# Robotics Reading Group
## @ Instituto Superior Técnico

Session #4
29-11-2019

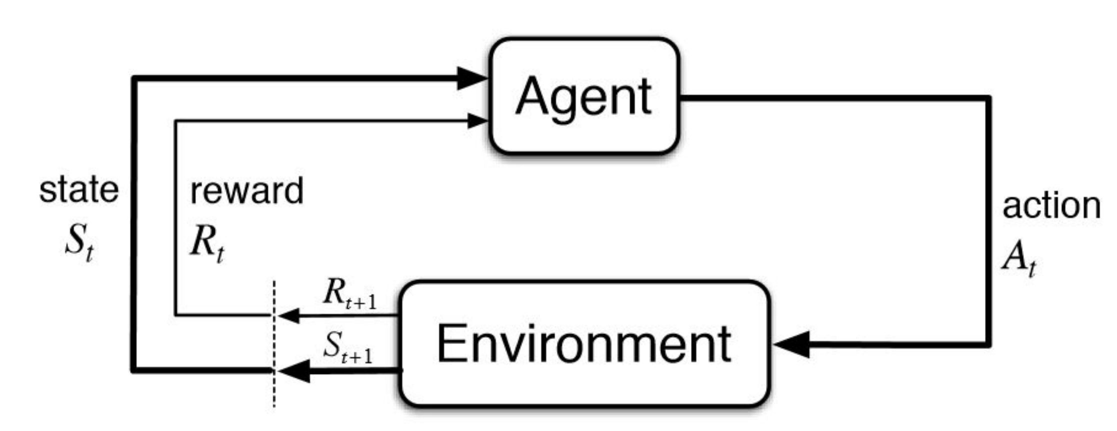
João Ribeiro

Google DeepMind

# DQN

## HUMAN-LEVEL CONTROL THROUGH **DEEP REINFORCEMENT LEARNING**

# Some background



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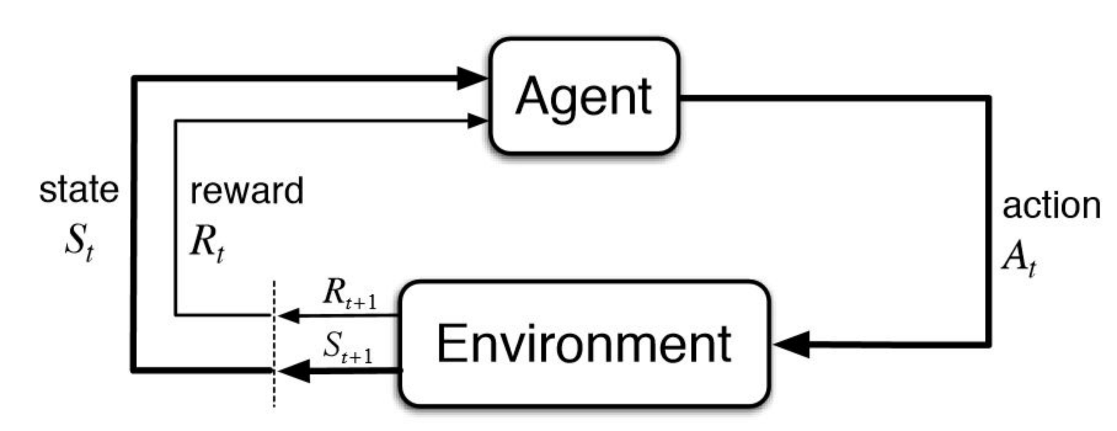


## Action-Value Function Q(s,a)

- *Expectation of how much future discounted reward the agent will obtain by executing action **a** in state **s***

