- Reference is based on predictions

$$r+\gamma \cdot argmax_{a'} Q\left(s_{t+1}, a'\right)$$

- Any error in Q approximation is propagated to neighbors
- If some Q(s,a) is mistakenly over-exaggerated, neighboring qvalues will also be increased in a cascade
- Worst case: divergence
- **Any ideas?**

Target networks

Idea: use older network snapshot
to compute reference

$$L = \left(Q(s_t, a_t) - \left[r + \gamma \cdot argmax_a{}' Q^{old}(s_{t+1}, a')\right]\right)^2$$

- Update Q old periodically
  - Slows down training

Target networks

Idea: use older network snapshot
to compute reference

$$L=\left(Q\left(s_t,a_t\right)-\left[r+\gamma\cdot argmax_a{'}Q^{old}\left(s_{t+1},a'\right)\right]\right)^2$$

- Update Q old periodically
  - Slows down training

- Smooth version:
  - use moving average

$$\theta^{old}:=\left(1-\alpha\right)\cdot\theta^{old}+\alpha\cdot\theta^{new}$$

  - Θ = weights

Final problem

Left or right?

Problem:

Most practical cases are partially observable:

Agent observation does not hold all information about process state (e.g. human field of view).

Any ideas?

Problem:

Most practical cases are partially observable:

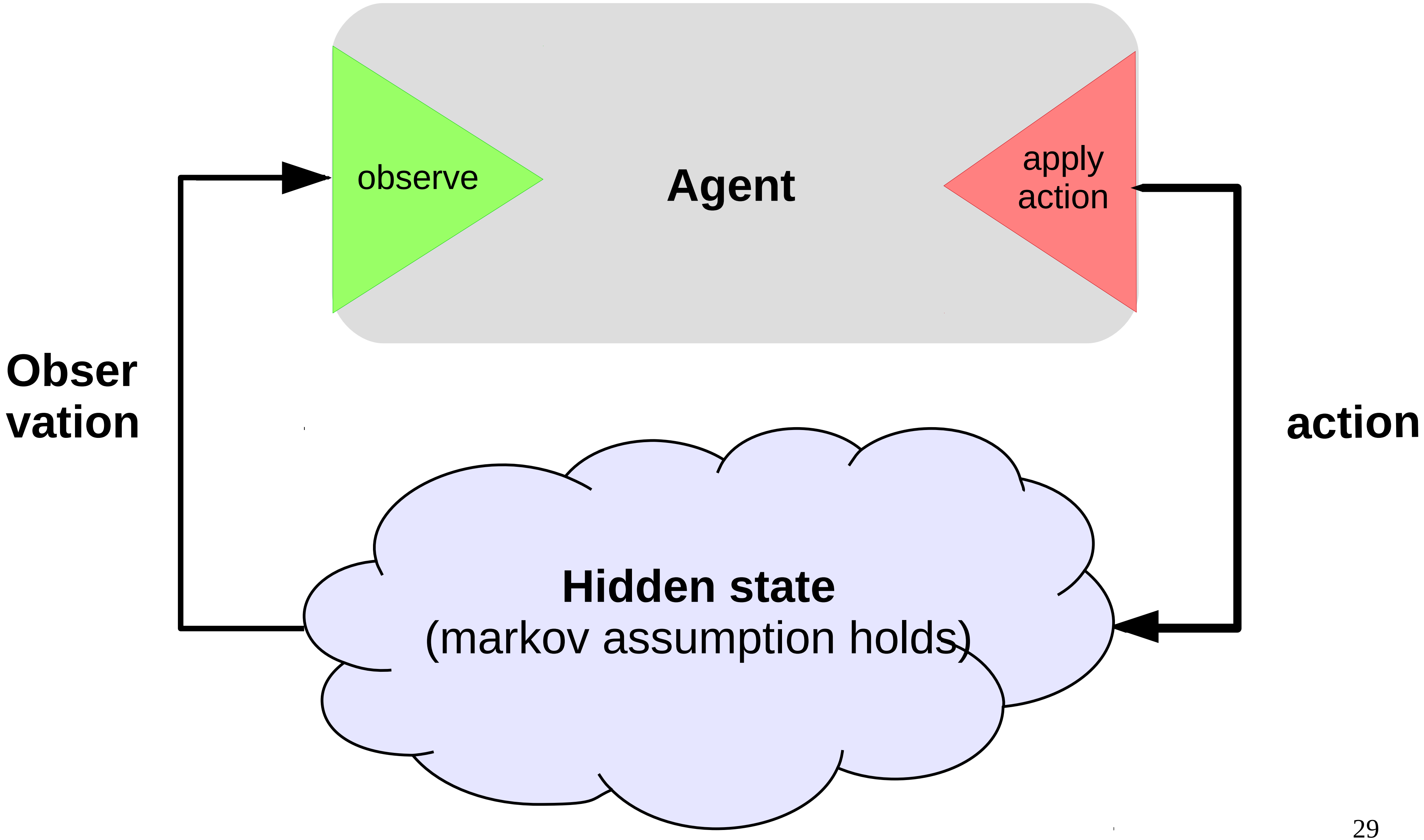
Agent observation does not hold all information about process state (e.g. human field of view).

