HackConf 2019

Playing ATARI Games with Deep Reinforcement Learning

Dr. Svetlin Penkov

SCIRO RESEARCH

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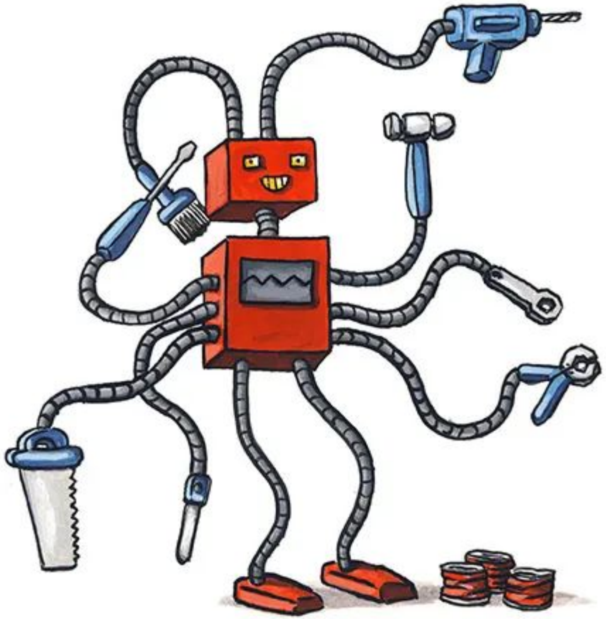
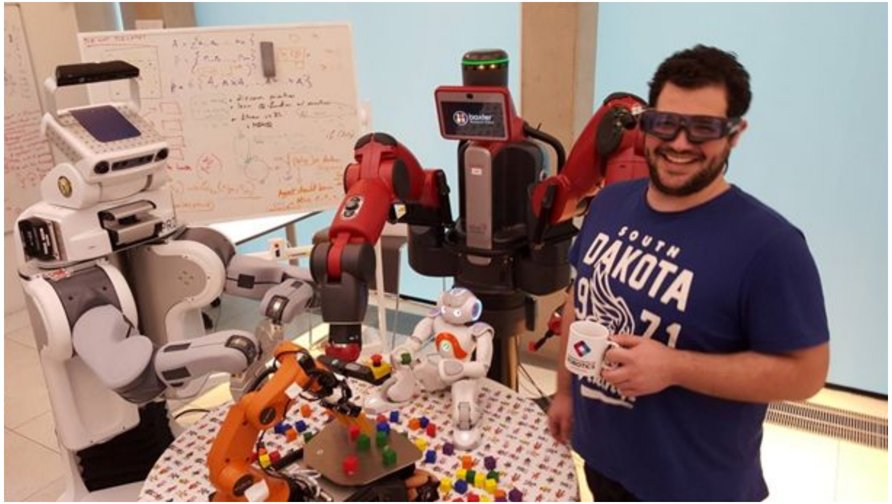
About me

Dreaming about building intelligent robots since the age of 6...



by [Becky Barnicoat]

About me



PhD in Robotics & AI

THE UNIVERSITY of EDINBURGH

FIVE AI

Research Scientist & Team Lead

About me

Robots should learn to program themselves…

- Team of world experts in AI and robotics
- Design, develop and deploy AI based solutions in **challenging domains**
- Research new **state-of-the-art AI methods**

Agenda

www.github.com/svepe/atari-dqn-workshop

10:30 - 11:20	Introduction to RL and OpenAI gym
Break	
11:30 - 12:20	Introduction to deep neural networks and Chainer
Break	
12:30 - 13:20	Implementing a Deep Q-learning Network (DQN) agent to play ATARI games

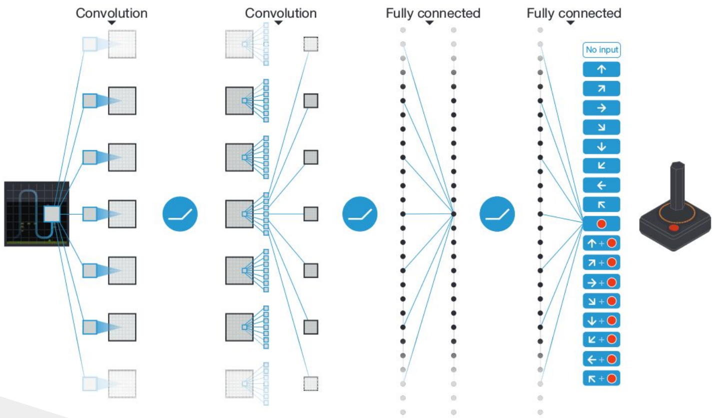
Goal

LETTER

doi:10.1038/nature14236

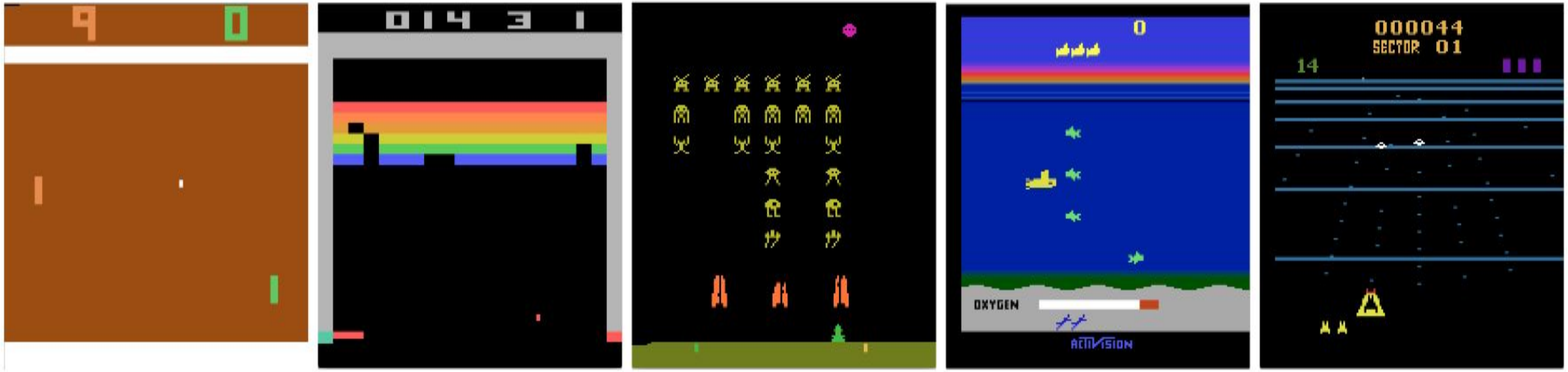
Human-level control through deep reinforcement learning

Volodymyr Mnih[1]*, Koray Kavukcuoglu[1]*, David Silver[1]*, Andrei A. Rusu[1], Joel Veness[1], Marc G. Bellemare[1], Alex Graves[1], Martin Riedmiller[1], Andreas K. Fidjeland[1], Georg Ostrovski[1], Stig Petersen[1], Charles Beattie[1], Amir Sadik[1], Ioannis Antonoglou[1], Helen King[1], Dharshan Kumaran[1], Daan Wierstra[1], Shane Legg[1] & Demis Hassabis[1]