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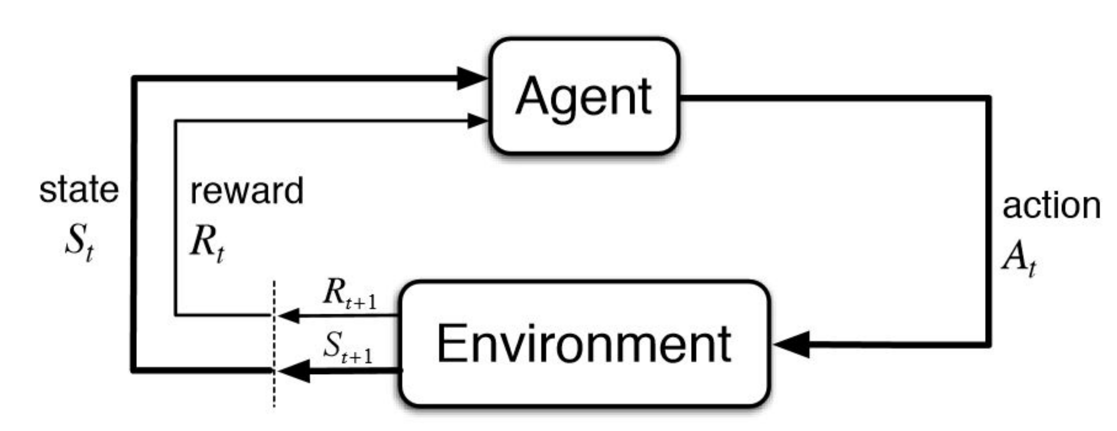


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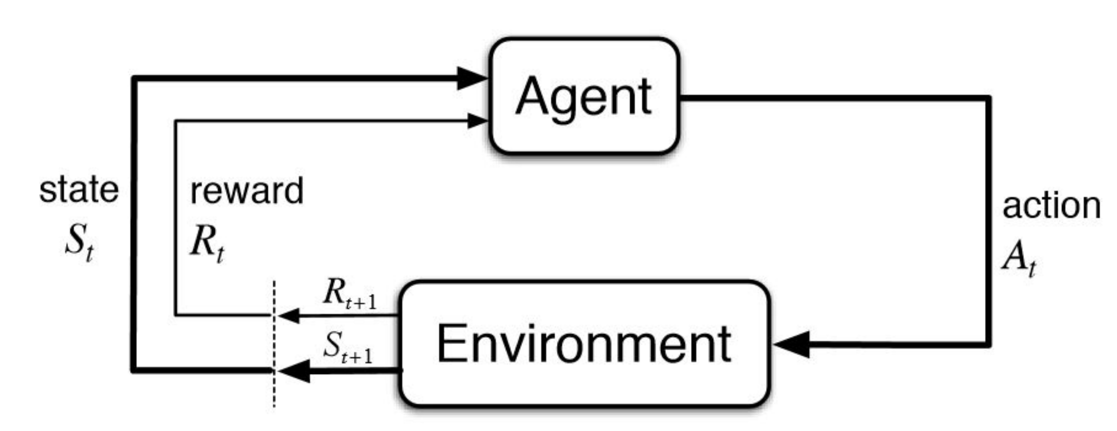


## Action-Value Function Q(s,a)

- *Expectation of how much future discounted reward the agent will obtain by executing action **a** in state **s***

