Teaching computer to play Doom from visual input

Anssi Kanervisto

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Why teaching?

Why visual input?

Why Doom?

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- Computer can learn previously unseen environments
- Possibly not limited by human knowledge

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Why visual input?

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Why Doom?

- Secure, modifiable and compact environment
- Fun

Teaching computer to play

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Example: Training your dog to sit on command.

1) Initial state: Dog is standing (also dog likes treats)
2) You command dog to sit.
3) Dog sits down (or trots away).
4) You give dog a treat (or not).

Repeating this with enough treats will result dog to always sit down on command.

Reinforcement learning

In terms of reinforcement learning and Doom...

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The state: Visual image

$$s_t \in \mathbb{R}^{\text{height} \times \text{width} \times \text{channels}}$$

Time (discrete integers)

Reinforcement learning

In terms of reinforcement learning and Doom...

The action: Positive integer*

$$a_t \in \mathbb{N}$$

Time (discrete integers)

(*) Also can represent any action between earth and the heaven**
(**) Withing the limits of the provided environment***
(***) Which can also be the physical world

Reinforcement learning

In terms of reinforcement learning and Doom...

The treat: Reward function

Previous state

$$R(s_t, a_t, s_{t+1}) = \begin{cases} 1 & \text{if collects a medkit} \\ -1 & \text{if agent dies} \\ \dots & \dots \end{cases}$$

Action taken

Next state

Reinforcement learning

In terms of reinforcement learning and Doom...

The goal: Maximize treats

Interact till terminal state.
E.g. Play one game of Doom

$$\max \sum_{t=1}^{T} R(s_t, a_t, s_{t+1})$$

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After training, the dog sits down on command as it expects to receive a treat [citation needed]. **Q-learning** takes a similar approach.

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The value of an action

$$Q(s_t, a_t) = \mathbb{E}\left[\sum_{i=t}^{T} R(s_i, a_i, s_{i+1})\right]$$

Read: Expected sum of the future reward

Learning to take good actions

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Learning from the experience

Discount factor.
How short sighted agent is.

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha \left(r_t + \gamma \max_a Q(s_t, a) - Q(s_t, a_t) \right)$$

Learning rate

Reward obtained
after taking the action

Expected reward in next state.
Connection to the future.

Learning to take good actions

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Taking knowledged actions

$$a_t = \arg\max_a Q(s_t, a)$$

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Thank you for your attention!

anssi.kanervisto@uef.fi

Learning from interaction

Current state
s_t

Process the image, produce action to be taken. Action can be currently known optimal, or e.g. random action.

Action (fire)
a_t

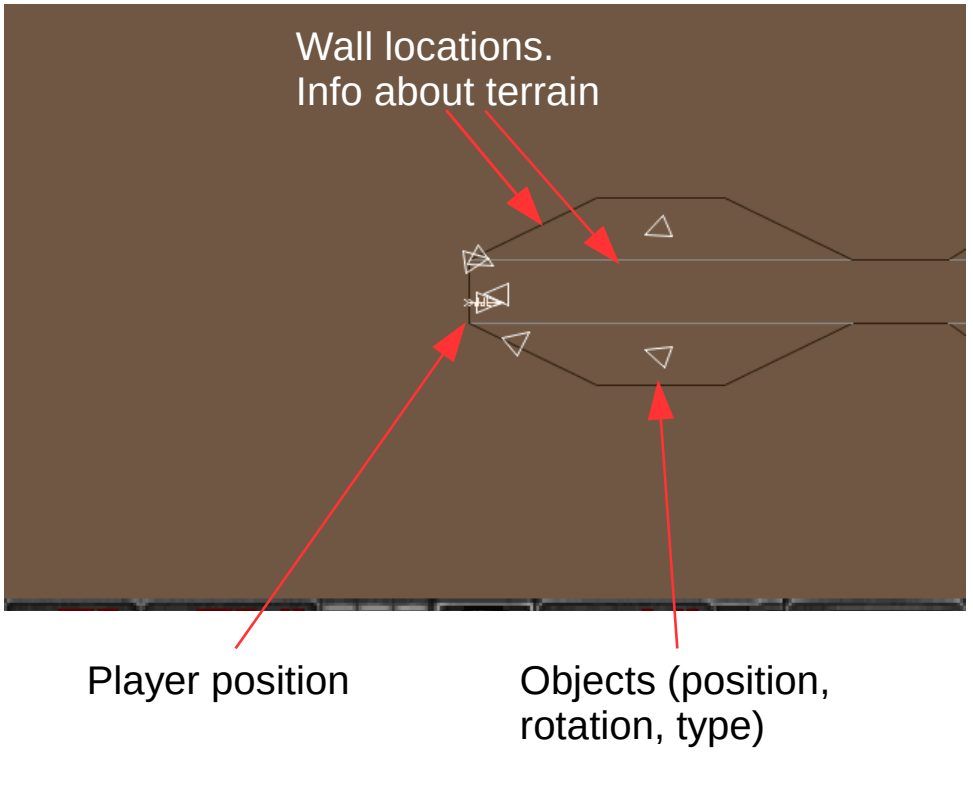
Environment processes the action and moves to next state

Successor state
s_{t+1}
r_t

Proceeding state and the reward obtained.
In this example, agent killed an enemy and thus is reward with positive reward.

Visual input

Instead of giving computer this...



… we give this.

Screen buffer / pixels.
= What human player would see