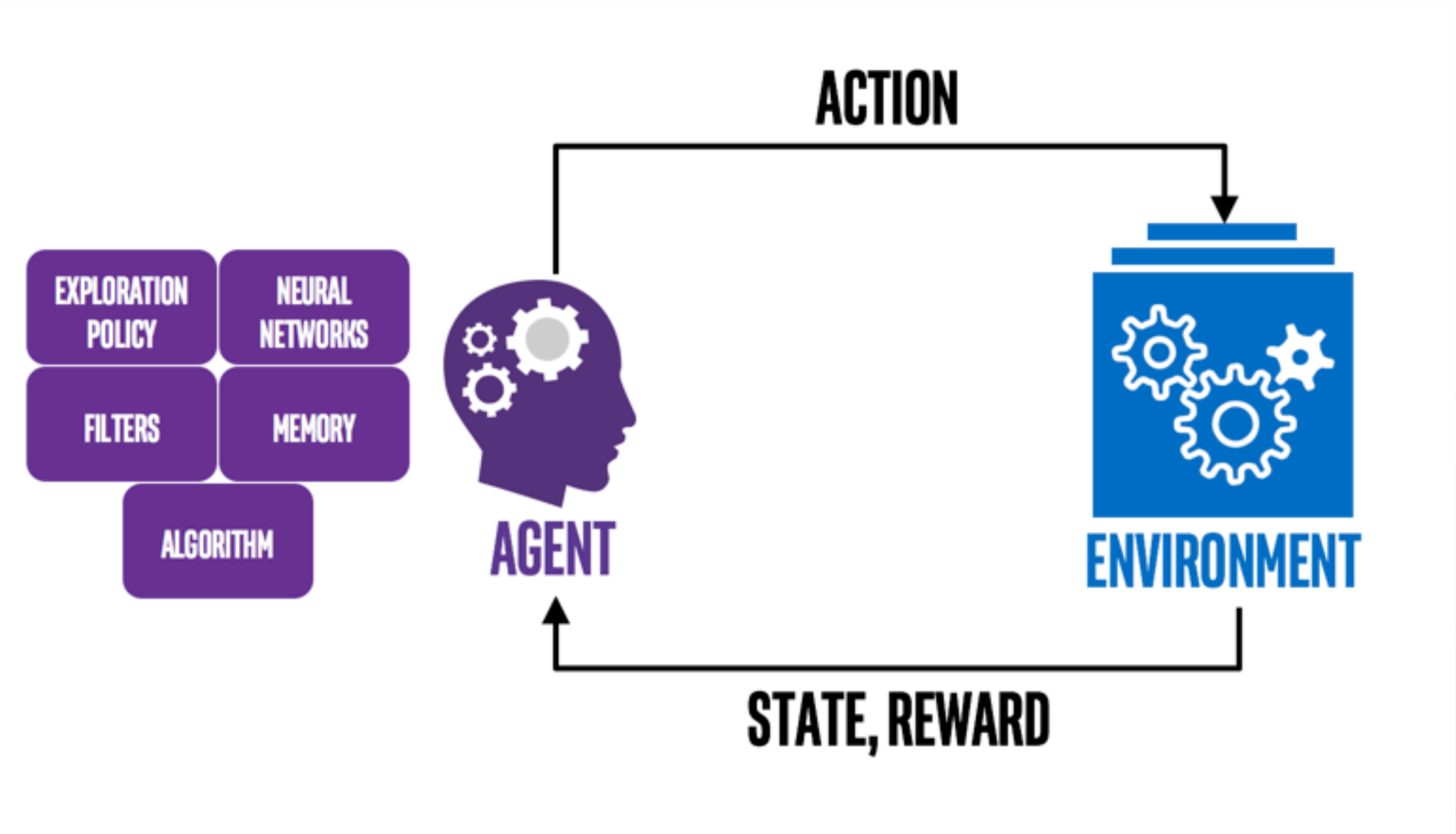
Taken from: https://nervanasystems.github.io/coach/



Seminar: AI for Games 6/15/2019

Human level control through deep reinforcement learning

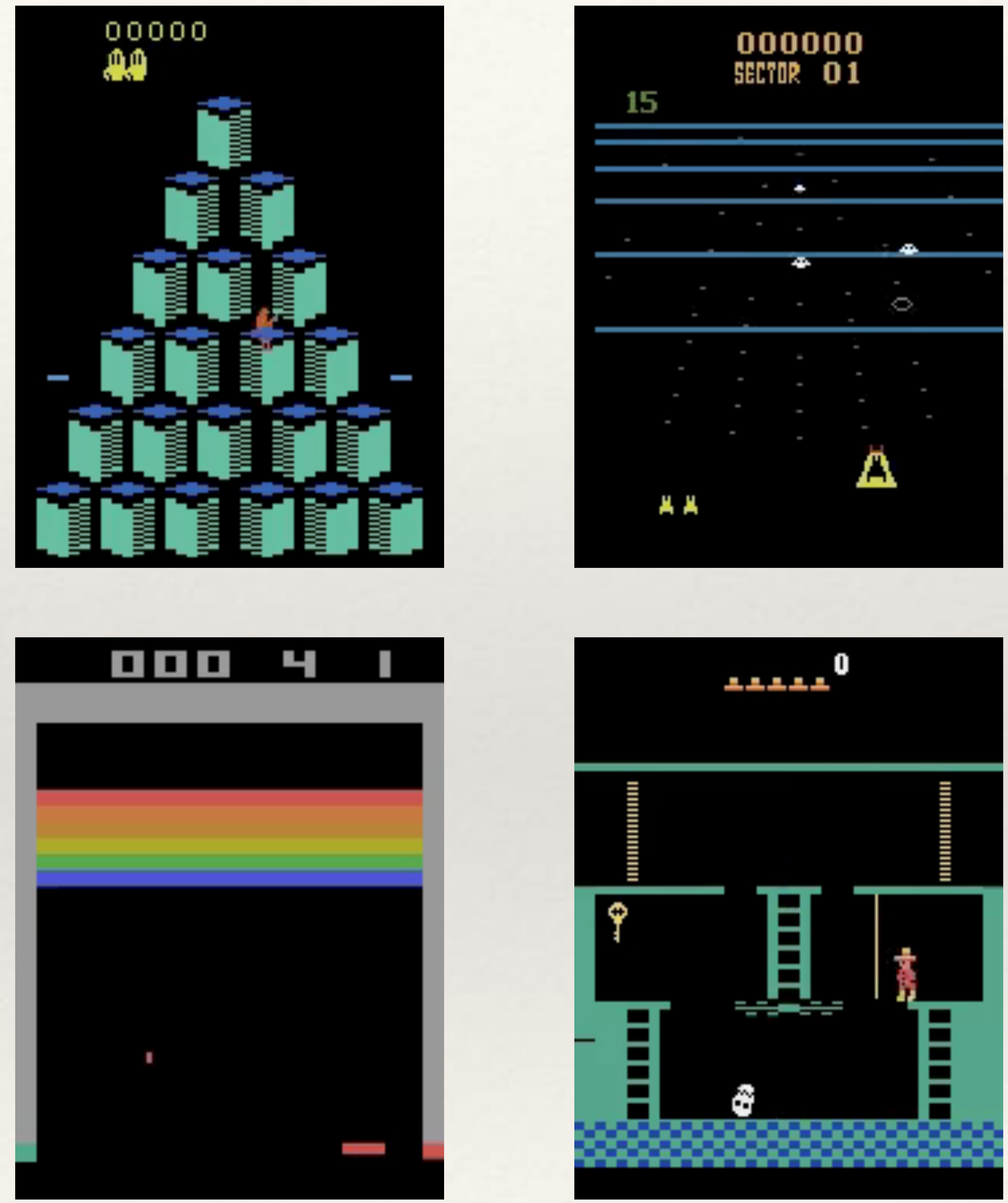
Paper by: V. Mnih, K. Kavukcuoglu, D. Silver et al.
Presented by: Carsten Lüth
Supervisor: Professor U. Köthe

