Generalization and Function Approximation

COMP4211

THE DEPARTMENT OF
COMPUTER SCIENCE & ENGINEERING
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Generalization and Function Approximation

Example (9×9 Go)

- $|S| = 10^{38}$ and $|A| = 81$
- too many states to visit them all in training
- too many states to hold the Q-tables in memory

what should we do?

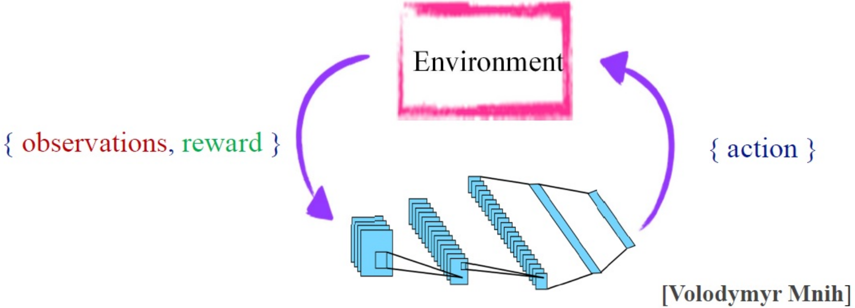
- learn about a few states from experience
- generalize that experience to new, similar states

Replace $\hat{Q}$ table with a function approximator

Deep Reinforcement Learning

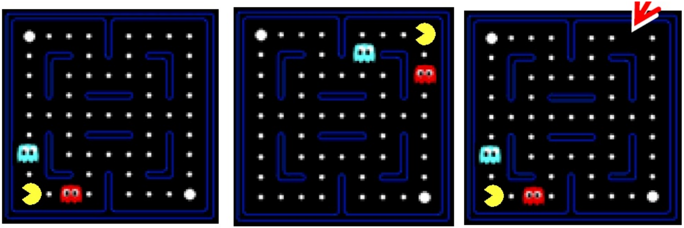
Example (function approximator= neural net)

deep reinforcement learning



Examples

good or bad?



Feature-Based Representations

describe a state using a vector of features

- features are functions from states to real numbers that capture important properties of the state
- example features:
  - distance to closest ghost
  - distance to closest dot
  - number of ghosts
  - $1/(\text{dist to dot})^2$
- can also describe a Q-state (s, a) with features
  - e.g., action moves closer to food

Function Approximation

linear feature functions

$$Q(s,a) = w_1 f_1(s,a) + w_2 f_2(s,a) + \cdots + w_n f_n(s,a)$$

- advantage: experience is summed up in a few numbers

Recall Q-learning

- $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[\text{difference}]$
- difference $= r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)$

how to update w_i's?

Function Approximation...

$$
\begin{aligned}
\text{error}(w) &= \frac{1}{2}\left(y - \sum_k w_k f_k(x)\right)^2 \\
\frac{\partial \text{error}(\text{w})}{\partial w_i} &= -\left(y - \sum_k w_k f_k(x)\right) f_i(x) \\
w_i &\leftarrow w_i + \alpha\left(y - \sum_k w_k f_k(x)\right) f_i(x)
\end{aligned}
$$

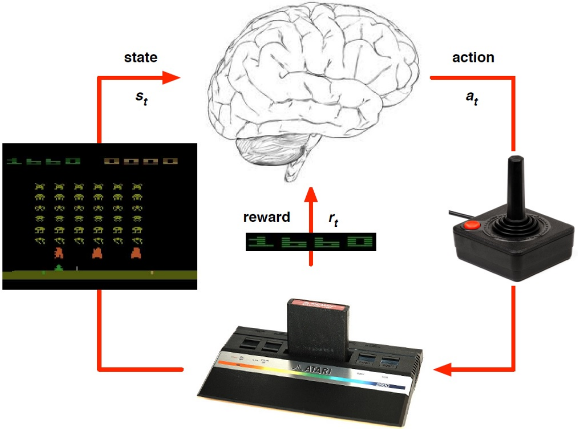
In Q-learning

- target: $r_t + \gamma \max_a Q(s_{t+1}, a)$
- prediction: $Q(s_t, a_t)$
- $w_i \leftarrow w_i + \alpha[\text{difference}] f_i(s_t, a_t)$

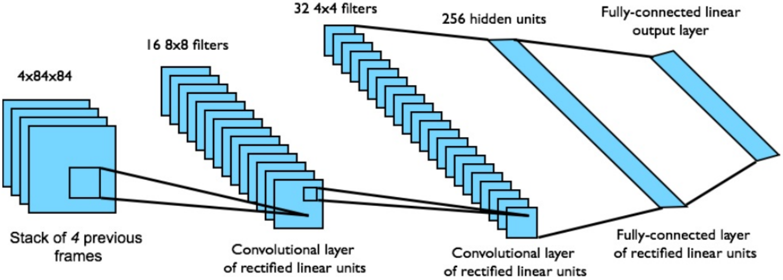
Q-learning with Linear Approximators

begin
  initialize parameter values;
  repeat
    select an action a and execute it;
    receive immediate reward r;
    observe the new state s';
    difference $= r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)$;
    for $i = 1$ **to** n **do**
      $w_i \leftarrow w_i + \alpha[\text{difference}] f_i(s_t, a_t)$;
    end
    $s \leftarrow s'$;
  until;
end

Deep Q-Network in Atari

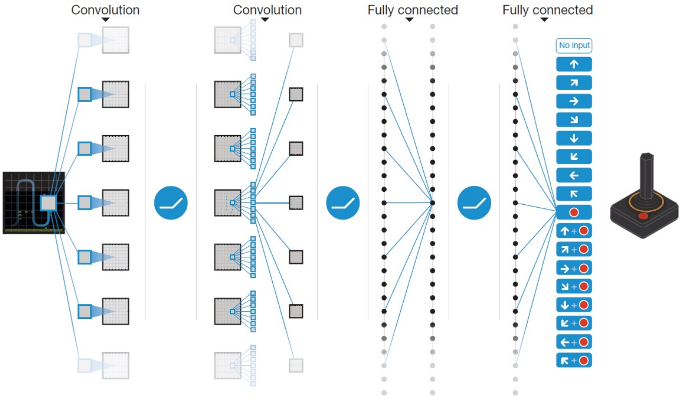


Deep Q-Network in Atari...

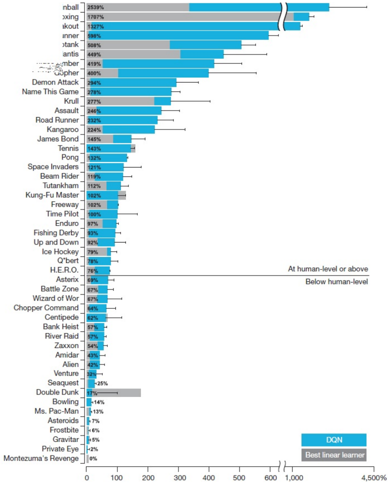


- learning of values $Q(s, a)$ from pixels s
- input state s is stack of raw pixels from last 4 frames
- output is $Q(s, a)$ for 18 joystick/button positions
- reward is change in score for that step

Deep Q-Network in Atari...



Performance



- performance is normalized with respect to a professional human games tester (100% level) and random play (0% level)