- However, we can try to infer hidden states from sequences of observations.

$$s_t \simeq m_t : P\left(m_t \middle| o_t, m_{t-1}\right)$$

- Intuitively that's agent memory state.

Partially observable MDP



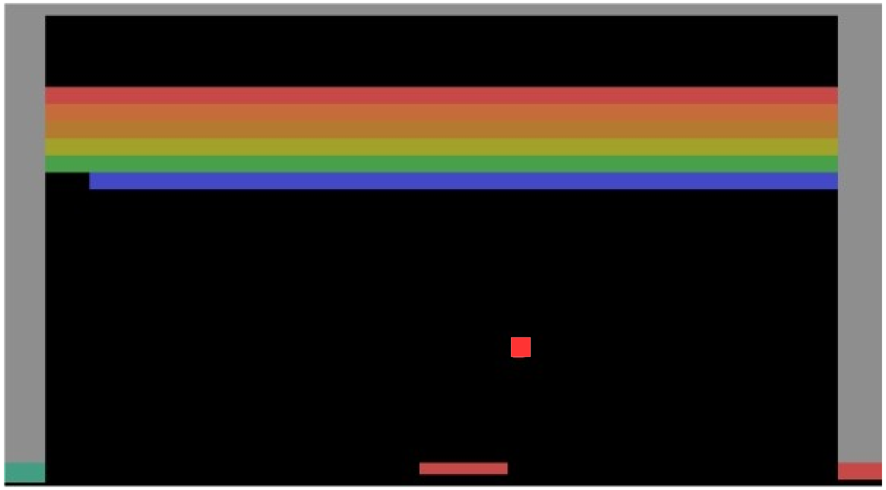
N-gram heuristic

Idea:

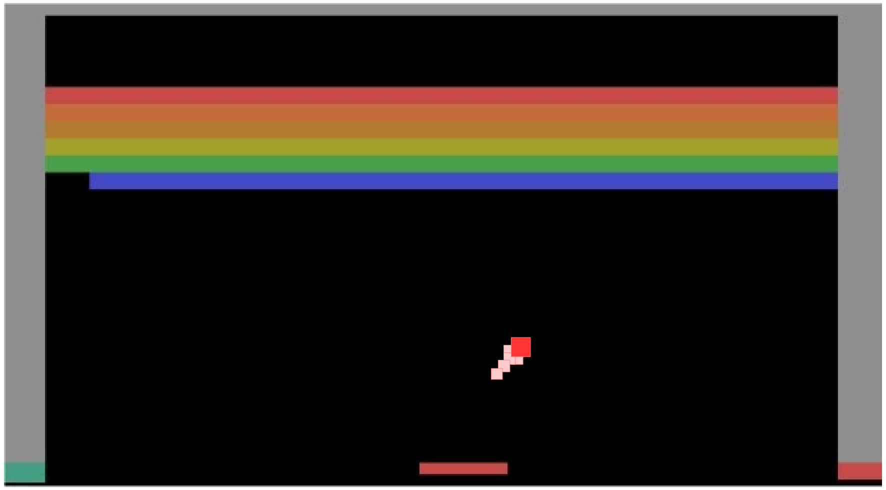
$$s_t \neq o(s_t)$$

$$s_t \approx (o(s_{t-n}), a_{t-n}, \ldots, o(s_{t-1}), a_{t-1}, o(s_t))$$

e.g. ball movement in breakout

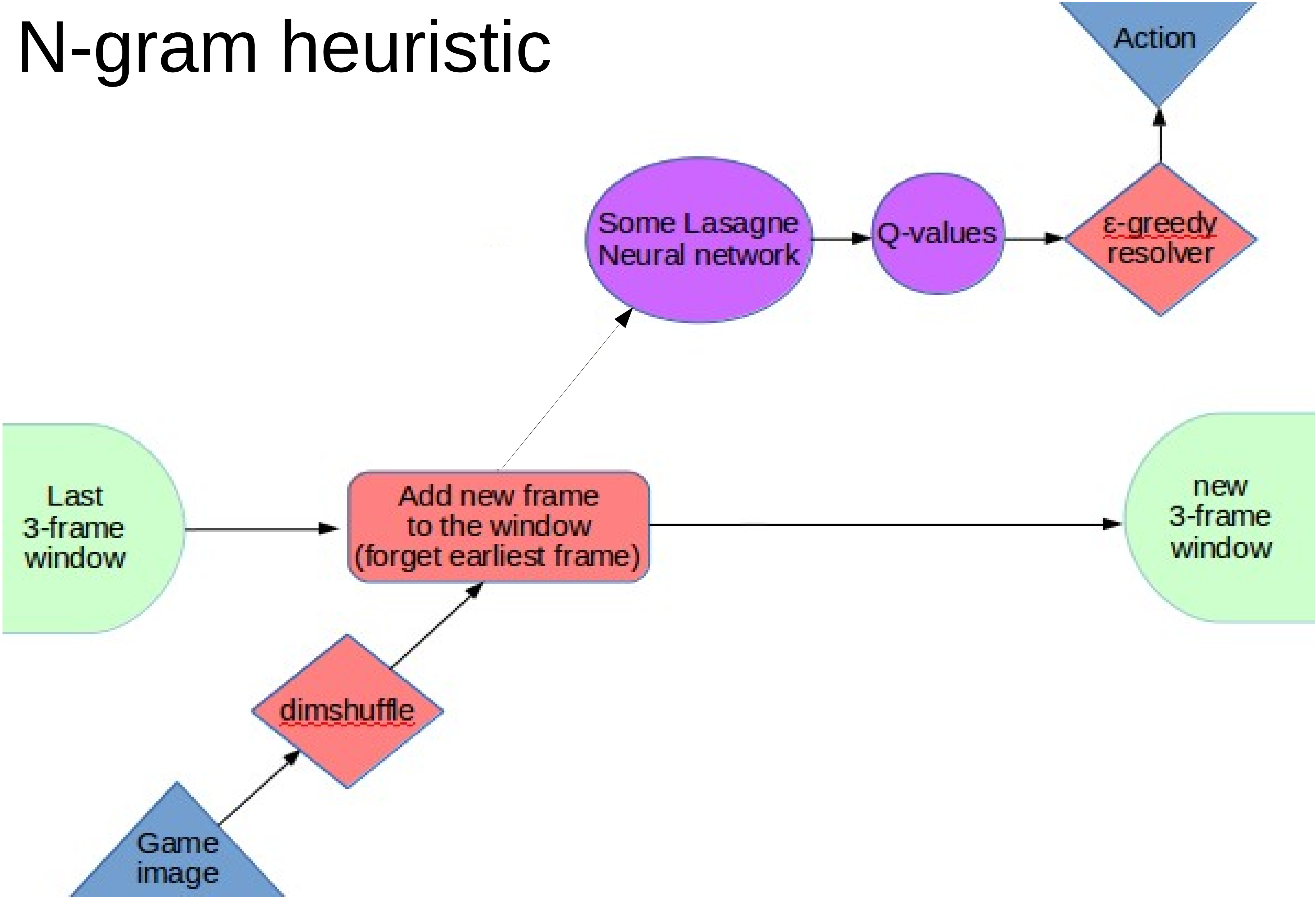


· One frame

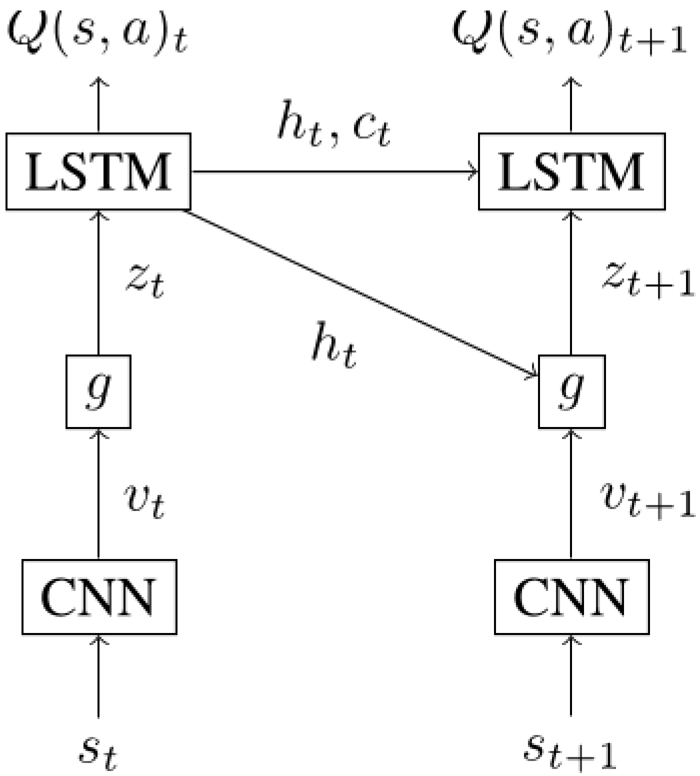


· Several frames

N-gram heuristic