Contents

1. Why do we play video games?

- Humans play to:
  - learn
  - test their abilities
  - compete with each other

- Agents are trained on games:
  - because it is easier, faster and safer than in the real world
  - to benchmark their performance in different environments



ATARI2600 games

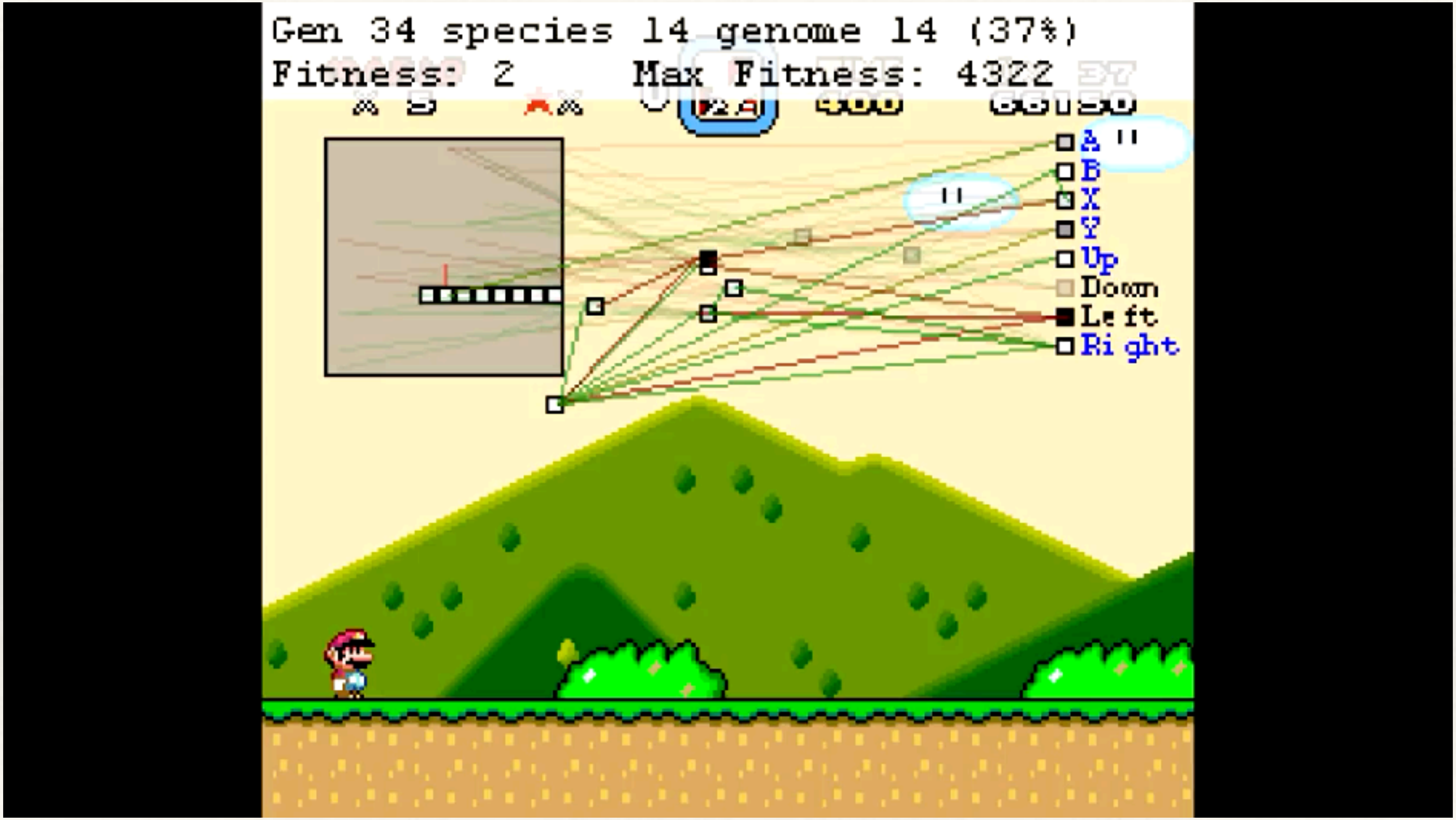
Taken from: https://gym.openai.com/envs/#atari

1. How do we play Video Games?

- Humans:
    1. See and hear the video game
        - ?
    2. interpret the input
        - ?
    3. decide to do something
        - ?

- Agents before DQN:
    1. Get the pixels of the video input
    2. interpret the input
        - derive features from the pixels
            - hand-crafted features
    3. decide to do something
        - linear value functions, policy representations etc.