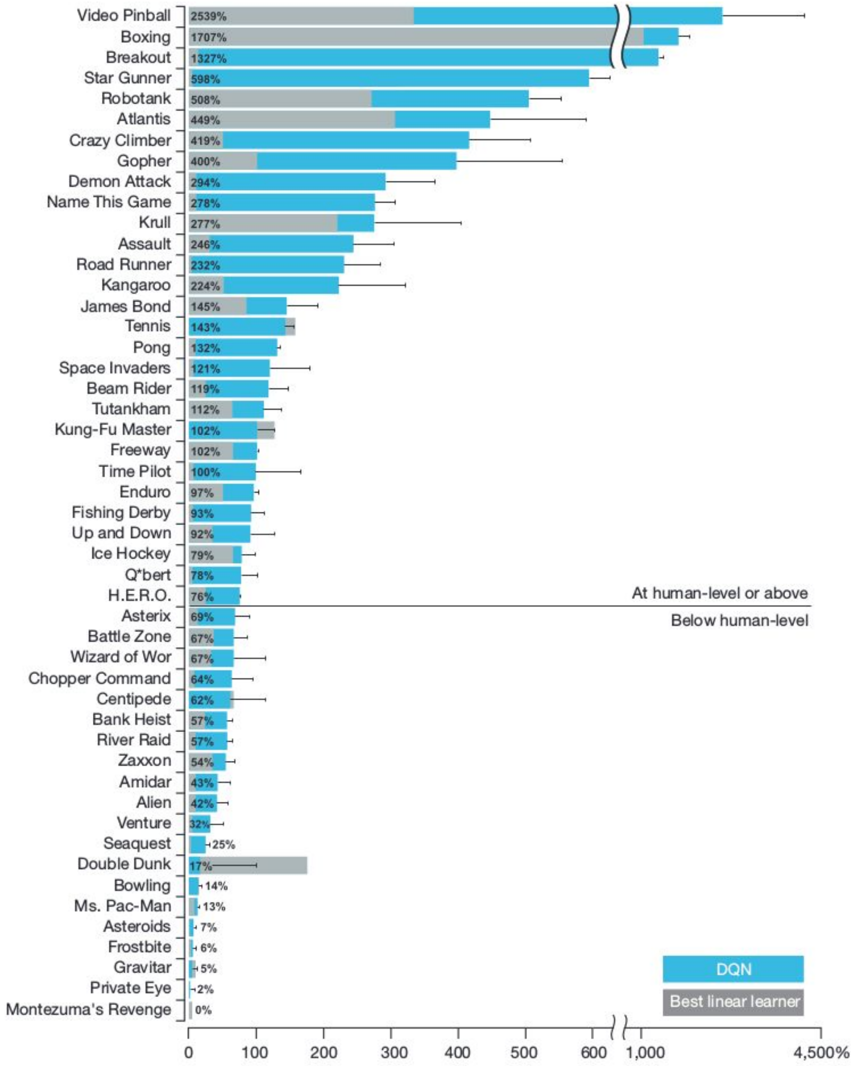


Mnih et al., *Nature*, 2015

Playing ATARI Games

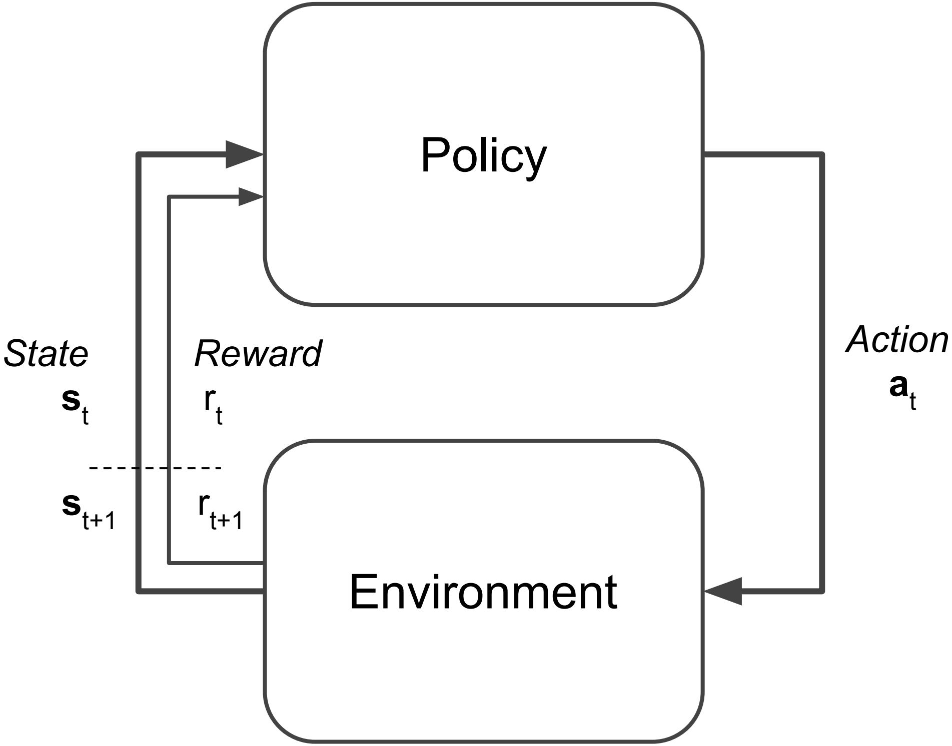


Mnih et al., *Nature*, 2015

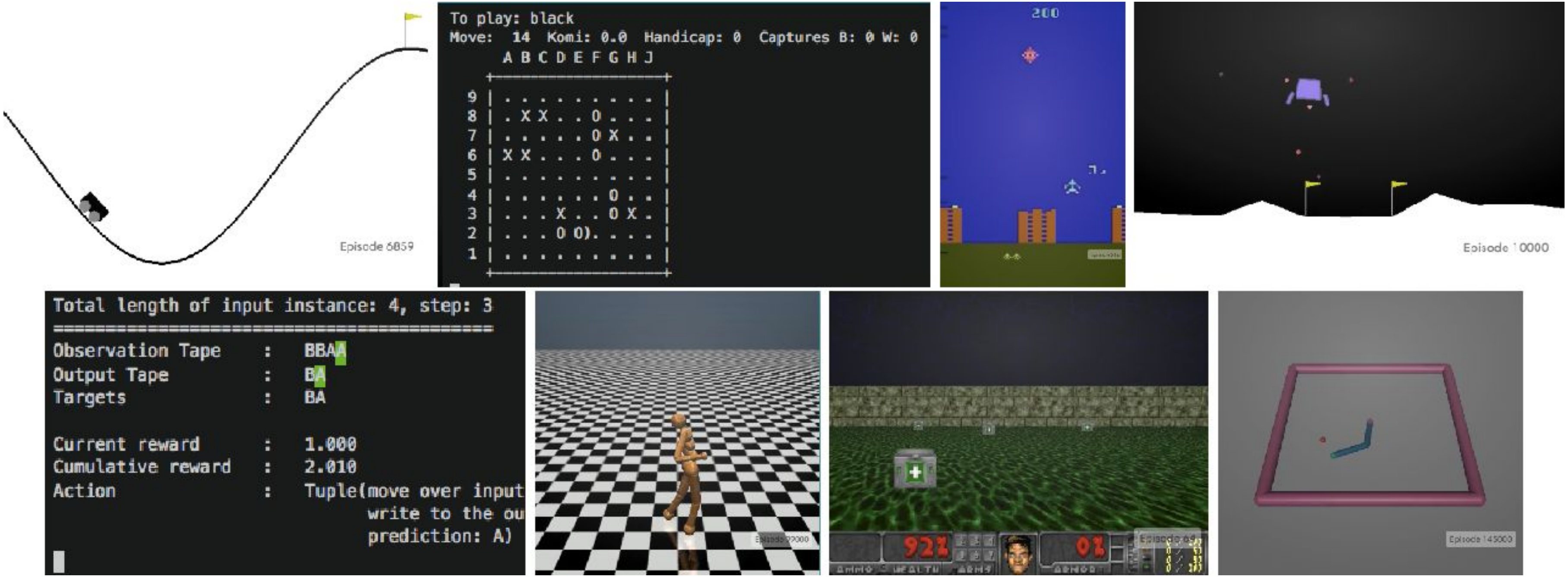


Mnih et al., *Nature*, 2015

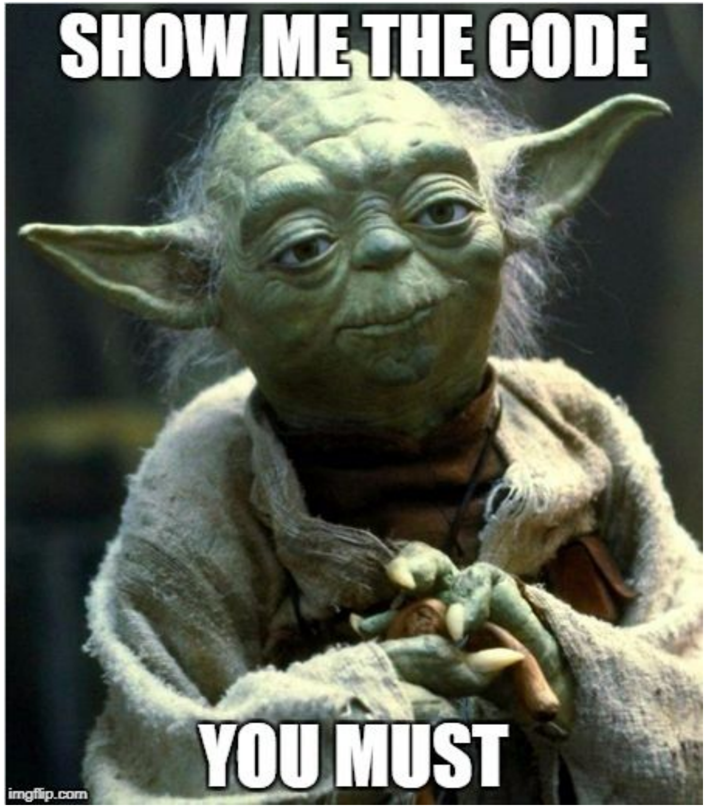
Reinforcement Learning 101



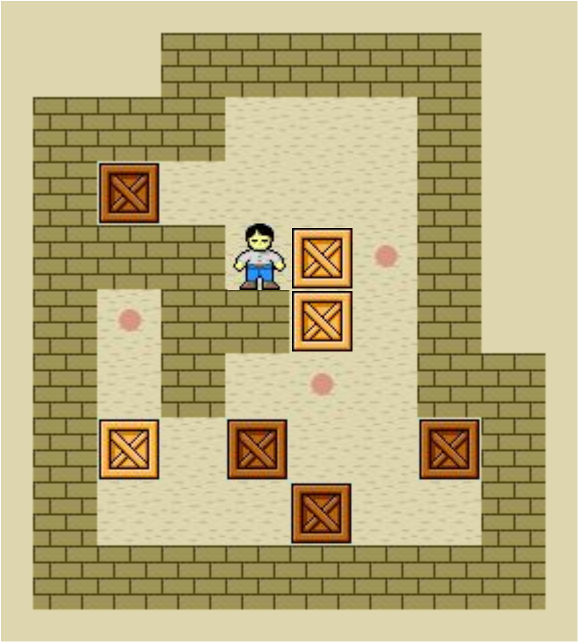
OpenAI Gym


Episode 6859
To play: black
Move: 14 Komi: 0.0 Handicap: 0 Captures B: 0 W: 0
A B C D E F G H J
200
Episode 10000
Total length of input instance: 4, step: 3
Observation Tape : BBAA
Output Tape : BA
Targets : BA
Current reward : 1.000
Cumulative reward : 2.010
Action : Tuple(move over input
write to the ou
prediction: A)

OpenAI Gym

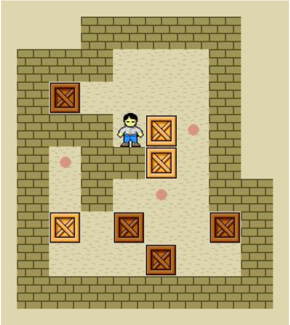


Sokoban Example



Episode 1

$\mathbf{s}_0 \in \mathbf{S}$

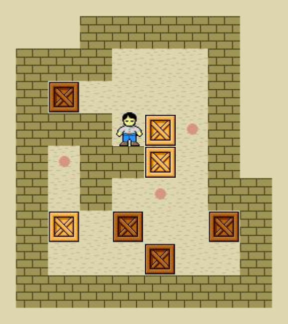


$\mathbf{a}_1 \in \{\mathrm{move}_1, \mathrm{move}_2, \mathrm{move}_3, \mathrm{move}_4\} = \mathbf{A}$