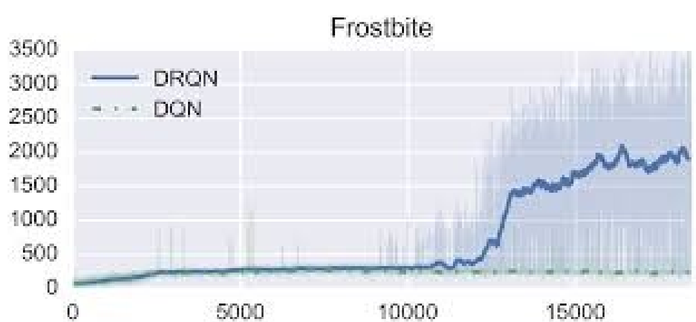


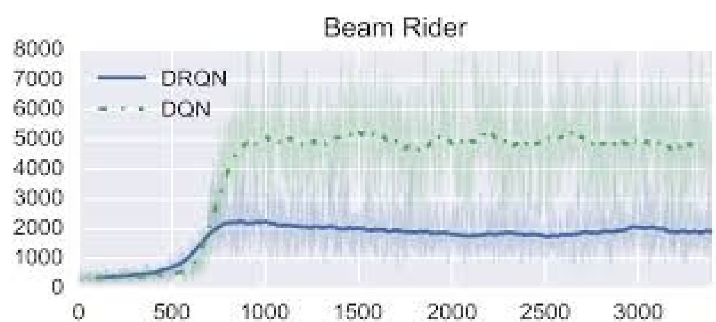
Deep Recurrent RL

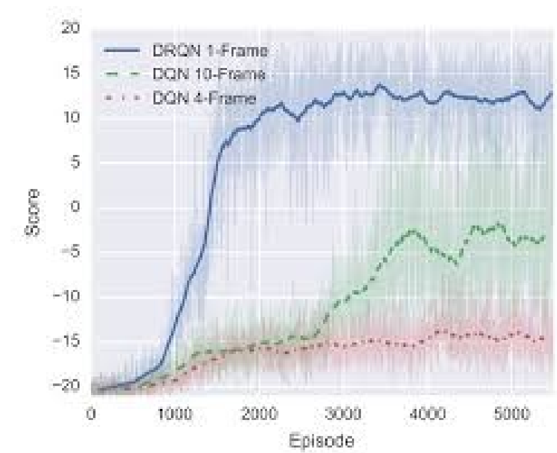


Recurrent agent memory

- Agent has his own hidden state.
- Trained via BPTT with a fixed depth
- Problem: next input depends on chosen action
- Even more autocorrelations :)