1. MARI\0 - NEAT



Taken from: https://www.youtube.com/watch?v=qv6UVOQ0F44&t=224s

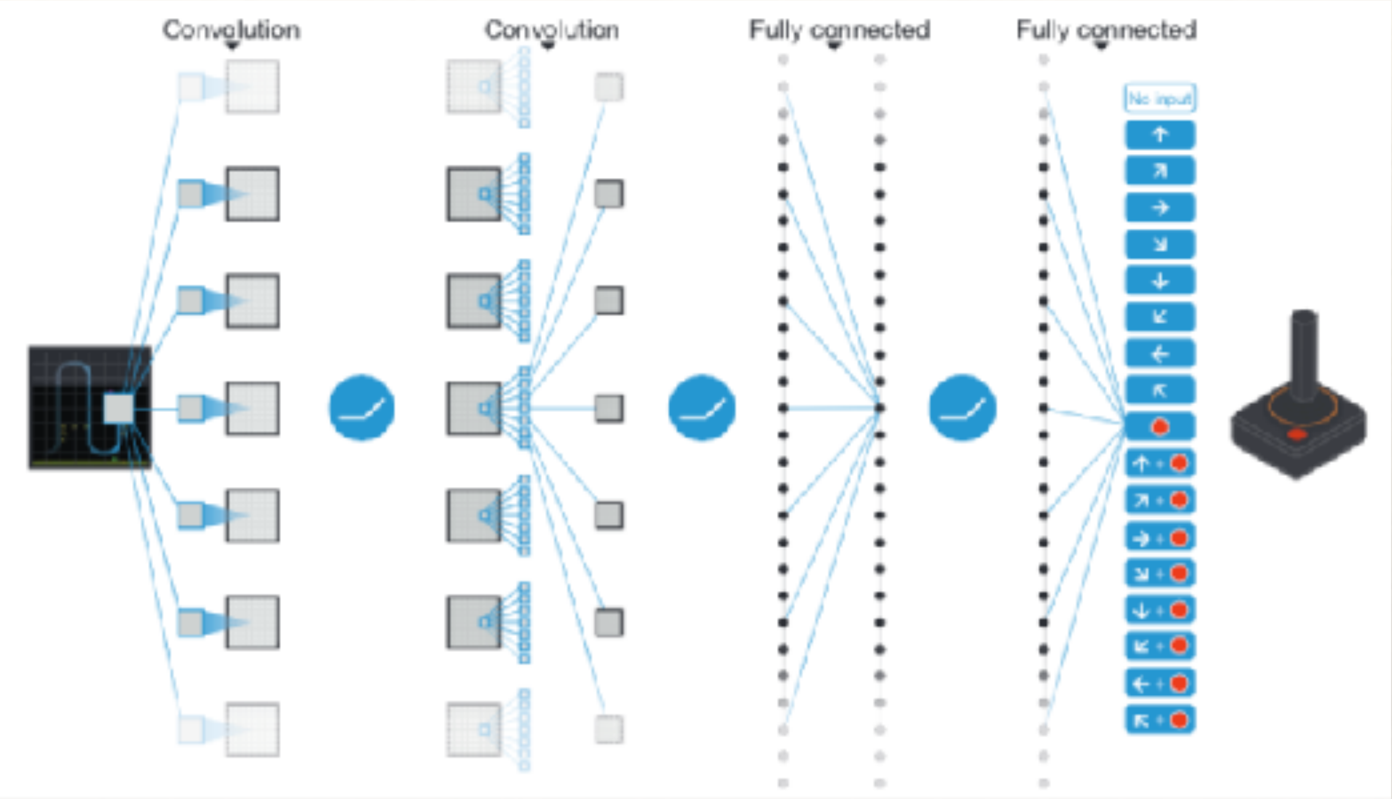
1. Hand-Crafted Features

- Why are they used?
  - Computervision: raw pixels of videos or images are bad features
    - high dimensional, highly correlated
  - distill human knowledge into the agents

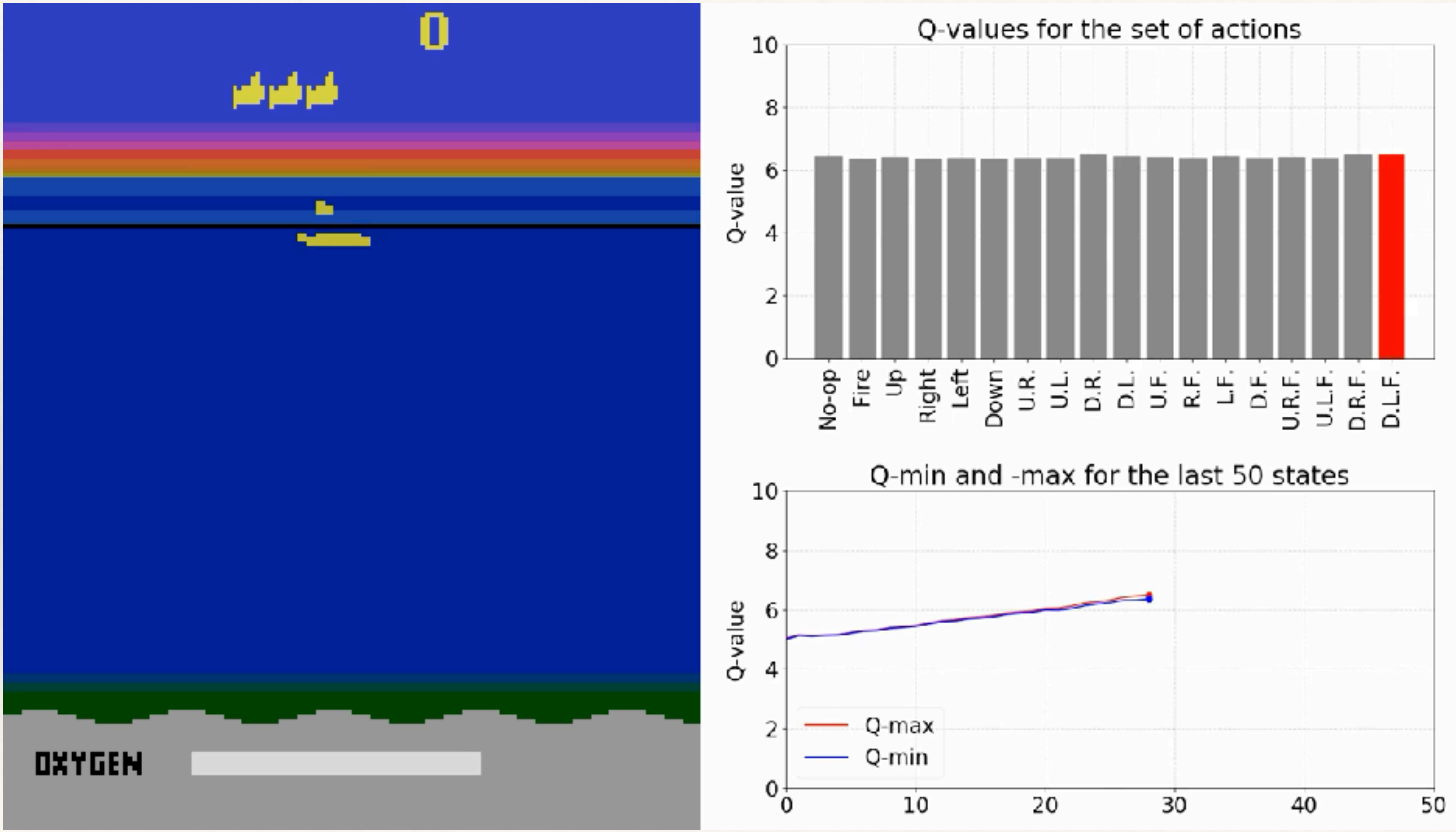
- Problems:
  - costly and often not generalizable from a game like pac-man to Super Mario
  - agents performance is limited by the features