$\mathbf{a}_1 = ? \mid \mathbf{s}_0$

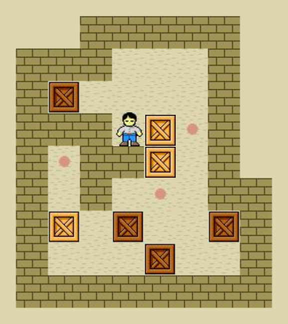
Episode 1

$s_0 \in S$

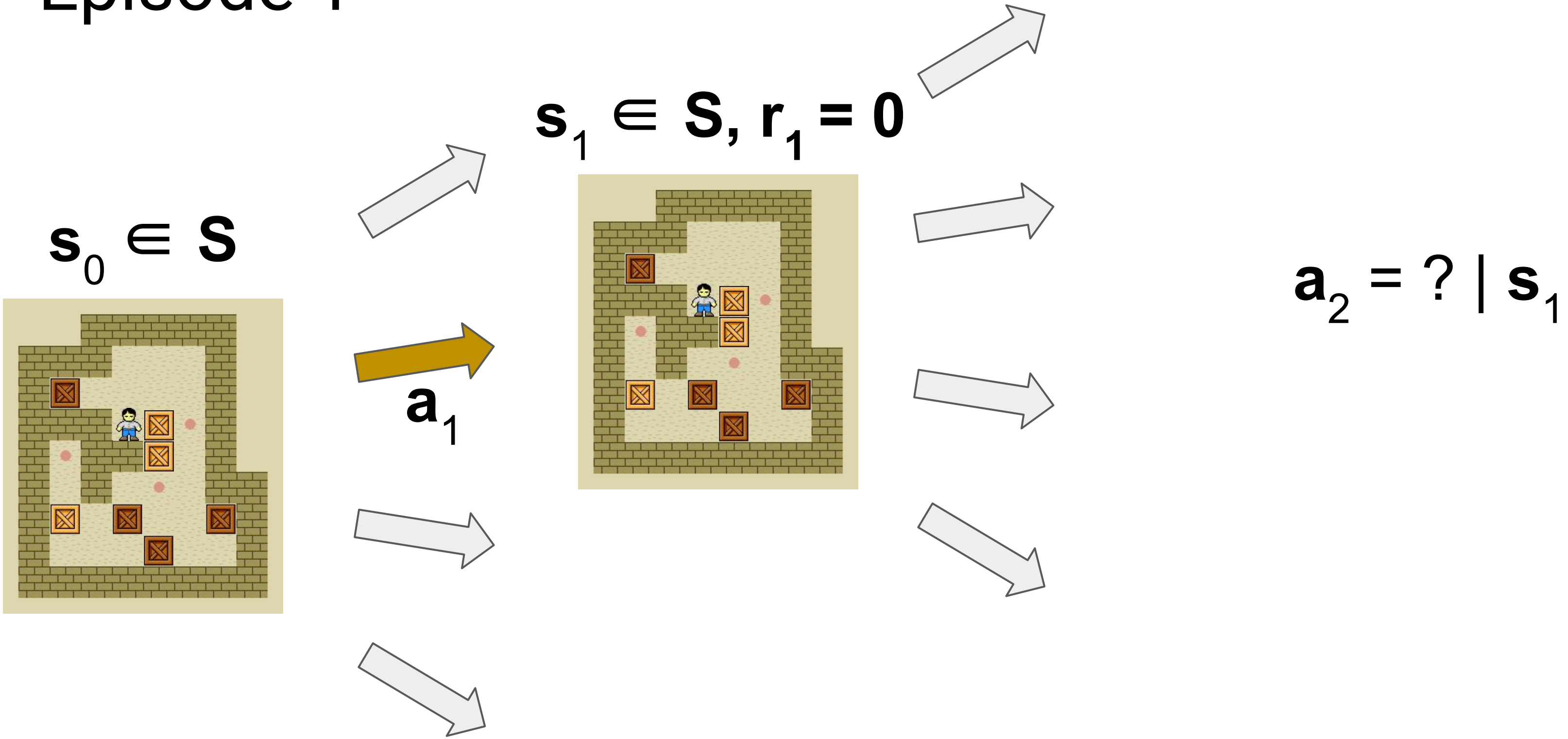


a_1

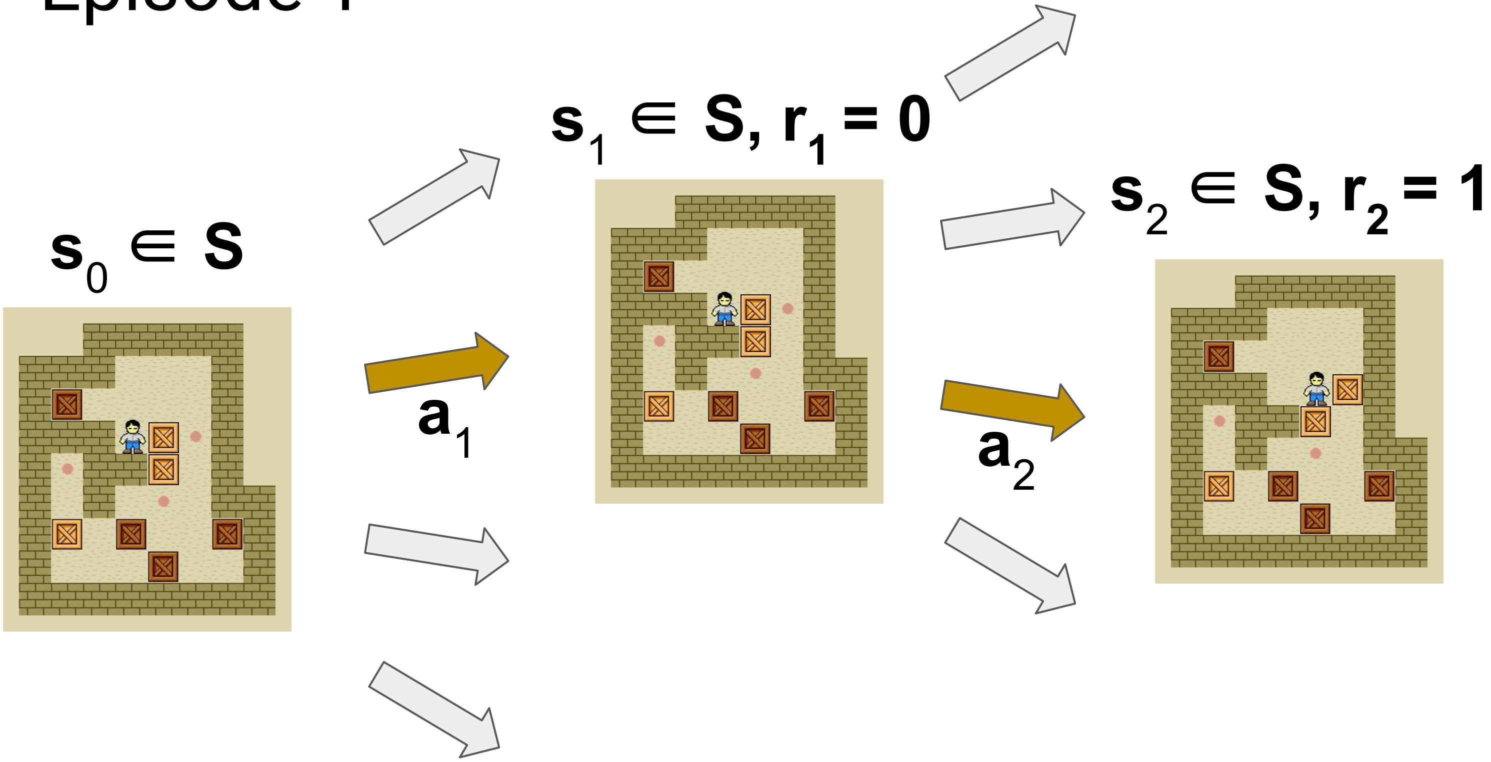
$s_1 \in S, r_1 = 0$



Episode 1



Episode 1



Episode Trace

$$
\begin{array}{ccccccccccccccccccccccc}
\mathbf{s}_0 & \rightarrow & \mathbf{a}_1 & \rightarrow & \mathbf{s}_1 & \rightarrow & \mathbf{a}_2 & \rightarrow & \mathbf{s}_2 & \rightarrow \cdots \rightarrow & \mathbf{a}_t & \rightarrow & \mathbf{s}_t & \rightarrow & \mathbf{a}_{t+1} & \rightarrow & \mathbf{s}_{t+1} & \rightarrow \cdots \rightarrow & \mathbf{a}_T & \rightarrow & \mathbf{s}_T \\
 & & & & r_1 & & & & r_2 & & & & r_t & & & & r_{t+1} & & & & r_T
\end{array}
$$

State Value

$$\mathbf{s}_0 \to \mathbf{a}_1 \to \mathbf{s}_1 \to \mathbf{a}_2 \to \mathbf{s}_2 \to \cdots \to \mathbf{a}_t \to \mathbf{s}_t \to \mathbf{a}_{t+1} \to \mathbf{s}_{t+1} \to \cdots \to \mathbf{a}_T \to \mathbf{s}_T$$

$$r_1 \qquad r_2 \qquad r_t \qquad r_{t+1} \qquad r_T$$

$$\mathbf{V}(\mathbf{s}_t) = r_t + r_{t+1} + r_{t+2} + \cdots + r_T$$

Discounted State Value

$$\mathbf{s}_0 \rightarrow \mathbf{a}_1 \rightarrow \mathbf{s}_1 \rightarrow \mathbf{a}_2 \rightarrow \mathbf{s}_2 \rightarrow \cdots \rightarrow \mathbf{a}_t \rightarrow \mathbf{s}_t \rightarrow \mathbf{a}_{t+1} \rightarrow \mathbf{s}_{t+1} \rightarrow \cdots \rightarrow \mathbf{a}_T \rightarrow \mathbf{s}_T$$

$$r_1 \qquad r_2 \qquad r_t \qquad r_{t+1} \qquad r_T$$

$$\mathbf{V}(\mathbf{s}_t) = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} \cdots + \gamma^{T-t} r_T$$

$\gamma \in [0, 1)$ - discount factor

RL Objective

$$\mathbf{s}_0 \rightarrow \mathbf{a}_1 \rightarrow \mathbf{s}_1 \rightarrow \mathbf{a}_2 \rightarrow \mathbf{s}_2 \rightarrow \cdots \rightarrow \mathbf{a}_t \rightarrow \mathbf{s}_t \rightarrow \mathbf{a}_{t+1} \rightarrow \mathbf{s}_{t+1} \rightarrow \cdots \rightarrow \mathbf{a}_T \rightarrow \mathbf{s}_T$$

$$r_1 \qquad r_2 \qquad r_t \qquad r_{t+1} \qquad r_T$$

Choose $\mathbf{a}_1, \mathbf{a}_2 \ldots, \mathbf{a}_T$ such that we maximise

$$\mathbf{V}(\mathbf{s}_1) = r_1 + \gamma r_2 + \gamma^2 r_3 \cdots + \gamma^T r_T$$

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Temporal Difference (TD-learning)

$$\mathbf{s}_0 \rightarrow \mathbf{a}_1 \rightarrow \mathbf{s}_1 \rightarrow \mathbf{a}_2 \rightarrow \mathbf{s}_2 \rightarrow \cdots \rightarrow \mathbf{a}_t \rightarrow \mathbf{s}_t \rightarrow \mathbf{a}_{t+1} \rightarrow \mathbf{s}_{t+1} \rightarrow \cdots \rightarrow \mathbf{a}_T \rightarrow \mathbf{s}_T$$

$$r_1 \quad r_2 \quad r_t \quad r_{t+1} \quad r_T$$

$$\mathbf{V}(\mathbf{s}_1) = r_1 + \gamma r_2 + \gamma^2 r_3 \cdots + \gamma^T r_T$$

$$= r_1 + \gamma (r_2 + \gamma^1 r_3 \cdots + \gamma^{T-1} r_T)$$

$$= r_1 + \gamma \mathbf{V}(\mathbf{s}_2)$$

Temporal Difference (TD-learning)

$$\mathbf{s}_0 \rightarrow \mathbf{a}_1 \rightarrow \mathbf{s}_1 \rightarrow \mathbf{a}_2 \rightarrow \mathbf{s}_2 \rightarrow \cdots \rightarrow \mathbf{a}_t \rightarrow \mathbf{s}_t \rightarrow \mathbf{a}_{t+1} \rightarrow \mathbf{s}_{t+1} \rightarrow \cdots \rightarrow \mathbf{a}_T \rightarrow \mathbf{s}_T$$

$$r_1 \qquad r_2 \qquad r_t \qquad r_{t+1} \qquad r_T$$

$$\mathbf{V}(\mathbf{s}_1) = r_1 + \gamma \mathbf{V}(\mathbf{s}_2)$$

$$\Downarrow$$

$$r_1 + \gamma \mathbf{V}(\mathbf{s}_2) - \mathbf{V}(\mathbf{s}_1) = 0$$

Temporal Difference (TD-learning)

$$\mathbf{s}_0 \rightarrow \mathbf{a}_1 \rightarrow \mathbf{s}_1 \rightarrow \mathbf{a}_2 \rightarrow \mathbf{s}_2 \rightarrow \cdots \rightarrow \mathbf{a}_t \rightarrow \mathbf{s}_t \rightarrow \mathbf{a}_{t+1} \rightarrow \mathbf{s}_{t+1} \rightarrow \cdots \rightarrow \mathbf{a}_T \rightarrow \mathbf{s}_T$$

$$r_1 \quad r_2 \quad r_t \quad r_{t+1} \quad r_T$$

$$\mathbf{V}(\mathbf{s}_t) = r_t + \gamma \mathbf{V}(\mathbf{s}_{t+1})$$

$$\Downarrow$$

$$r_t + \gamma \mathbf{V}(\mathbf{s}_{t+1}) - \mathbf{V}(\mathbf{s}_t) = 0$$

Temporal Difference (TD-learning)

$$\mathbf{s}_0 \rightarrow \mathbf{a}_1 \rightarrow \mathbf{s}_1 \rightarrow \mathbf{a}_2 \rightarrow \mathbf{s}_2 \rightarrow \cdots \rightarrow \mathbf{a}_t \rightarrow \mathbf{s}_t \rightarrow \mathbf{a}_{t+1} \rightarrow \mathbf{s}_{t+1} \rightarrow \cdots \rightarrow \mathbf{a}_T \rightarrow \mathbf{s}_T$$

$$r_1 \quad r_2 \quad r_t \quad r_{t+1} \quad r_T$$

$$r_t + \gamma \mathbf{V}(\mathbf{s}_{t+1}) - \mathbf{V}(\mathbf{s}_t) = 0 \quad \text{for any} \quad (\mathbf{s}_t, r_t, \mathbf{s}_{t+1})$$

Choose $\mathbf{a}_1$, $\mathbf{a}_2$..., $\mathbf{a}_T$ such that… but how?

Action Value Function (Q-value)

$$\mathbf{s}_0 \rightarrow \mathbf{a}_1 \rightarrow \mathbf{s}_1 \rightarrow \mathbf{a}_2 \rightarrow \mathbf{s}_2 \rightarrow \cdots \rightarrow \mathbf{a}_t \rightarrow \mathbf{s}_t \rightarrow \mathbf{a}_{t+1} \rightarrow \mathbf{s}_{t+1} \rightarrow \cdots \rightarrow \mathbf{a}_T \rightarrow \mathbf{s}_T$$

$$r_1 \quad r_2 \quad r_t \quad r_{t+1} \quad r_T$$

Q(**s**, **a**) - the value of choosing **a** in state **s**

a* = argmax$_{\mathbf{a}}$ Q(**s**, **a**) - the best action in state **s**

Action Value Function (Q-value)

$$\mathbf{s}_0 \rightarrow \mathbf{a}_1 \rightarrow \mathbf{s}_1 \rightarrow \mathbf{a}_2 \rightarrow \mathbf{s}_2 \rightarrow \cdots \rightarrow \mathbf{a}_t \rightarrow \mathbf{s}_t \rightarrow \mathbf{a}_{t+1} \rightarrow \mathbf{s}_{t+1} \rightarrow \cdots \rightarrow \mathbf{a}_T \rightarrow \mathbf{s}_T$$

$$r_1 \quad r_2 \quad r_t \quad r_{t+1} \quad r_T$$

$$\mathbf{V}(\mathbf{s}) = \max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}, \mathbf{a})$$

$$r_t + \gamma \mathbf{V}(\mathbf{s}_{t+1}) - \mathbf{V}(\mathbf{s}_t) = 0 \quad \text{for all} \quad (\mathbf{s}_t, r_t, \mathbf{s}_{t+1})$$

Action Value Function (Q-value)

$$\mathbf{s}_0 \rightarrow \mathbf{a}_1 \rightarrow \mathbf{s}_1 \rightarrow \mathbf{a}_2 \rightarrow \mathbf{s}_2 \rightarrow \cdots \rightarrow \mathbf{a}_t \rightarrow \mathbf{s}_t \rightarrow \mathbf{a}_{t+1} \rightarrow \mathbf{s}_{t+1} \rightarrow \cdots \rightarrow \mathbf{a}_T \rightarrow \mathbf{s}_T$$

$$r_1 \quad r_2 \quad r_t \quad r_{t+1} \quad r_T$$

$$\mathbf{V}(\mathbf{s}) = \max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}, \mathbf{a})$$

$$r_t + \gamma \max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}_{t+1}, \mathbf{a}) - \max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}_t, \mathbf{a}) = 0 \quad \text{for all} \quad (\mathbf{s}_t, r_t, \mathbf{s}_{t+1})$$

Action Value Function (Q-value)

$$\mathbf{s}_0 \rightarrow \mathbf{a}_1 \rightarrow \mathbf{s}_1 \rightarrow \mathbf{a}_2 \rightarrow \mathbf{s}_2 \rightarrow \cdots \rightarrow \mathbf{a}_t \rightarrow \mathbf{s}_t \rightarrow \mathbf{a}_{t+1} \rightarrow \mathbf{s}_{t+1} \rightarrow \cdots \rightarrow \mathbf{a}_T \rightarrow \mathbf{s}_T$$

$$r_1 \quad r_2 \quad r_t \quad r_{t+1} \quad r_T$$

$$r_t + \gamma \max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}_{t+1}, \mathbf{a}) - \boxed{\max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}_t, \mathbf{a})} = 0 \quad \text{for all} \quad (\mathbf{s}_t, r_t, \mathbf{s}_{t+1})$$

