Creating Intelligent Agents with Reinforcement Learning

Deep Q Learning

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Outline

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Outline

1. Reinforcement Learning
2. Deep Q Learning
3. Code vs Zombies
4. Experiments and Results

Traditional ML

Supervised Learning:

- input to output examples
- find mapping from input to known output

Unsupervised Learning:

- input examples
- find underlying pattern

Current predictions **do not** affect future predictions!

How RL differs

Reinforcement Learning:

- current input and current reward
- find optimal behaviour (series of decisions) to perform a task

Current predictions **do** affect future predictions!

Reinforcement Learning
Terminology

- Agent: entity that is making the decisions (our program)
- Environment: the world the agent interacts with
- State: current configuration of environment
- Action: a way in which the agent can interact with the environment
- Reward: the feedback the environment gives us

Reinforcement Learning

What is RL?

Branch of machine learning that deals with:

- making sequential decisions
- modelling behaviour $\rightarrow$ policy

Model a setup where some agent interacts with some environment.

Reinforcement Learning
Approaches

In what ways can we do this?

- Model-based
  Learn how the environment reacts to the agent's actions
- Value-based / Policy-search
  (Learn how to decide what action to take)
  - Policy-search:
    $\rightarrow$ Directly predict the action that results in highest cumulative reward
  - Value-based:
    $\rightarrow$ Assign value to states (value = cumulative reward)
    $\rightarrow$ perform action that would put the agent in the state with the highest value

Outline

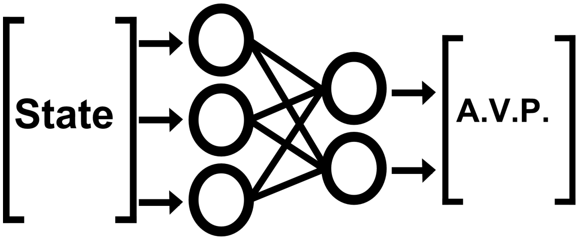
Deep Q Learning

Value-based

Learn a function that maps state to action-values using a neural network

Action-value: value of state agent will be in if specific action is performed

This is then called a Q network



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Deep Q Learning

How is it done in practice?

Episode: session of interactions with the environment

Algorithm 1 Q Learning

```
while environment.episode_in_progress():
    s = environment.get_state()
    a = Q.choose_action(s)
    environment.update(a)
    new_s, r = environment.observe()
    Q.update(s, a, r, new_s)
```

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Code vs Zombies
Description

Entities:

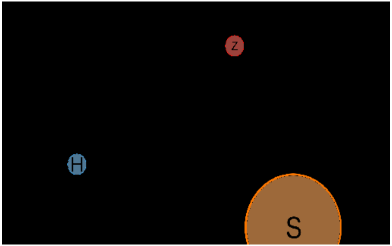
- a shooter → move towards player specified point
- humans → static
- zombies → move towards closest human (shooter is human)

Interactions:

- zombies kill humans → reduction in score
- shooter kills zombies → increase in score

Terminating states:

- no more humans → fail
- no more zombies → win



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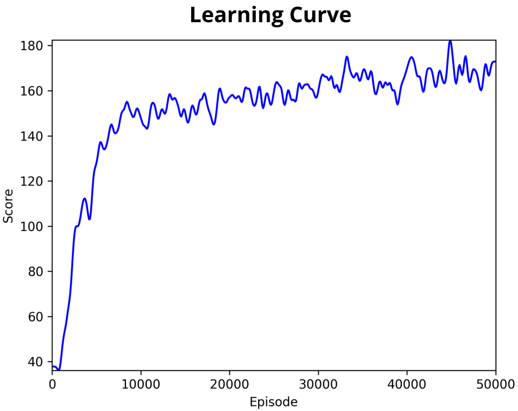
Experiments
Validation

Validation: time vs accuracy trade off

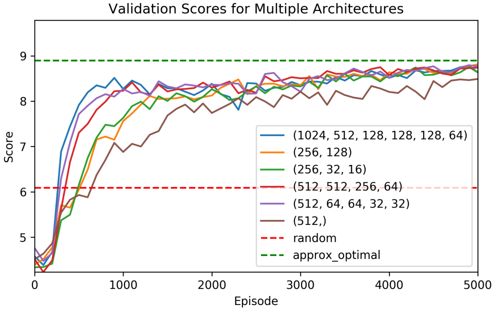
- validation score: average over 100 on-policy games



Results

Optimal score on some constrained versions:

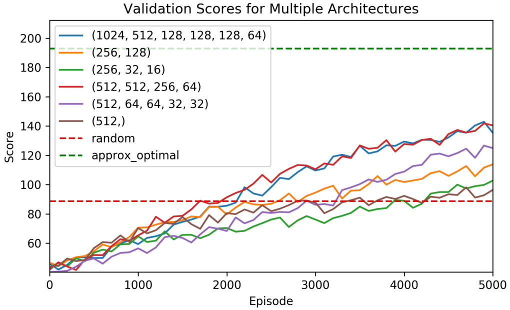
- 1 human
- 1 zombie



Results

Optimal score on some constrained versions:

- 3 humans
- 3 zombies



Want to find out more?

- Textbook:
  "Reinforcement Learning: An Introduction" by Sutton, R.S. and Barto, A.G.
- Papers:
  - Mnih, Volodymyr et al. (2015). Human-level control through deep reinforcement learning. In: Nature 518, pp. 529542
  - Hessel, M. et al. (2017). Rainbow: Combining Improvements in Deep Reinforcement Learning. arXiv:1710.02298
- Me:
  `https://elanvb.github.io/CV/`

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Demo

Questions?

Value-based method

Q learning

We focus on value-based methods:

- Value function: measure state desirability

Q learning:

- assign value to state-action pairs
- action-value function $\rightarrow$ Q function

$$Q(s,a) := r + \gamma \cdot \max_a Q(s', a)$$

Q learning

What are the problems with this approach?

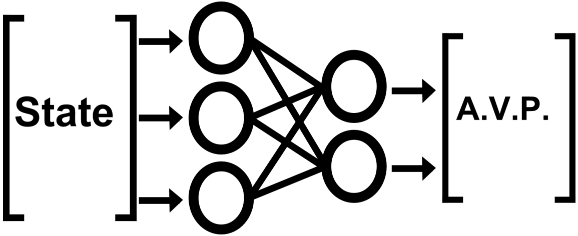
- usually modelled with Q matrix: $Q[s][a] = Q(s, a)$
- possible states as rows
- possible actions as columns
- as number of states and actions grow, matrix becomes very large
  $\rightarrow$ difficult to populate full matrix
  $\rightarrow$ does not generalise to unseen states

Deep Q Learning

Use a neural network to approximate the Q function:

$$\widehat{Q}(s, a, \theta) = NN(s, a, \theta)$$

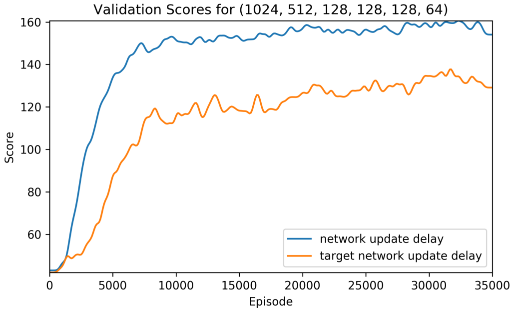
This is then called a Q network



Experiments

Training Methods

- target network update delay: use 2 networks for solution stability (Deep Mind - 2015)
- network update delay: achieve same benefits and more with a single network (Ours)



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