2.A Deep Q Network

- Fundamental Concept:
  - self learning feature maps
    - CNN extracts features
  - features used for a learned Q-function
    - Fully connected network
  - Agent trainable via backpropagation

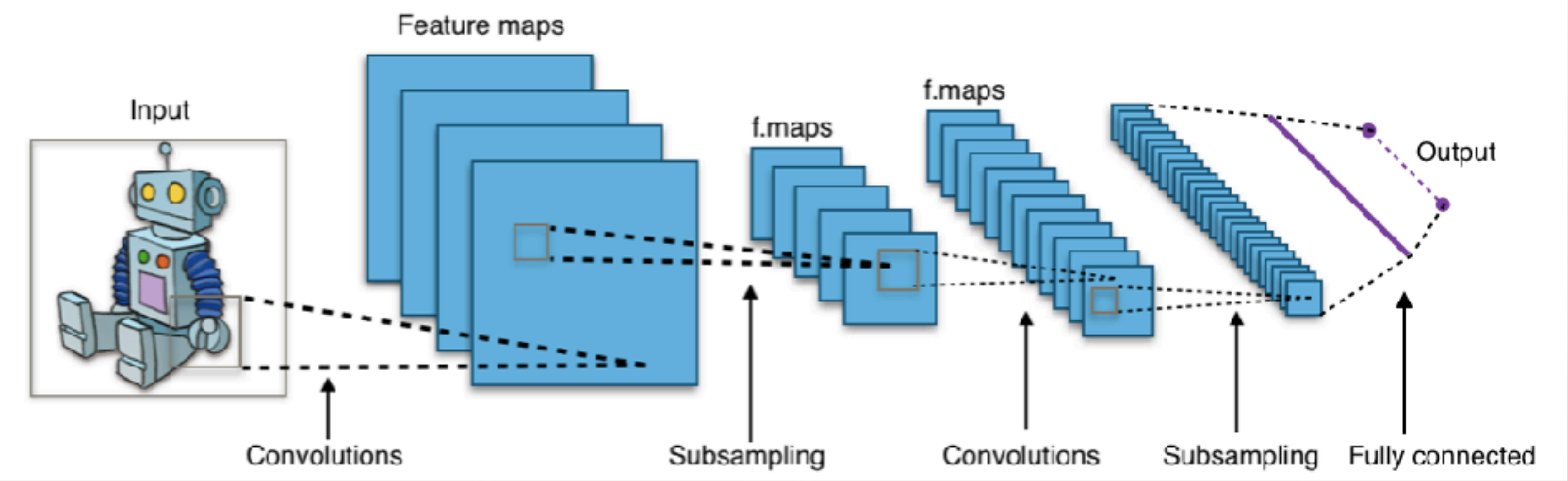


2.A DQN - playing Seaquest



Taken from: https://www.youtube.com/watch?v=XjsY8-P4WHM

2.B Convolutional Neural Network

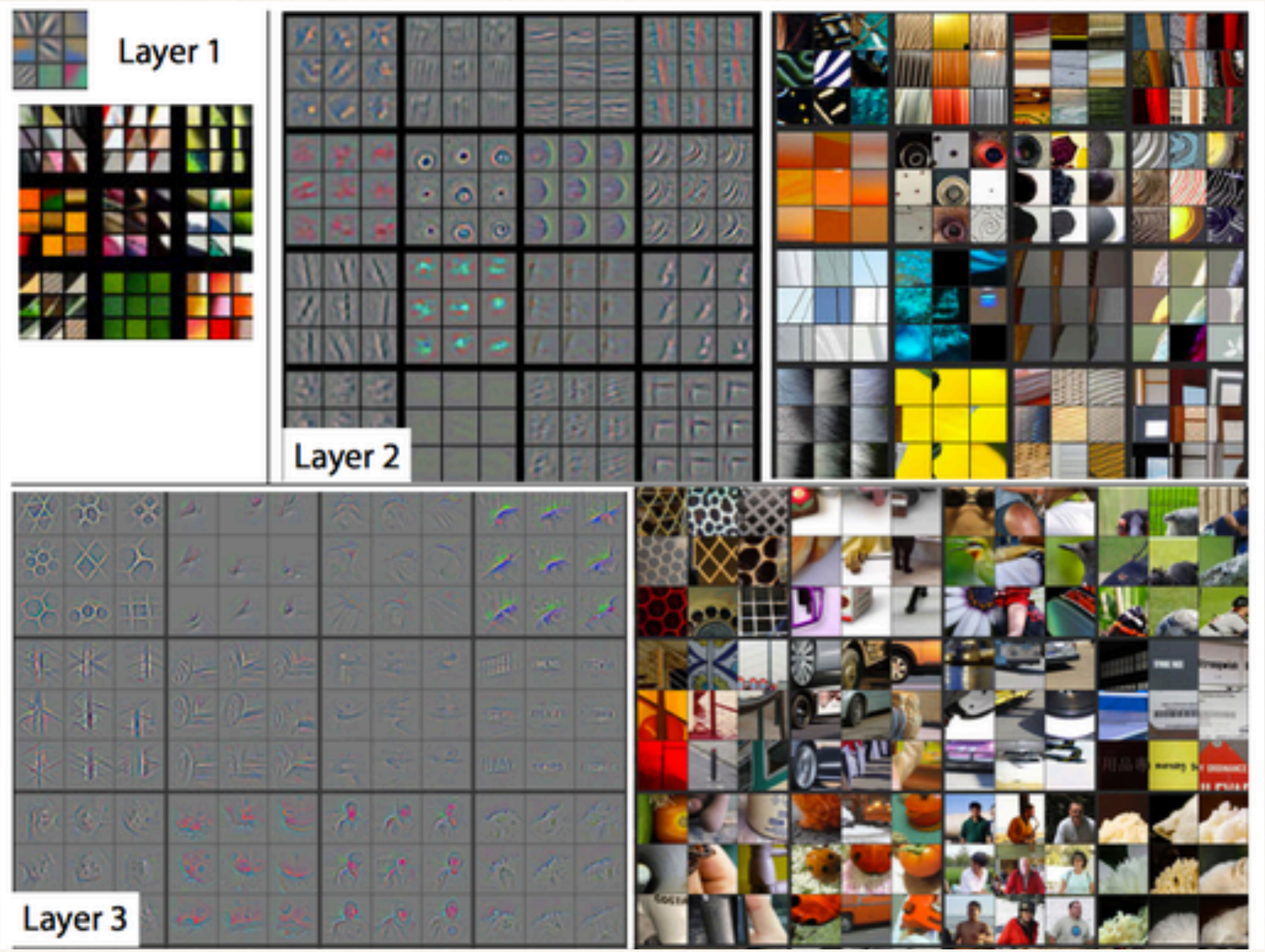


Taken from: https://en.wikipedia.org/wiki/Convolutional_neural_network#/media/File:Typical_cnn.png

- multiple convolutional Layers, each of those Layers uses a filter or kernel to create a new feature-map
- convolutions use the same filters on different locations of the image