Find the best action $\mathbf{a}_t$ for state $\mathbf{s}_t$

Q-learning

$$r_t + \gamma \max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}_{t+1}, \mathbf{a}) - \mathbf{Q}(\mathbf{s}_t, \mathbf{a}_t) = 0 \quad \text{for all} \quad (\mathbf{s}_t, \mathbf{a}_t, r_t, \mathbf{s}_{t+1})$$

Q-learning (annoying details)

$$r_t + \boxed{\gamma \max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}_{t+1}, \mathbf{a})} - \mathbf{Q}(\mathbf{s}_t, \mathbf{a}_t) = 0 \quad \text{for all} \quad (\mathbf{s}_t, \mathbf{a}_t, r_t, \mathbf{s}_{t+1})$$

If $\mathbf{s}_t$ is terminal there is no $\mathbf{s}_{t+1}$

Q-learning

$$y_t - \mathbf{Q}(\mathbf{s}_t, \mathbf{a}_t) = 0 \quad \text{for all} \quad (\mathbf{s}_t, \mathbf{a}_t, r_t, \mathbf{s}_{t+1})$$

$$y_t = \begin{cases} r_t + \gamma \max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}_{t+1}, \mathbf{a}) & \text{if } \mathbf{s}_t \text{ not terminal} \\ r_t & \text{otherwise} \end{cases}$$

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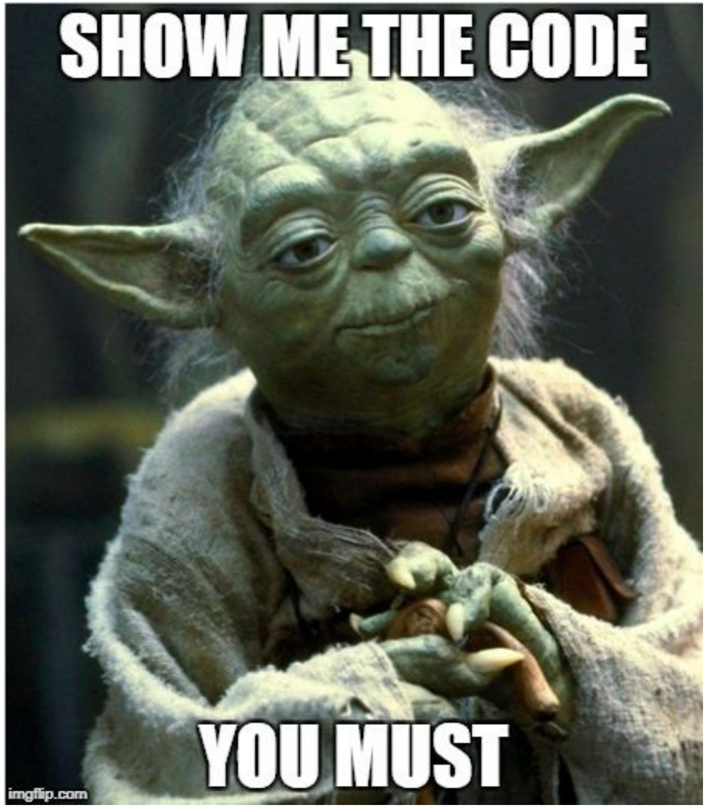
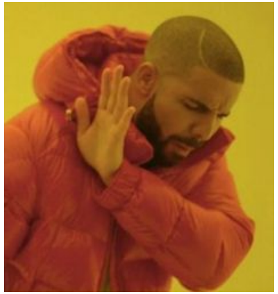
Gathering Experience



What is the Q-value function?

Q: $\boldsymbol{S} \times \boldsymbol{A} \rightarrow \mathbb{R}$




```
def Q(s: State, a: Action) -> float:
```

Tabular Q-learning

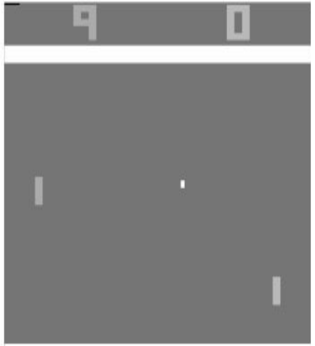
```
def Q(s: State, a: Action) -> float:
    return q[s, a]
```

.... for all $(\mathbf{s}_t, \mathbf{a}_t, r_t, \mathbf{s}_{t+1})$

Learning from Images

```
def Q(s: int, a: int) -> float:
    return q[s, a]
```

210



160

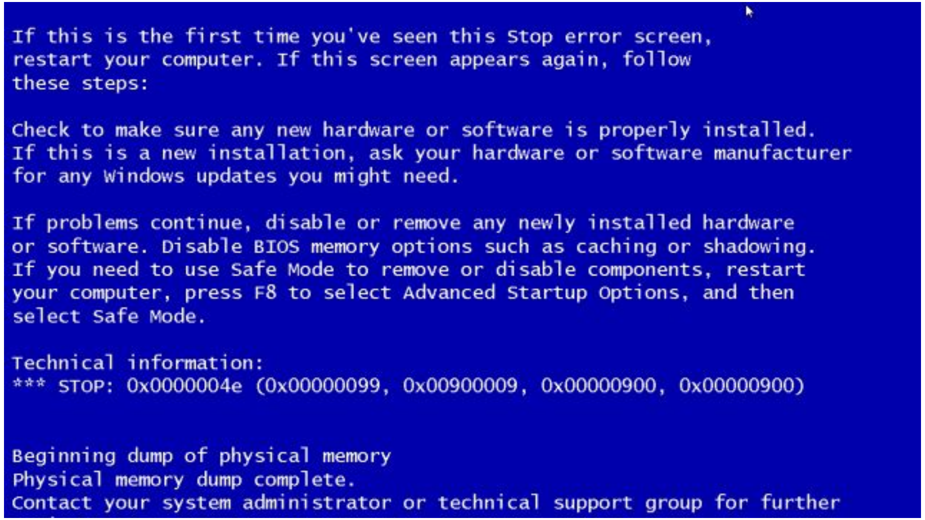
$255^{210*160}$ states

left, right, up, down, fire, NOOP

6 actions

Learning from Images

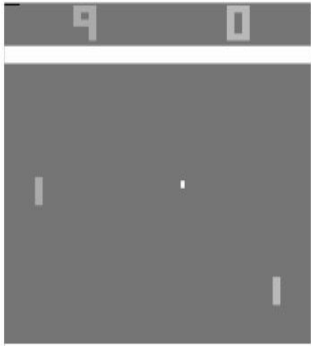
```
q = np.zeros((255**33600, 6))
```



Learning from Images

```
def Q(s: int, a: int) -> float:
    ???
```

210



160

$255^{210*160}$ states

left, right, up, down, fire, NOOP

6 actions

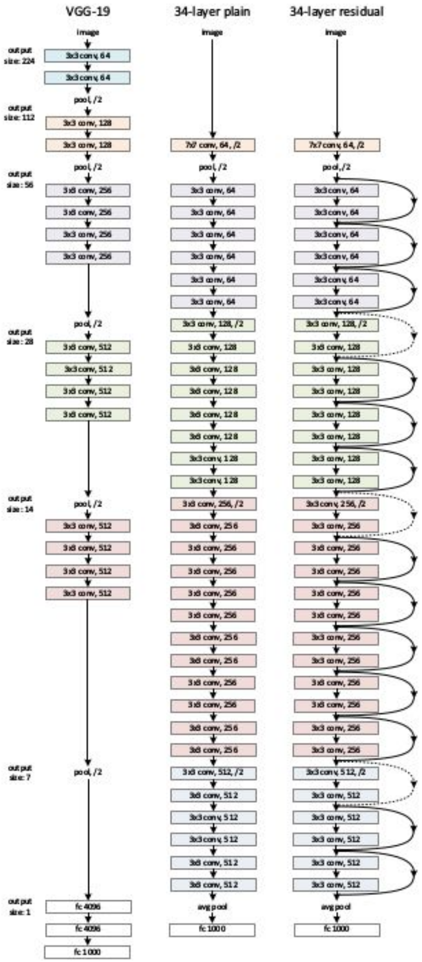
Deep Neural Networks

- Universal function approximators
- Lots of linear algebra run on GPU
- Typically gigabytes of parameters

architecture

$$y = f_{\theta}(x)$$

output parameters input



Neural Networks as Computational Graph

$$f(x, y)_\theta = ax^2 + bxy + cy^2$$

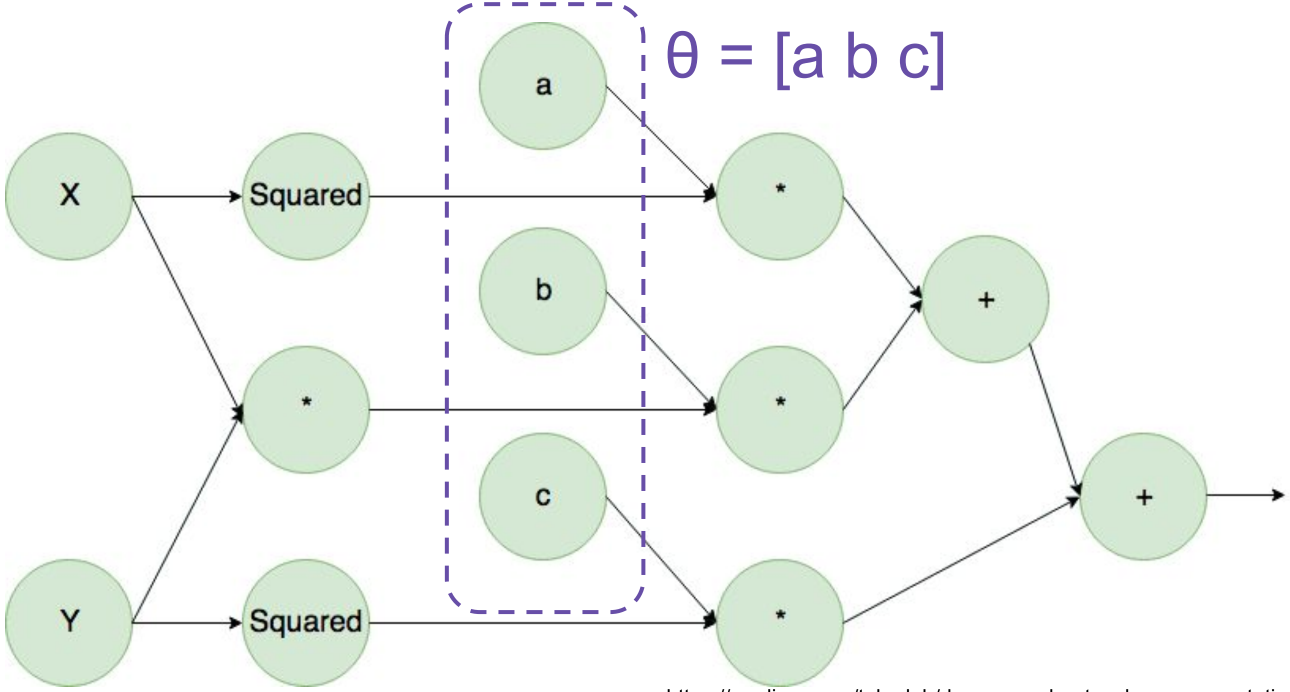
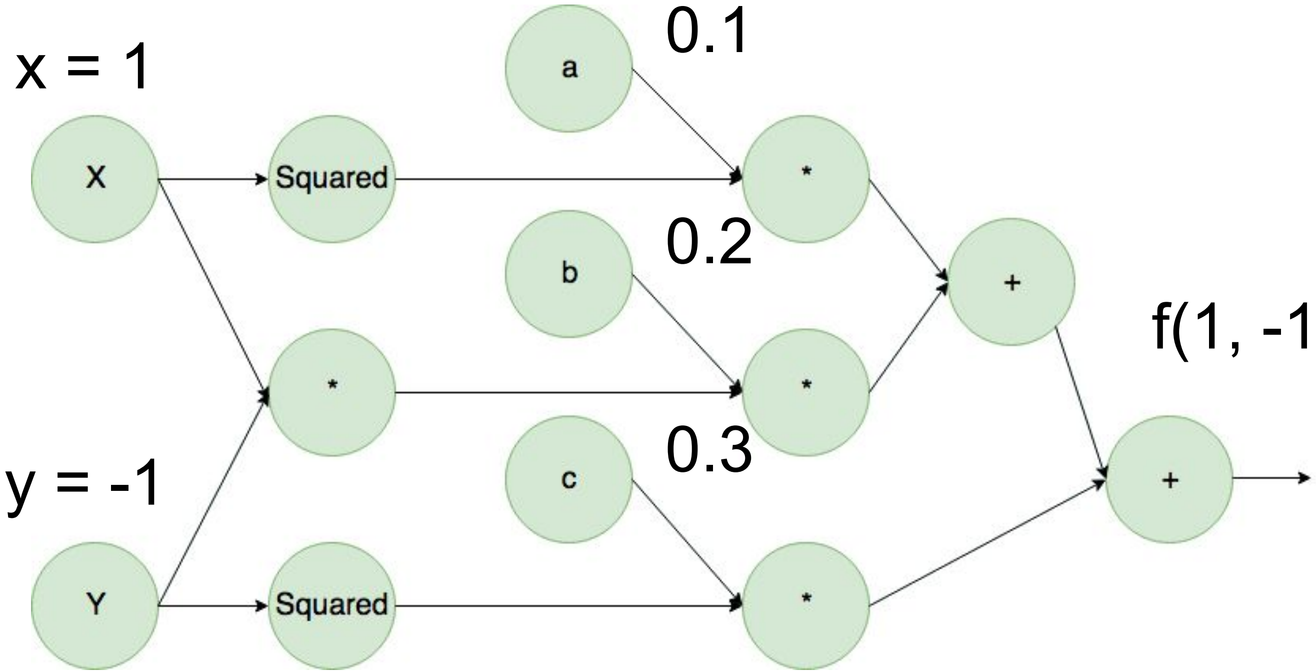