## (in other words)

- Expectation of *"how good executing action a in state s is for the agent"*

# Learning Q(s,a) (trial-and-error)

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*(known as Q-Learning)*

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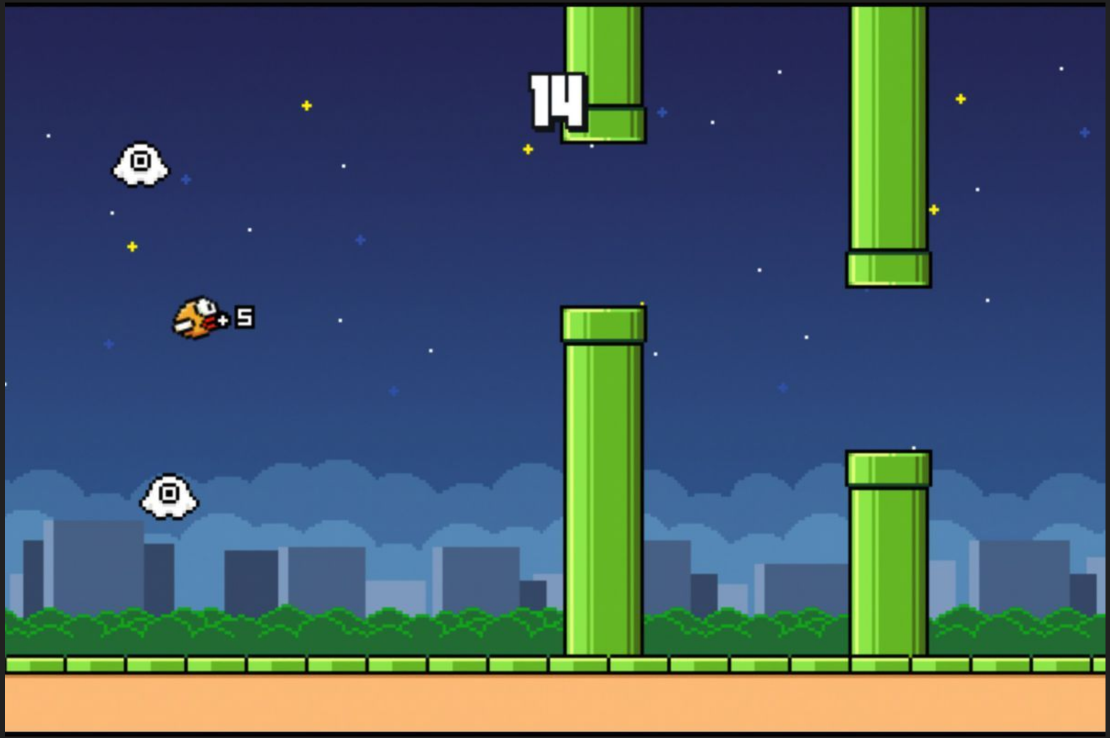
Loss (Mean Squared Error):

1/N sum (y-yhat)^2

# Three Problems

# 1 - How to design good feature representations?

state = ?



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state = [
  *Distance to pipes?*

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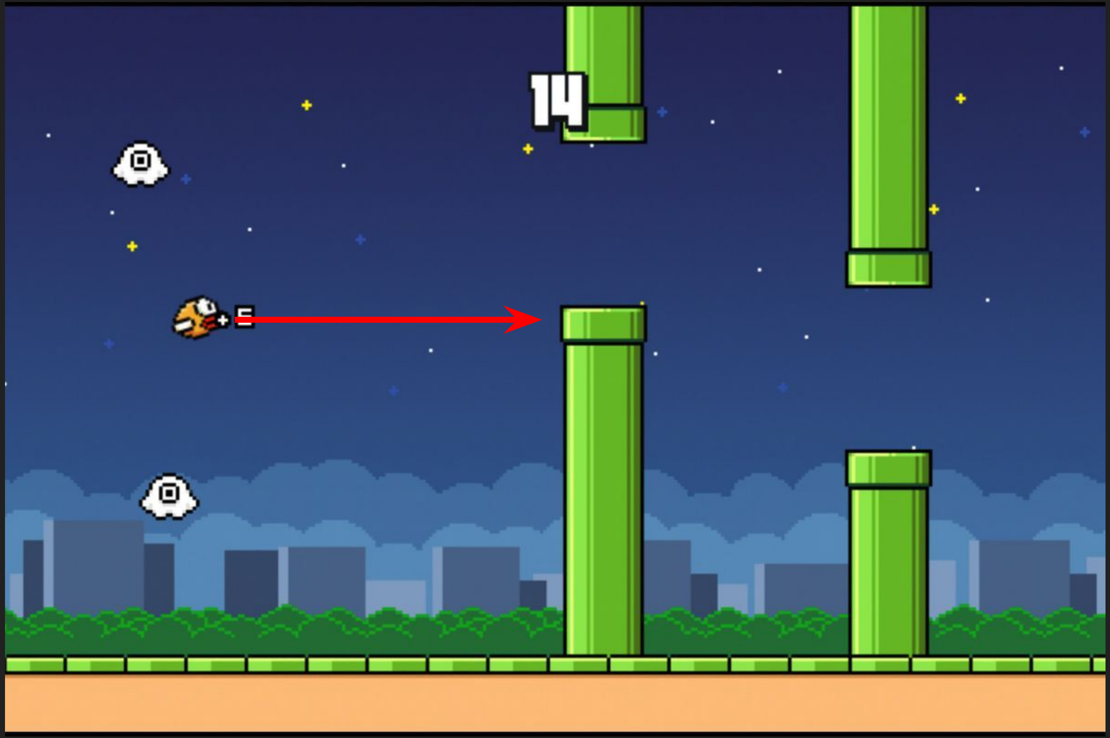