2.B Features of a CNN

Taken from: Visualizing and Understanding Convolutional Networks - Matthew D Zeiler, Rob Fergus



Filters of a VGG- Network trained on IMAGENET visualized

2.B Value Function

- Optimal Value function:

$$Q^*(s,a) = \max_{\pi} \mathbb{E}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots \mid s_t = s, a_t = a, \pi]$$

a : Action $\quad r_t$: Reward $\quad \gamma \in (0,1)$: Discount

s : State $\quad \pi = \mathbb{P}(a \mid s)$: Policy

  - maximum expected Reward given any policy, state and action

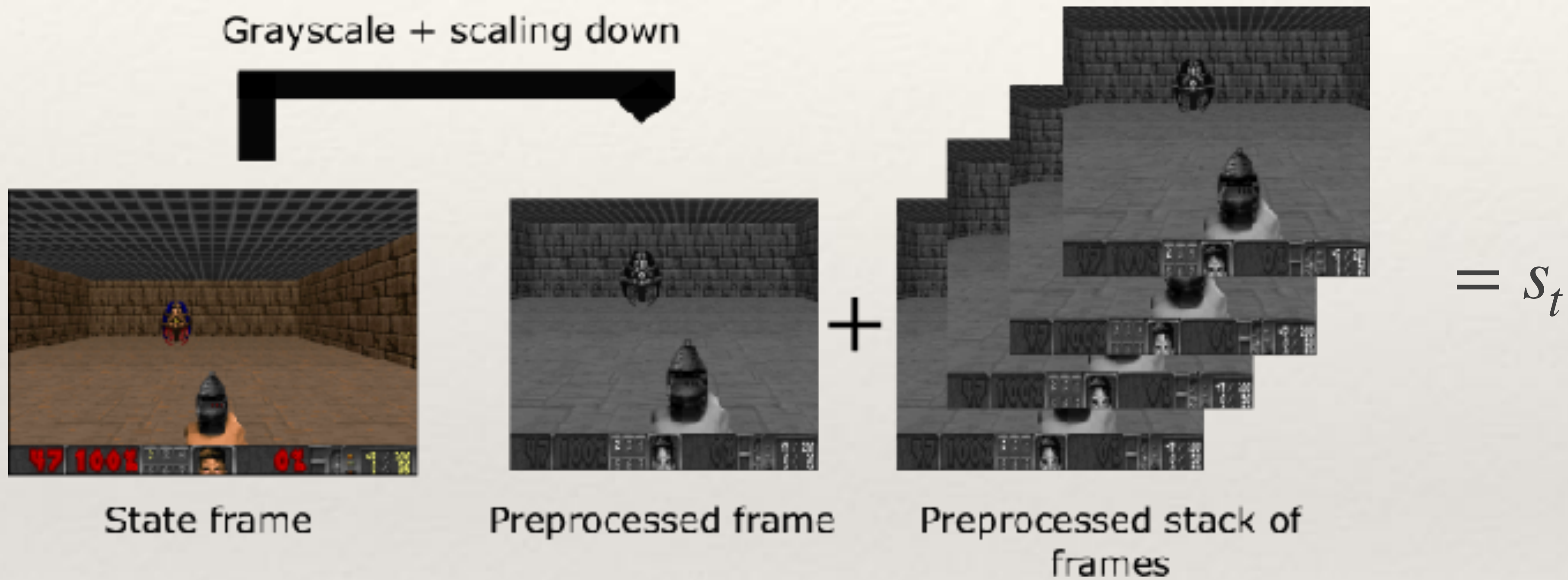
- Q-learning:

$$Q^{i+1}(s_t, a_t) \longleftarrow Q^i(s_t, a_t) + \alpha(r_t + \gamma \max_{a_{t+1}} Q^i(s_{t+1}, a_{t+1}) - Q^i(s_t, a_t))$$