Image adapted from:
https://medium.com/tebs-lab/deep-neural-networks-as-computational-graphs-867fcaa56ac9

Example

$$f(x, y)_\theta = 0.1x^2 + 0.2xy + 0.3y^2$$



$$f(1, -1)_\theta = 0.2$$

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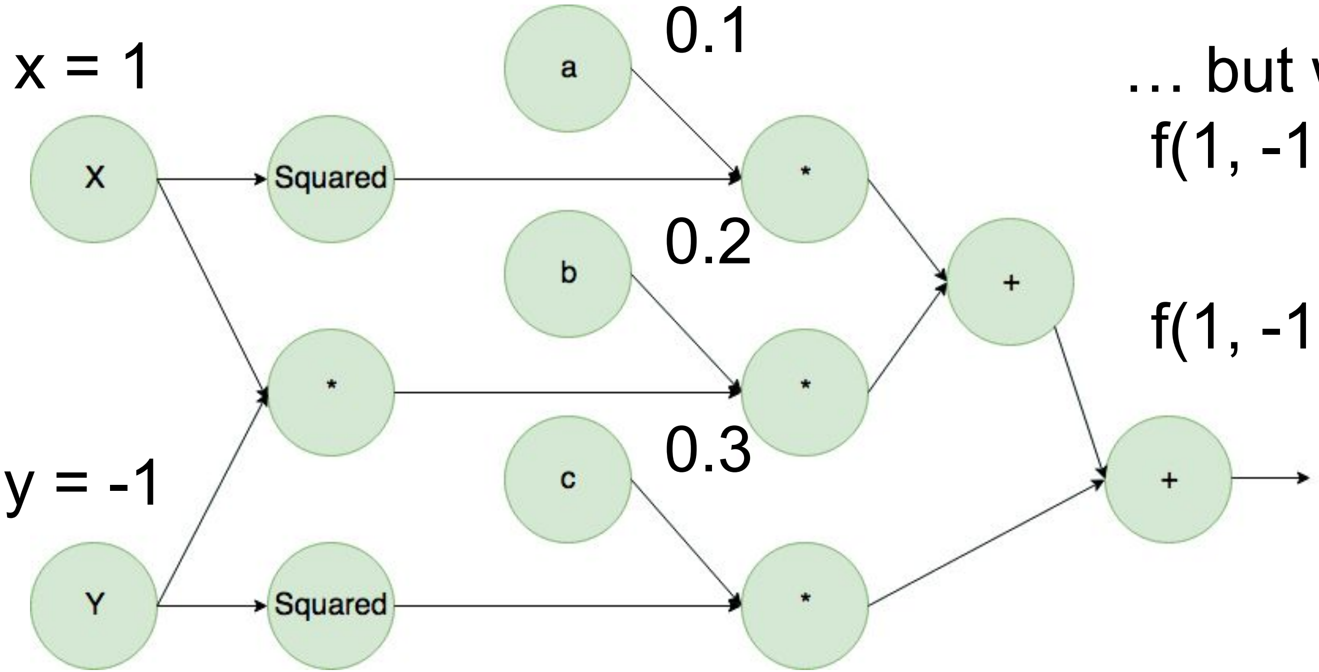
Example

$$f(x, y)_\theta = 0.1x^2 + 0.2xy + 0.3y^2$$

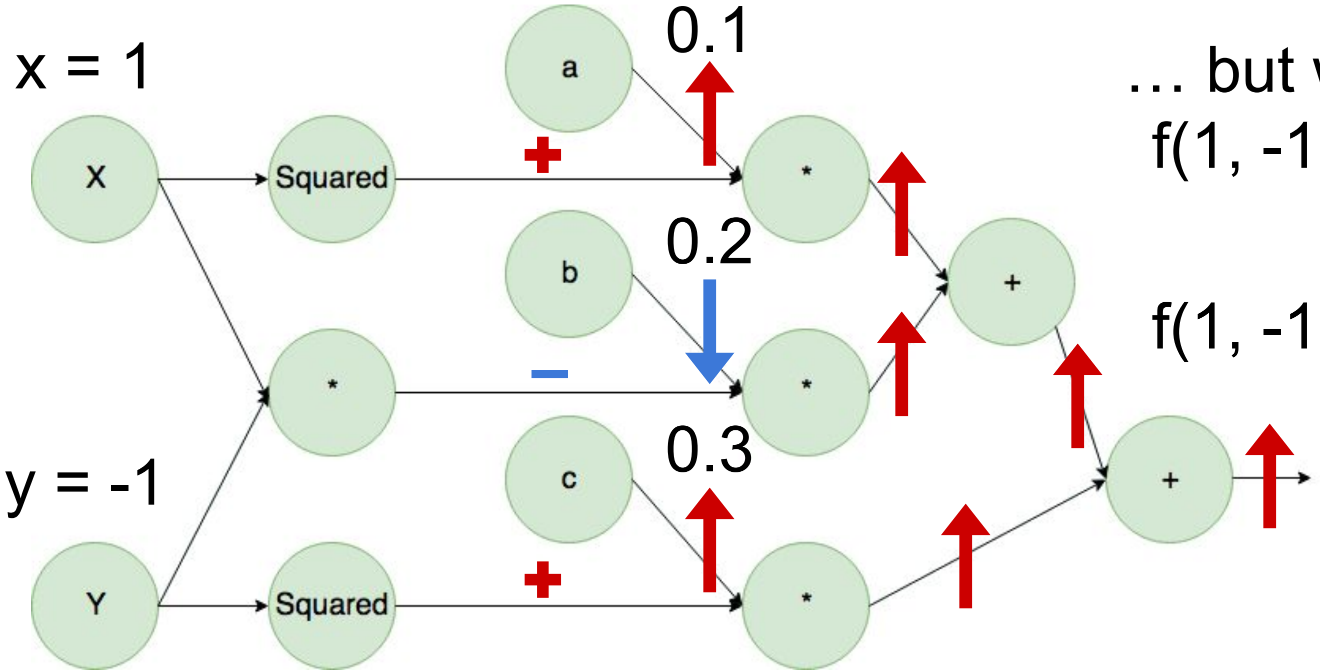


… but we want $f(1, -1)_\theta = 0.5$

$f(1, -1)_\theta = 0.2$

Automatic Differentiation

$$f(x, y)_\theta = 0.1x^2 + 0.2xy + 0.3y^2$$



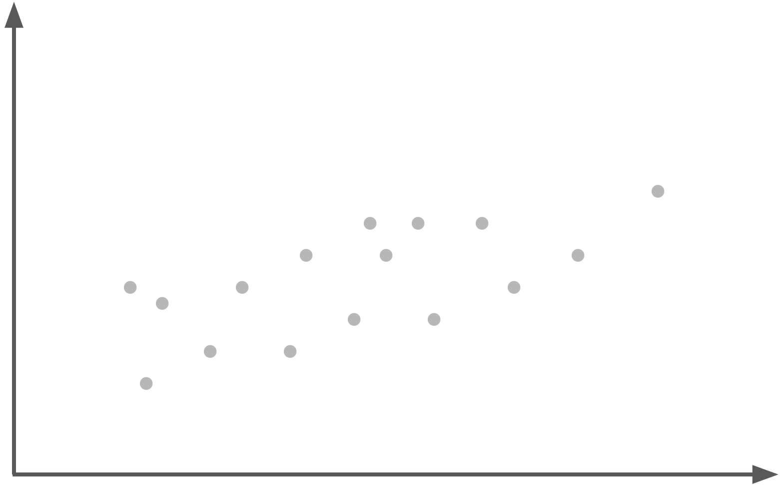
… but we want $f(1, -1)_\theta = 0.5$

$f(1, -1)_\theta = 0.2$

Automatic Differentiation

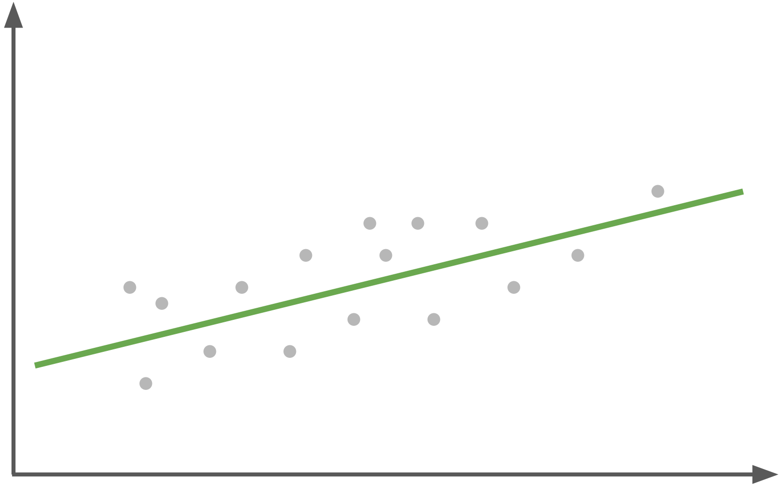
- Automatic differentiation packages calculate gradients automatically
- Deep learning packages are essentially fancy automatic differentiation libraries