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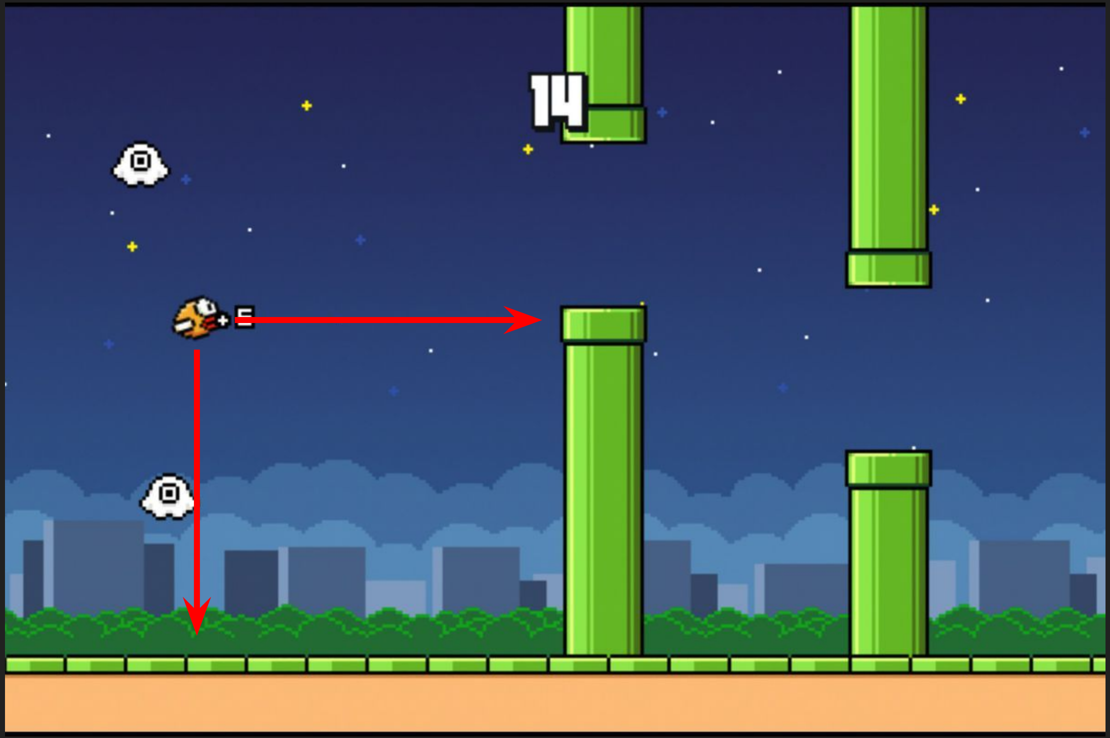