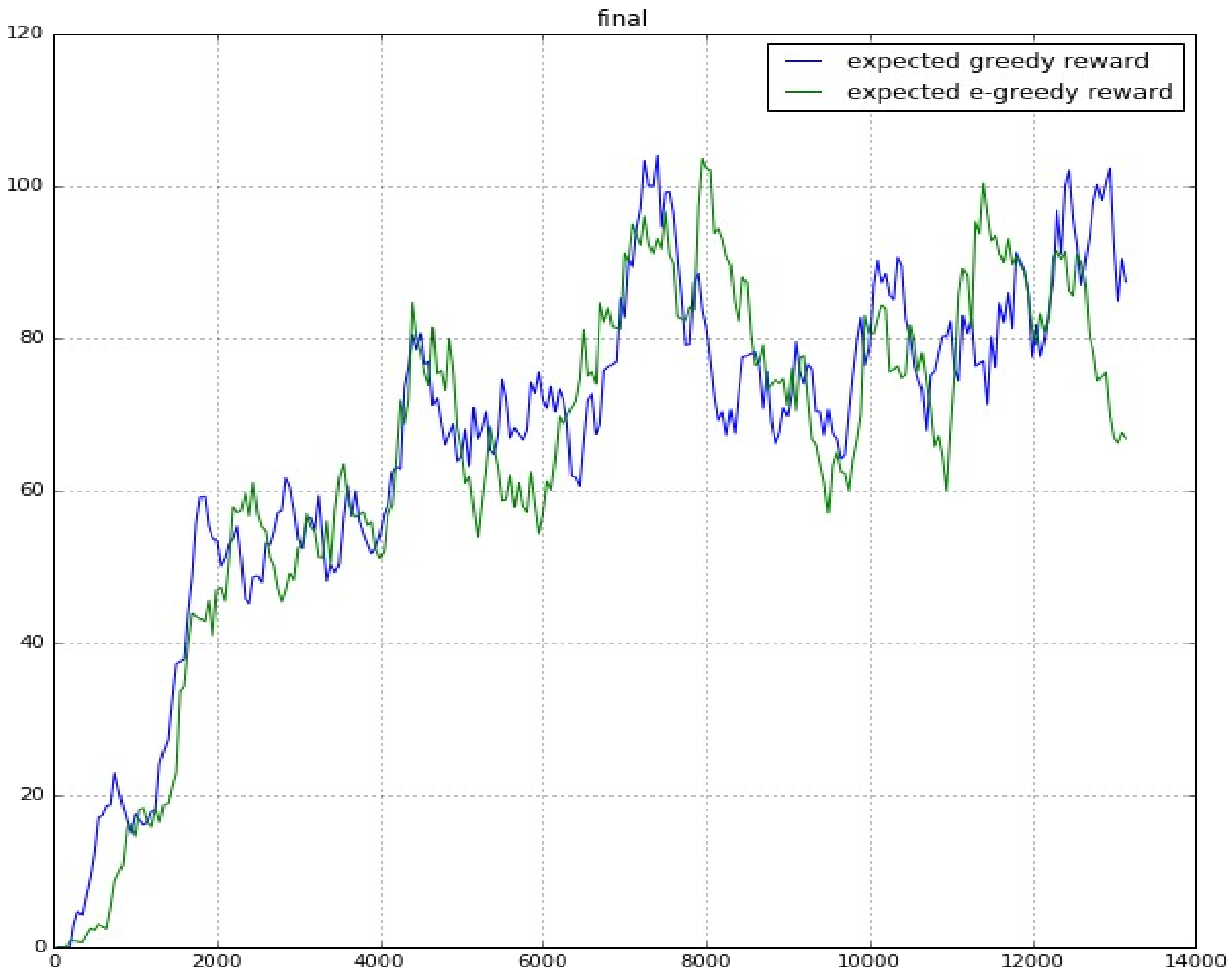






Deep Recurrent RL

Learning curves for KungFuMaster




CHALLENGE ACCEPTED
LET'S CODE IT
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Most important slide

RL isn't magical

- It won't learn everything in the world given any data and random architecture.
- Requires interaction
- Sparse and/or delayed rewards are a major problem
- Less playing Atari, more real world problems
  No, doom is not a real world problem, dummy!
- Getting rid of heuristics towards mathematical soundness
- Machine Intelligence revolution date TBA