Linear Regression Example



Data: $\{(x_i, y_i)\}^N_{i=1}$

Linear Regression Example



<u>Data:</u> $\{(x_i, y_i)\}^N_{i=1}$

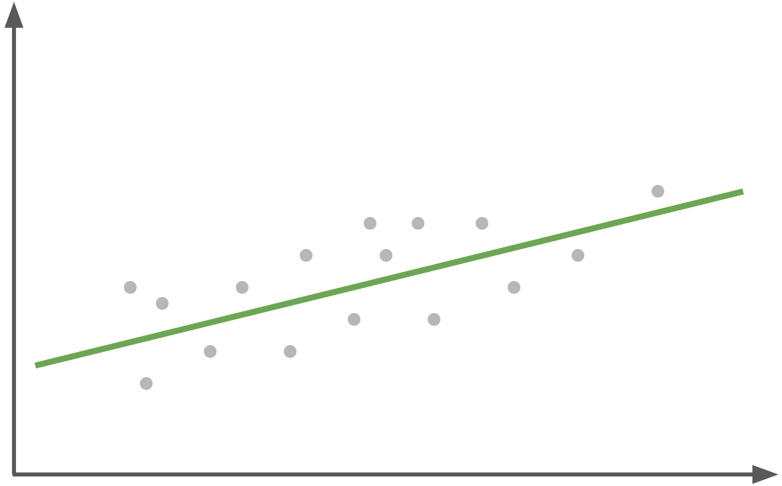
<u>2D line:</u>

$y = w_2x + w_1$

<u>Linear algebra notation:</u>

$y = \mathbf{w}^T\mathbf{x}$

Linear Regression Example



__Data:__ $\{(x_i, y_i)\}^N_{i=1}$

__2D line:__

$y = w_2 x + w_1$

__Linear algebra notation:__

$y = \mathbf{w}^T\mathbf{x}$

__Loss:__

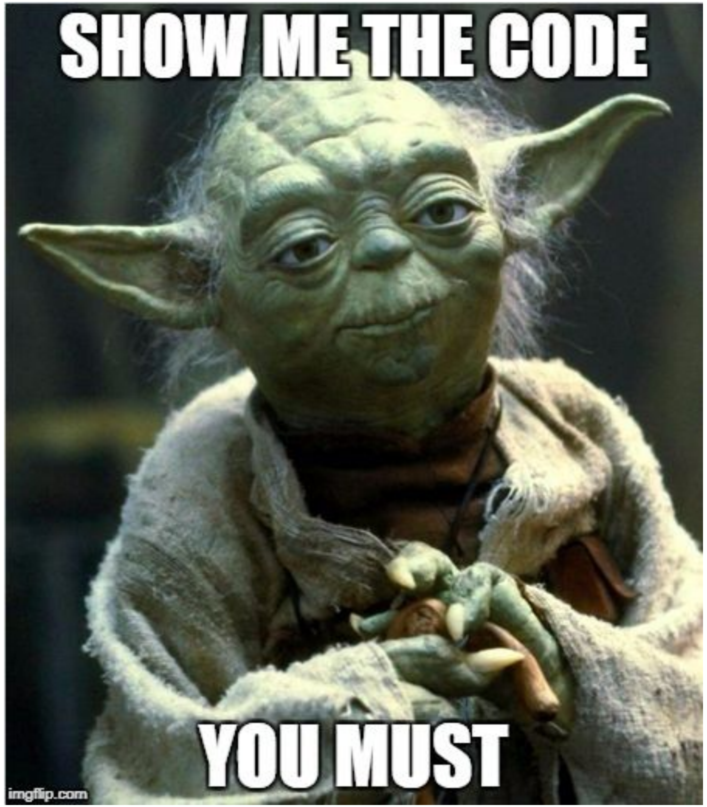
$L_{\mathbf{w}}(D) = (1 / N)\Sigma^N_{i=1}(y_i - \mathbf{w}^T\mathbf{x}_i)^2$

Chainer & CuPy

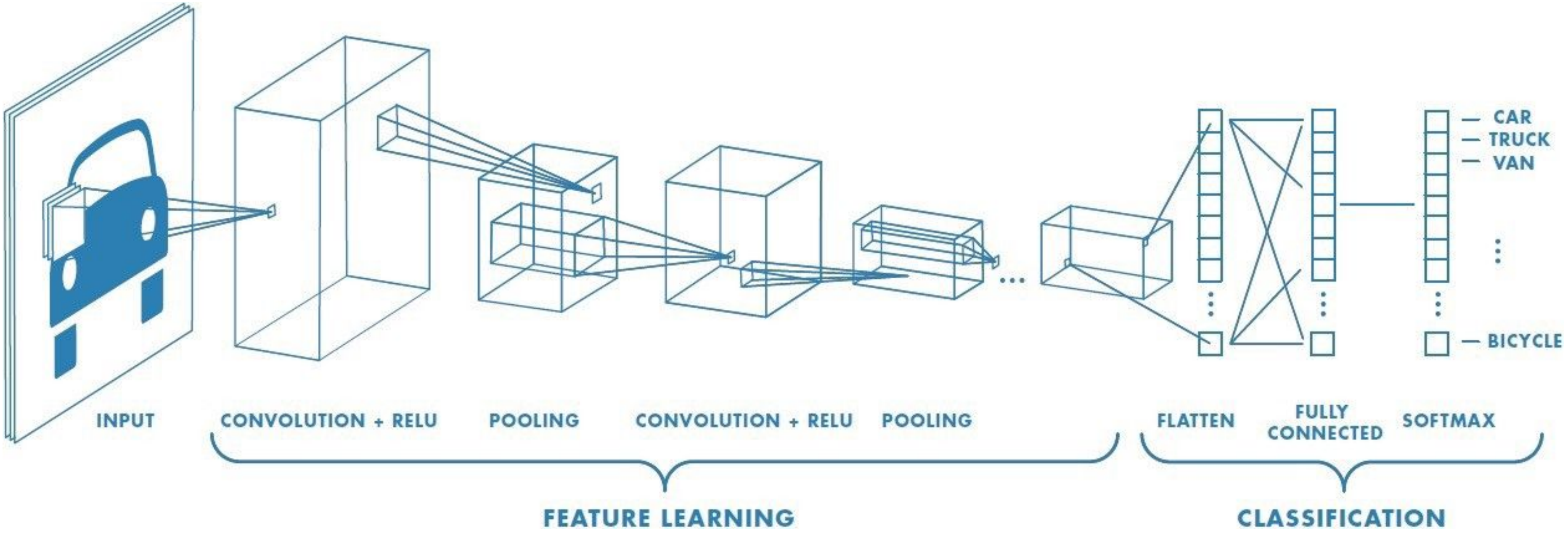
Chainer

CuPy

Chainer & CuPy

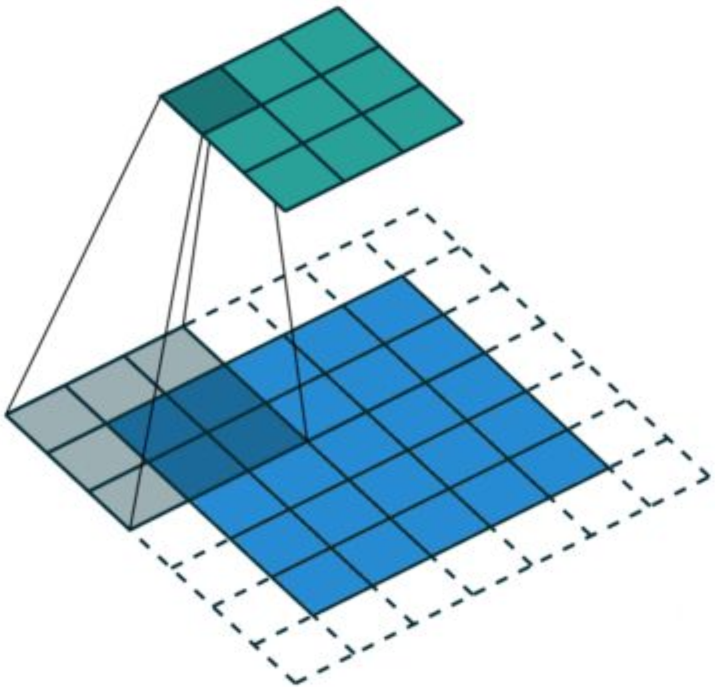


Convolutional Neural Networks (CNNs)



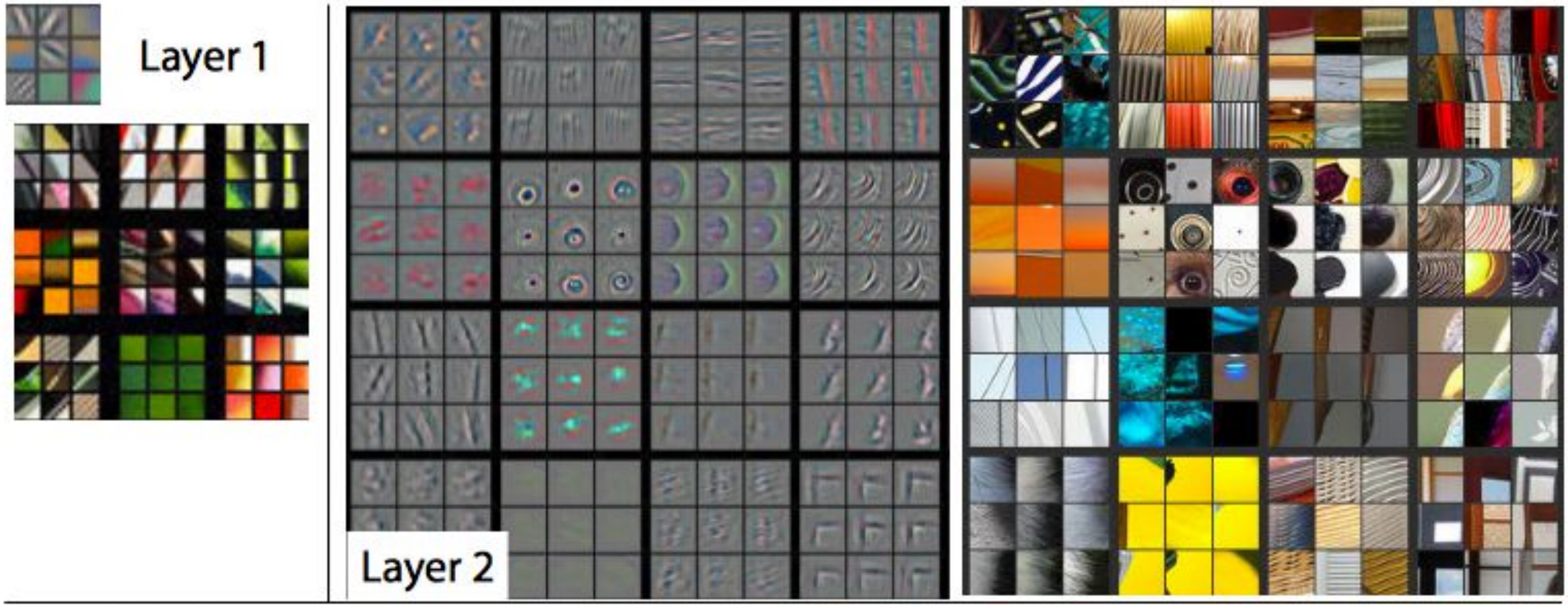
https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Image Convolution



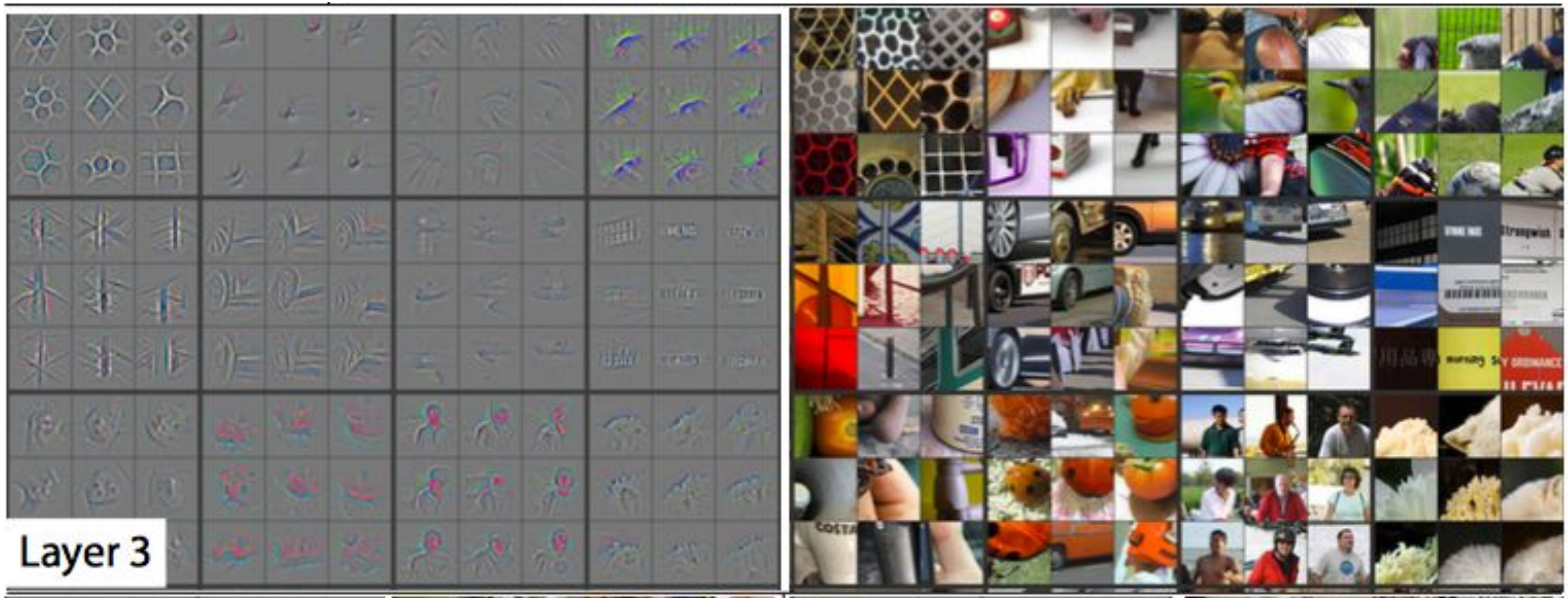
https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Why CNNs?



Zeiler, M. D., and R. Fergus. "Visualizing and understanding convolutional networks.", 2013

Why CNNs?