$$Q^i(s,a) \longrightarrow^{i \to \infty} Q^*(s,a)$$

2.B Designing the Input

- The state is a concatentation of consecutive downsampled and grayscaled frames

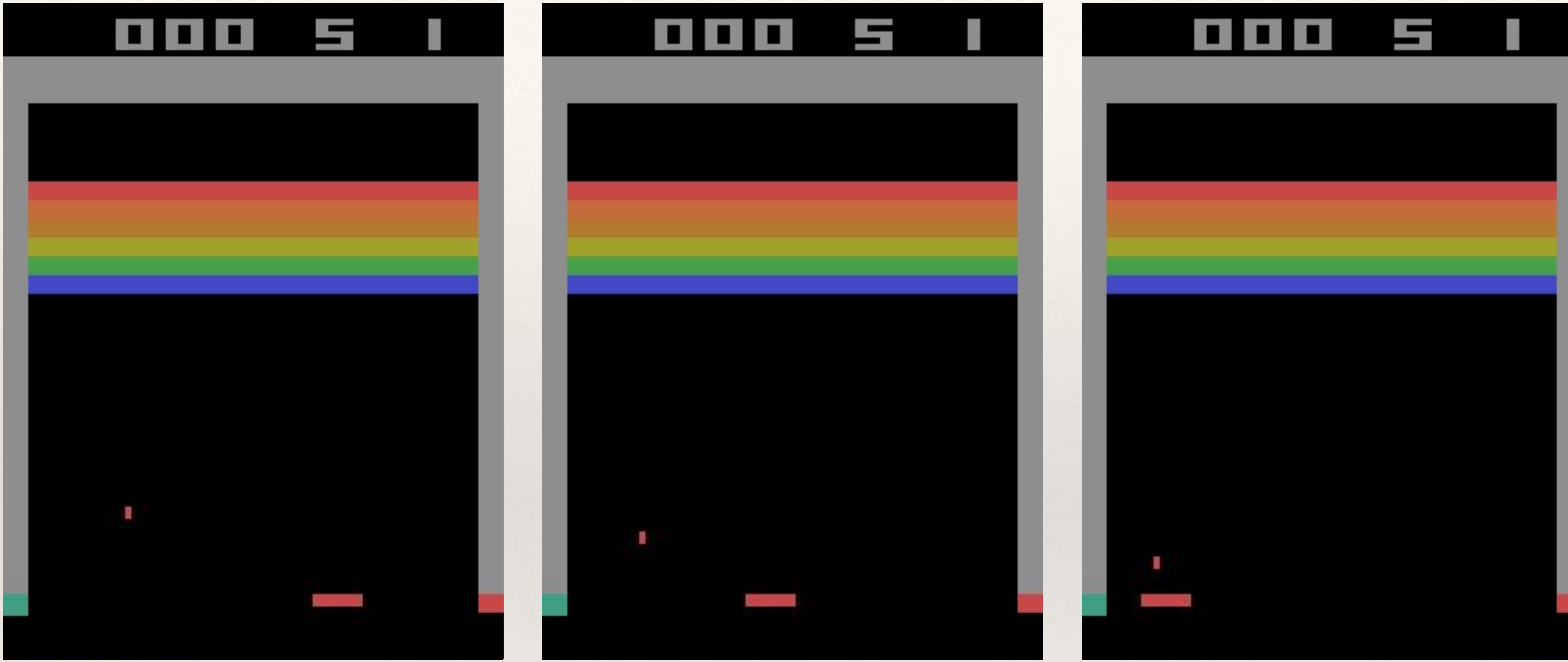


Taken from: https://www.freecodecamp.org/news/an-introduction-to-deep-q-learning-lets-play-doom-54d02d8017d8/

- Reward is the score difference of the ATARI games reached within the frames

$$r_t = \text{Score}_{t+1} - \text{Score}_t$$

2.B State: Concept of Time



Taken from: https://towardsdatascience.com/self-learning-ai-agents-part-ii-deep-q-learning-b5ac60c3f47

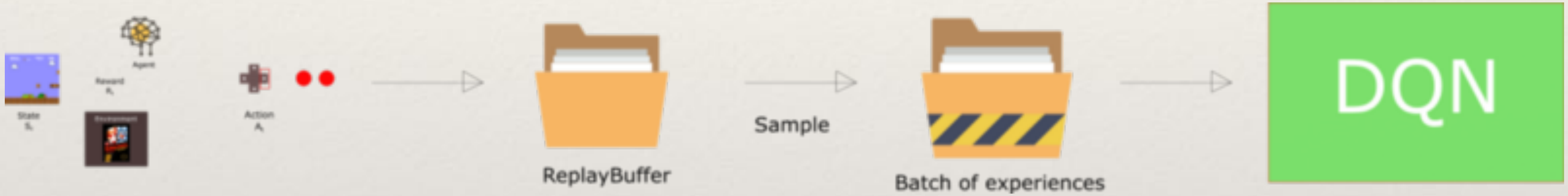
Multiple frames allow the agent to learn a concept of movement and time

s_t : Stack of consecutive frames

2.B Experience Replay

- Intuition:
  - Save past experiences so that the agent can learn from them

Taken from: https://www.freecodecamp.org/news/an-introduction-to-deep-q-learning-lets-play-doom-54d02d8017d8/



$e_t = (s_t, a_t, r_t, s_{t+1})$ $\quad D_t = \{e_1, e_2, e_3, \ldots, e_t\}$ $\quad (s, a, r, s') \sim U(D)$ $\quad$ Q-learning updates

- Benefits:
  - Avoids forgetting previous episodes
  - Reduce correlations between experiences

2.B Experience Replay
Forgetting Previous Episodes

Taken from: https://www.freecodecamp.org/news/an-introduction-to-deep-q-learning-lets-play-doom-54d02d8017d8/

Level 1

Level 2

2.B Training schedule

- Minimization Objective: $\hat{\theta} = \text{argmin}_{\theta}\mathscr{L}(\theta)$
  - Loss:

$$\mathscr{L}(\theta_i) = \mathbb{E}_{(s_t,a_t,r_t,s_{t+1})\sim U(D)}[(r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; \theta_i^-) - Q(s_t, a_t; \theta_i))^2]$$