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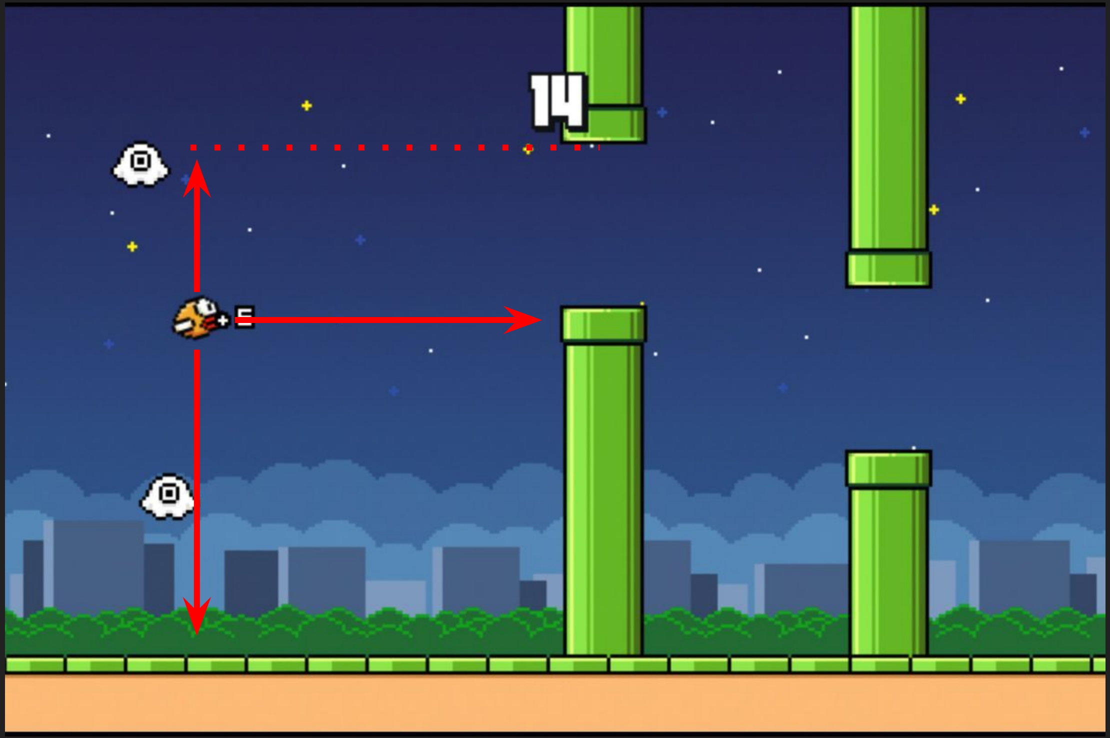

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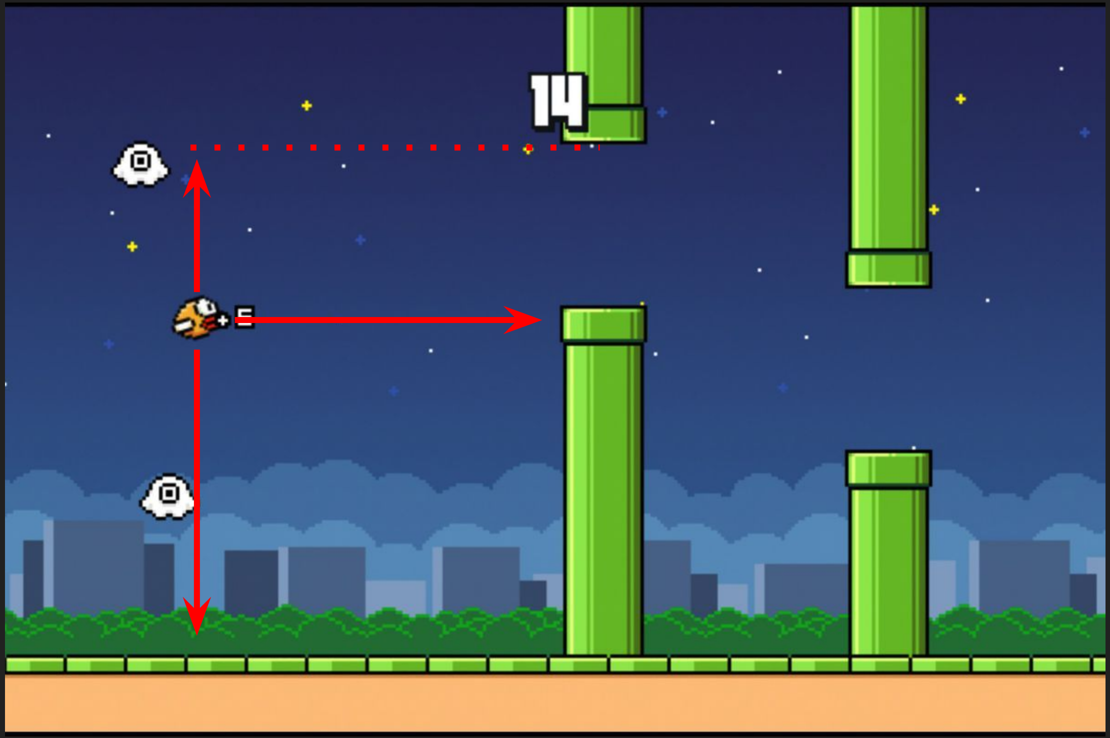