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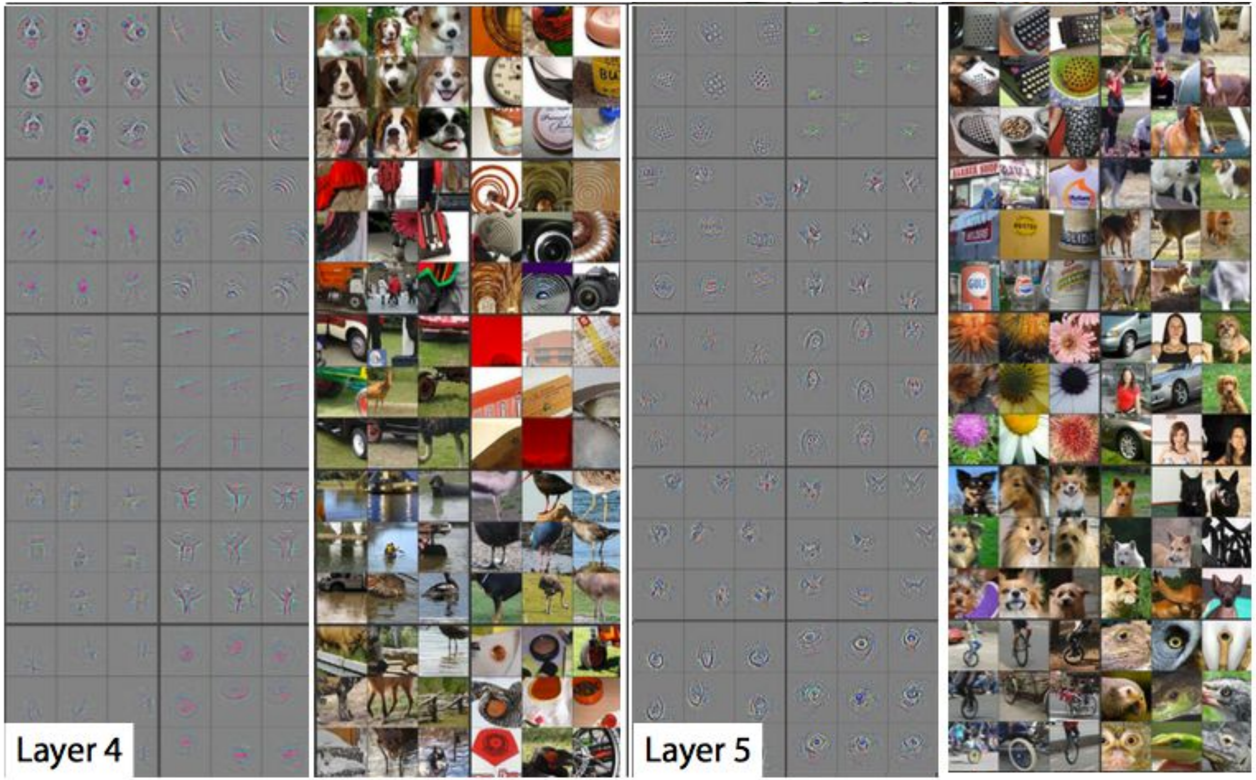
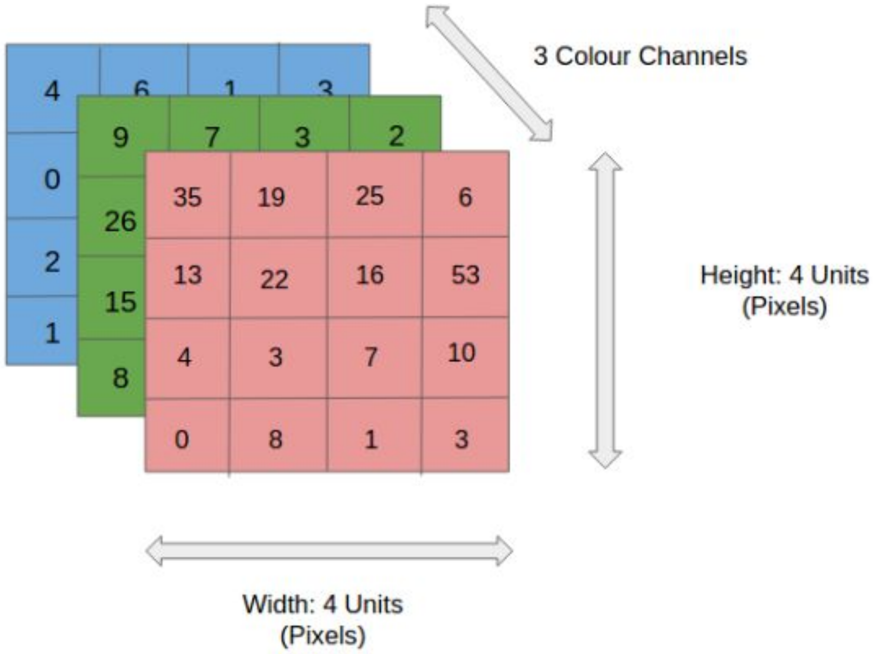
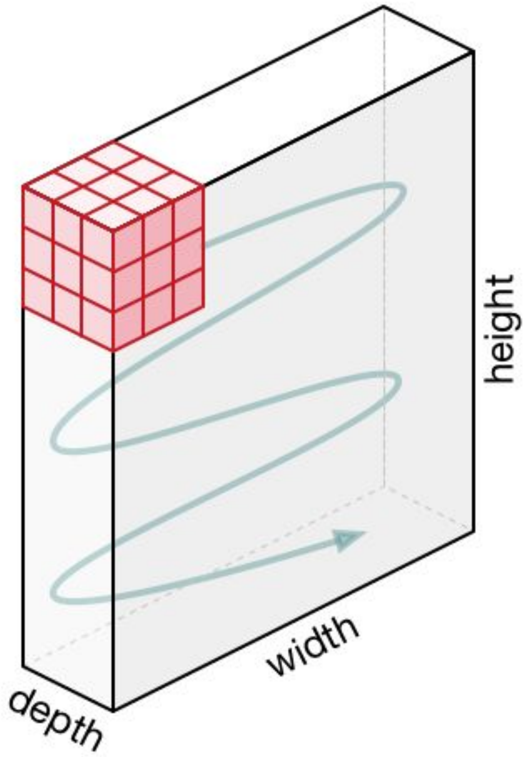
Why CNNs?



Zeiler, M. D., and R. Fergus. "Visualizing and understanding convolutional networks.", 2013

Image Convolution Kernels



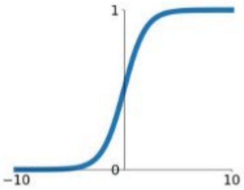


https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Activation Functions

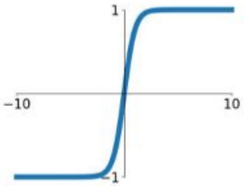
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



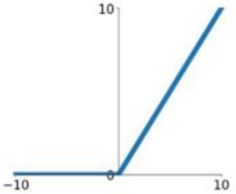
tanh

$\tanh(x)$



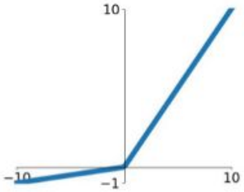
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

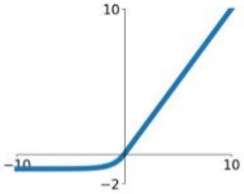


Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

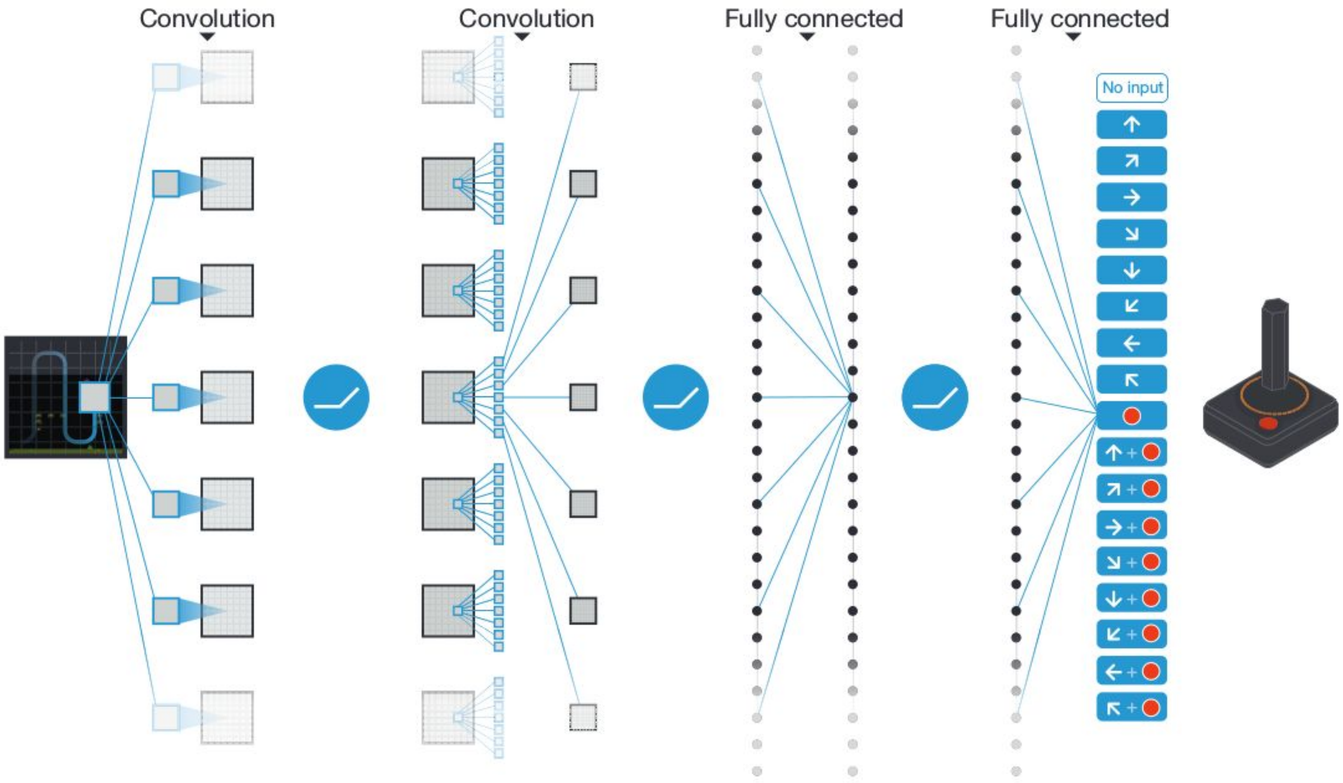
ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

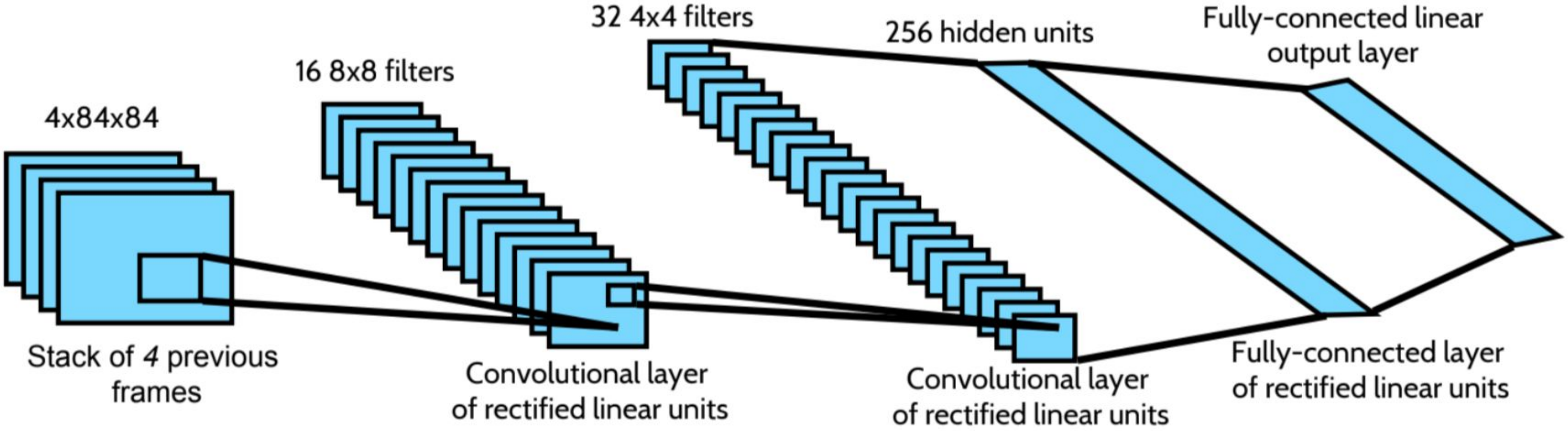


https://towardsdatascience.com/complete-guide-of-activation-functions-34076e95d044