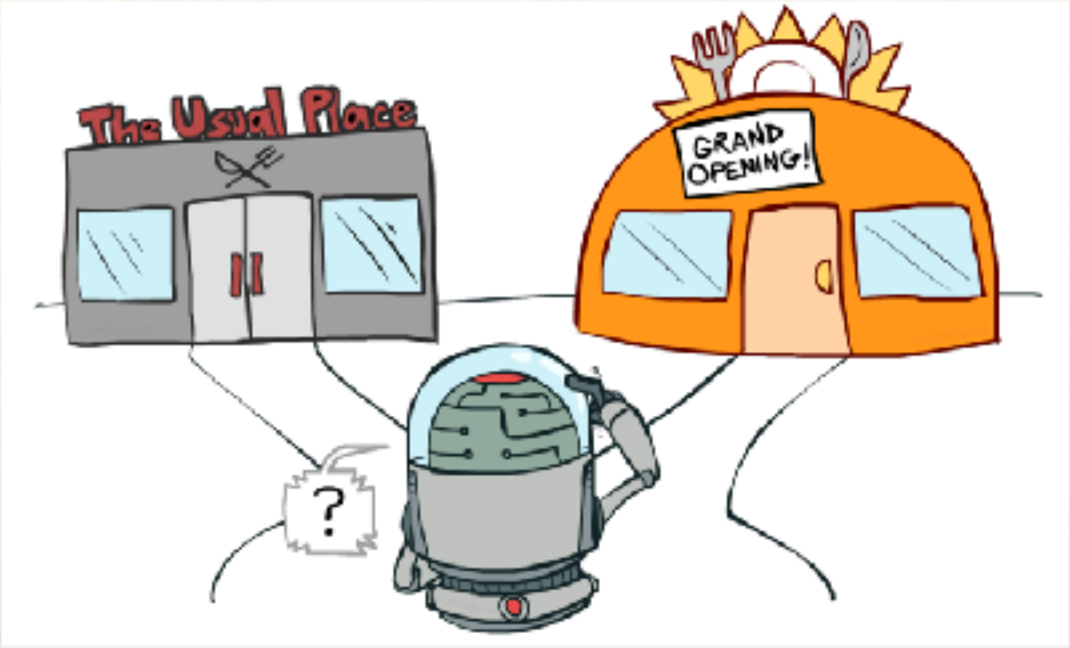
θ_i : Value function (iterative updates) θ_i^- : Target-Value function (periodic updates)

D : Experience Dataset

  - Define 2 value functions with different updates:
    - value function is updated by gradient descent w.r.t. target-value function
    - target value function gets updated periodically every C iterations

      $\theta_C^- = \theta_C$
  - Benefit: training is more stable

2.B Exploration vs. Exploitation



Taken from: https://lilianweng.github.io/lil-log/2018/01/23/the-multi-armed-bandit-problem-and-its-solutions.html

ϵ-Greedy

Describes the probability between exploration and exploitation by going off-policy during training of the agent

$$p(a|s) = \begin{cases} 1 - \epsilon + \epsilon/n & : a = \mathrm{argmax}_{a_0} Q(a_0|s) \\ \epsilon/n & : \mathrm{else} \end{cases}$$

n : # actions
ϵ gets annealed during the training from 1 to 0.1

2.C Algorithm

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N

Initialize action-value function Q with random weights θ

Initialize target action-value function $\hat{Q}$ with weights $\theta^{-} = \theta$

For episode = 1, M **do**

  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$

  For t = 1,T **do**

    With probability ε select a random action a_t

    otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$

Exploration vs. Exploitation

    Execute action a_t in emulator and observe reward r_t and image x_{t+1}

    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$

play

    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D

    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D

    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step } j+1 \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^{-}) & \text{otherwise} \end{cases}$

Experience Replay

    Perform a gradient descent step on $\left(y_j - Q(\phi_j, a_j; \theta)\right)^2$ with respect to the network parameters θ