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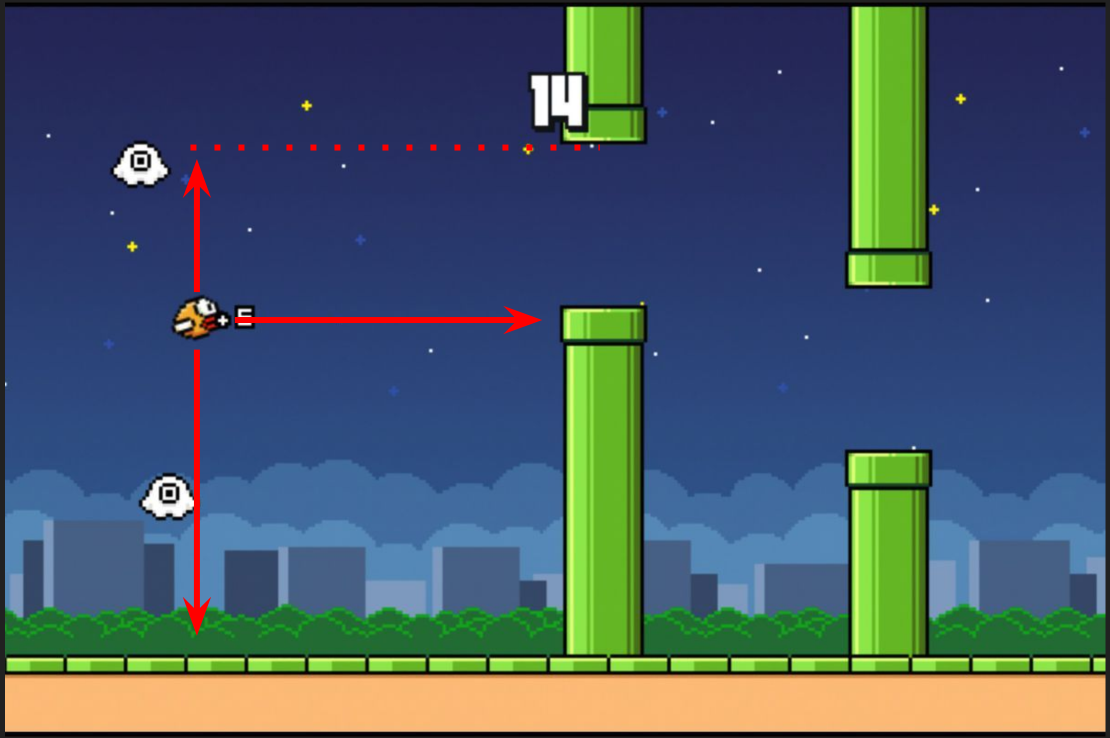