Deep Q-value Network (DQN)

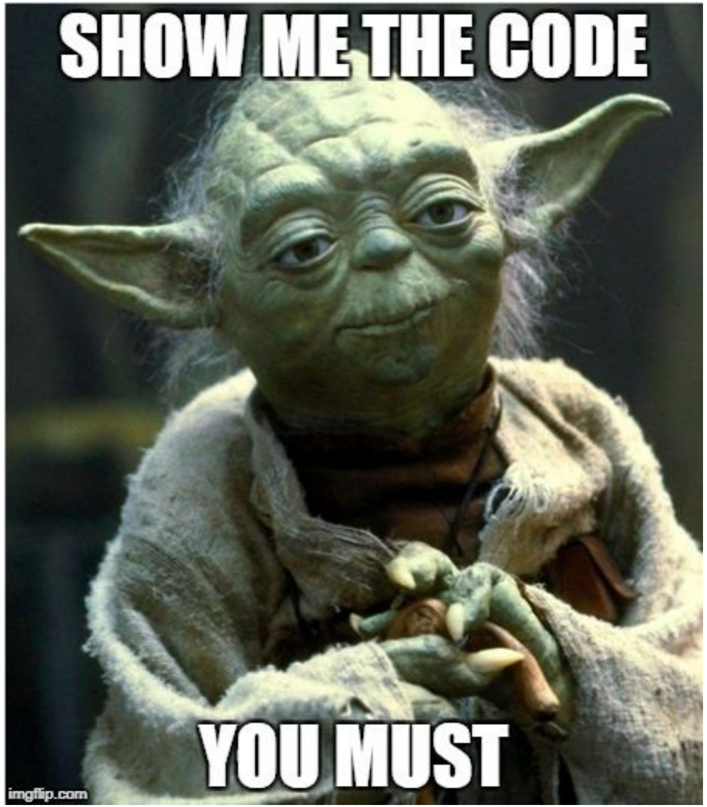


Deep Q-value Network (DQN)



https://medium.com/@jonathan_hui/rl-dqn-deep-q-network-e207751f7ae4

Implementing DQN



Putting Everything Together

Q-learning

$$y_t - \mathbf{Q}(\mathbf{s}_t, \mathbf{a}_t) = 0 \quad \text{for all} \quad (\mathbf{s}_t, \mathbf{a}_t, r_t, \mathbf{s}_{t+1})$$

$$y_t = \begin{cases} r_t + \gamma \max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}_{t+1}, \mathbf{a}) & \text{if } \mathbf{s}_t \text{ not terminal} \\ r_t & \text{otherwise} \end{cases}$$

Q-learning

$$r_t + \gamma \max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}_{t+1}, \mathbf{a}) - \mathbf{Q}(\mathbf{s}_t, \mathbf{a}_t) = 0 \quad \text{for all} \quad (\mathbf{s}_t, \mathbf{a}_t, r_t, \mathbf{s}_{t+1})$$

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Q-learning (annoying details cont'd)

$$r_t + \gamma \boxed{\max_{\mathbf{a}} \mathbf{Q}(\mathbf{s}_{t+1}, \mathbf{a}) - \mathbf{Q}(\mathbf{s}_t, \mathbf{a}_t)} = 0 \quad \text{for all} \quad (\mathbf{s}_t, \mathbf{a}_t, r_t, \mathbf{s}_{t+1})$$

If we update **Q** every timestep there is too much noise

Q-learning (annoying details cont'd)

$$r_t + \gamma \max_{\mathbf{a}} \mathbf{Q}_{\theta-}(\mathbf{s}_{t+1}, \mathbf{a}) - \mathbf{Q}_{\theta}(\mathbf{s}_t, \mathbf{a}_t) = 0 \quad \text{for all} \quad (\mathbf{s}_t, \mathbf{a}_t, r_t, \mathbf{s}_{t+1})$$

- Update $\mathbf{Q}_{\theta}$ every timestep
- Periodically Set $\mathbf{Q}_{\theta-} = \mathbf{Q}_{\theta}$

Q-learning

$$y_t - \mathbf{Q}_{\boldsymbol{\theta}\text{-}}(\mathbf{s}_t, \mathbf{a}_t) = 0 \quad \text{for all} \quad (\mathbf{s}_t, \mathbf{a}_t, r_t, \mathbf{s}_{t+1})$$

$$y_t = \begin{cases} r_t + \gamma \max_{\mathbf{a}} \mathbf{Q}_{\boldsymbol{\theta}}(\mathbf{s}_{t+1}, \mathbf{a}) & \text{if } \mathbf{s}_t \text{ not terminal} \\ r_t & \text{otherwise} \end{cases}$$

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Exploration vs. Exploitation

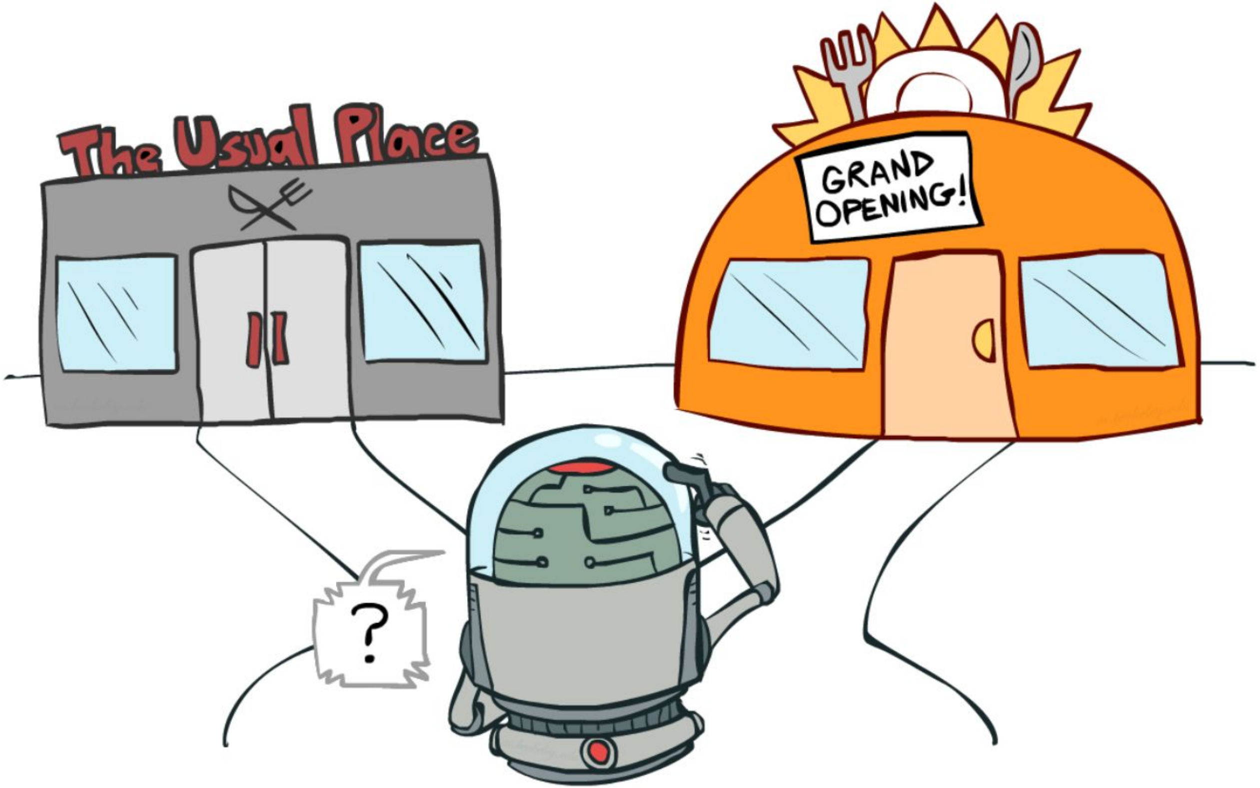


Image source: UC Berkeley AI course

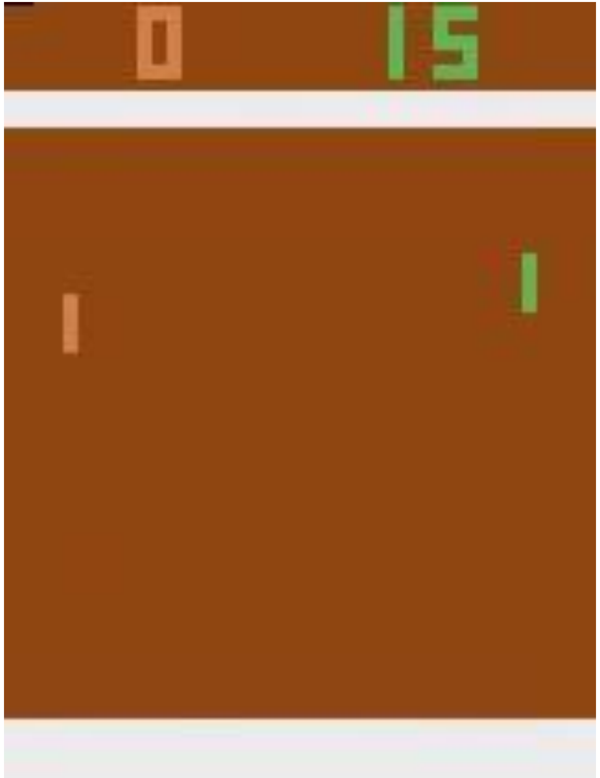
ε-greedy Policy

- Choose random action with probability ε
- Full exploration ε = 1.0
- Full exploitation ε= 0.0

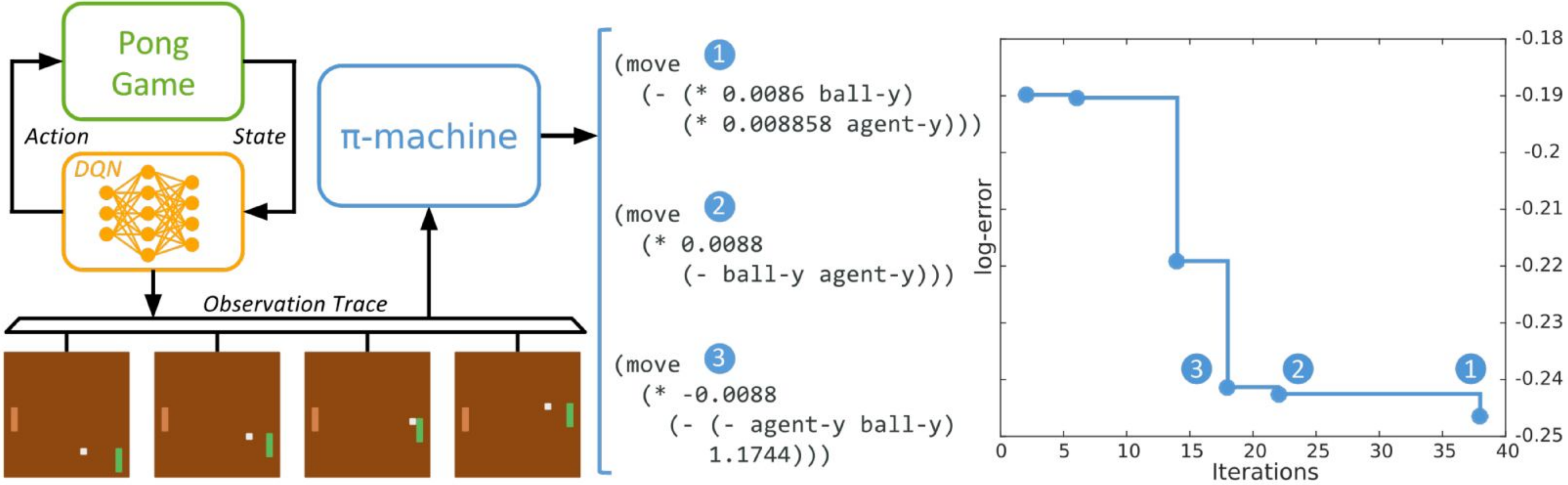
Training

- ~24 hours on i7 laptop with GTX1050
- Can be taken down to ~1 hour with a beefy machine and a few optimisations
- Deep RL is notorious for irreproducability
- Sometimes multiple runs are needed to get a working agent

Playing Better Than Human



Deep Q-learning Network



Human: 9.3 Program agent: 11.1 DQN: 18.9

Penkov & Ramamoorthy, ICML-WHI, 2017

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