    Every C steps reset $\hat{Q} = Q$

update Q-function

  End For

End For

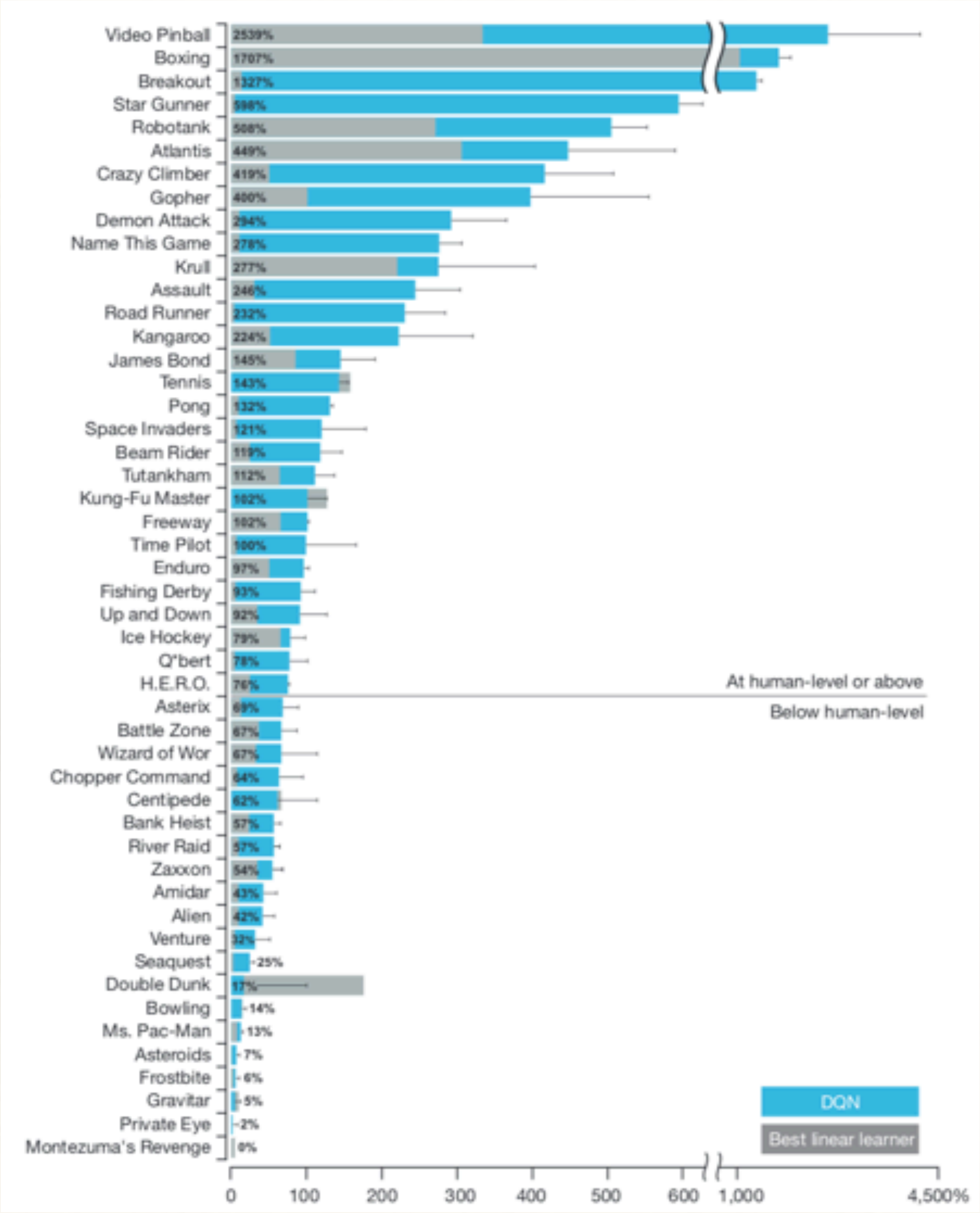
3. Performance on ATARI 2600

- Agents trained on 49 different games

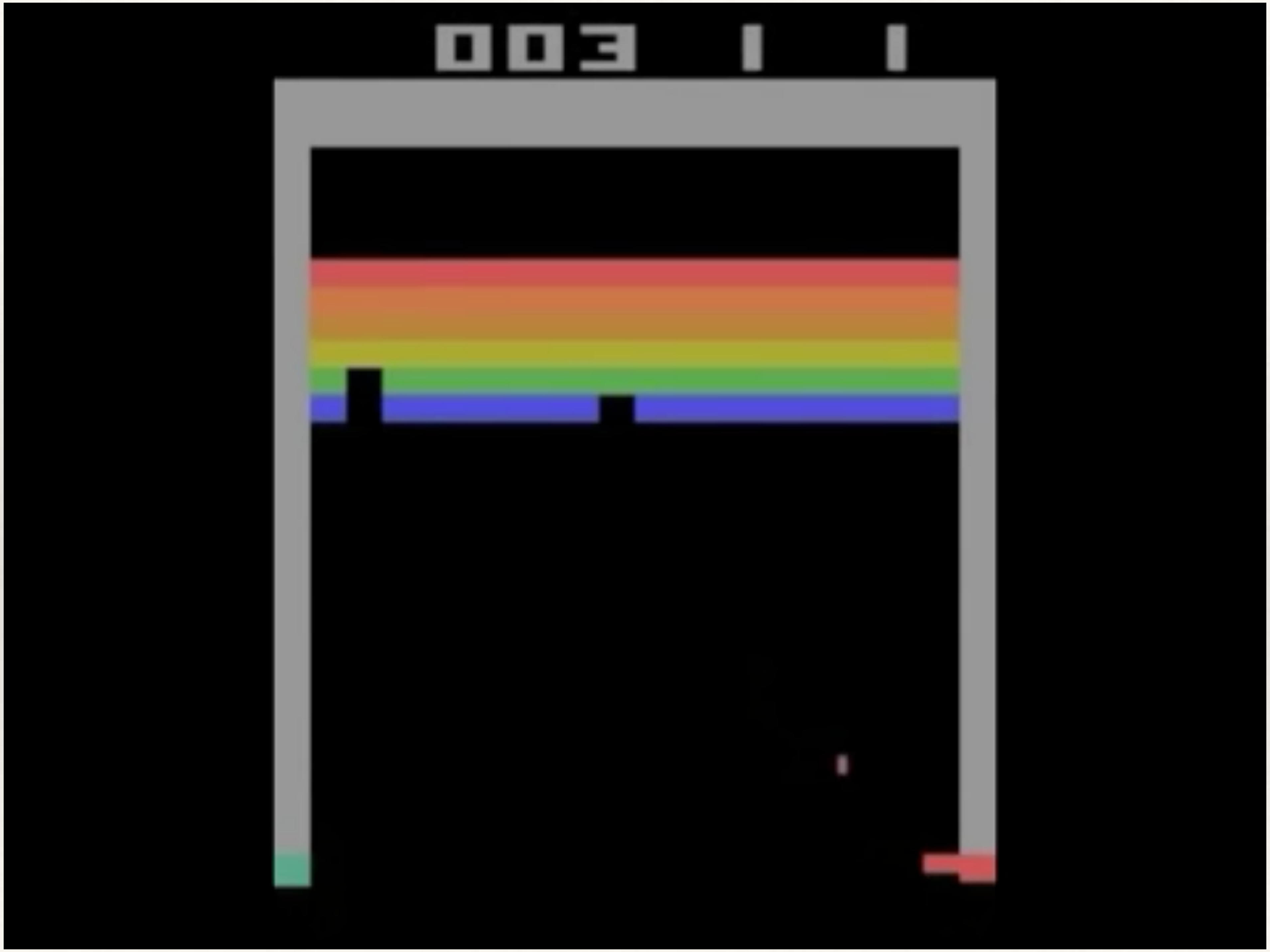
$$\text{Performance} = \frac{R_A - R_R}{R_H - R_R} \cdot 100$$

R_H : human gaming tester score
R_R : random play score
R_A : agent score

- Agents have an action frequency of 10 Hz



3. DQN - playing Breakout



Taken from: https://www.youtube.com/watch?v=TmPfTpjtdgg

4. Discussion

- Pros:
  - generalizes well to different environments
  - learns important features itself
    - minimizes human knowledge
  - outperforms most other algorithms (before 2015) and has the best overall score
- Cons:
  - decision horizon is rather short
  - algorithm learns slower than a human

Sources

- Scientific:
  - Human level control through deep reinforcement learning - V. Mnih, K. Kavukcuoglu, D. Silver et al.
  - Playing Atari with Deep Reinforcement Learning - Volodymyr Mnih, Koray Kavukcuoglu, David Silver et al.
  - Visualizing and Understanding Convolutional Networks - Matthew D Zeiler, Rob Fergus
  - The Arcade Learning Environment: An Evaluation Platform for General Agents - M. G. Bellemare, Y. Naddaf, J. Veness and M. Bowling
  - Further Reading:
    - Rainbow: Combining Improvements in Deep Reinforcement Learning - Ma. Hessel, J. Modayil, H. van Hasselt et al.
    - The bitter lesson - Richard Sutton: http://www.incompleteideas.net/IncIdeas/BitterLesson.html
    - Reinforcement Learning, Fast and Slow - M. Botvinick, Sam Ritter, Jane X. Wang et al.