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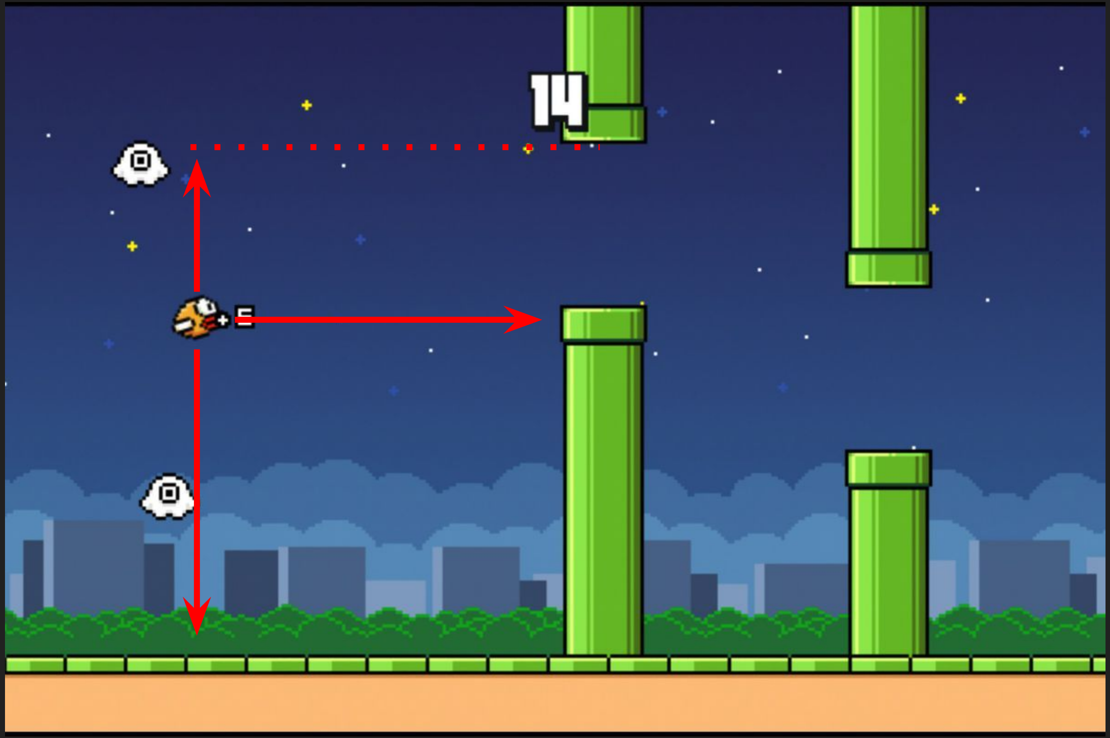


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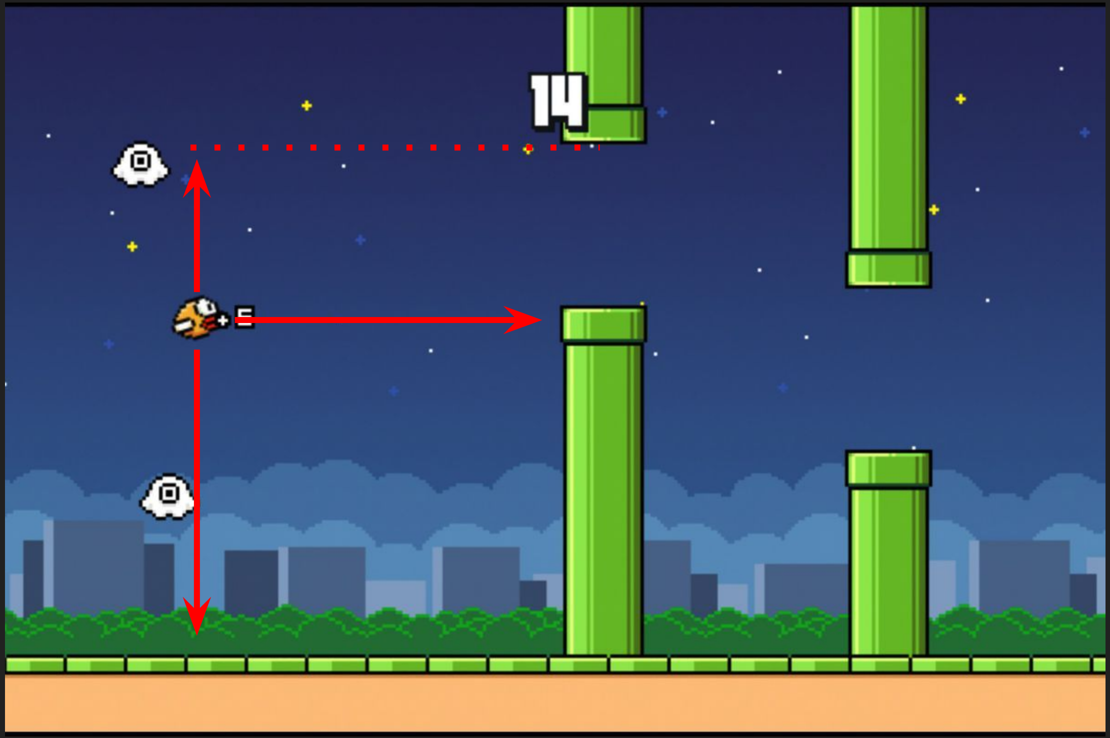


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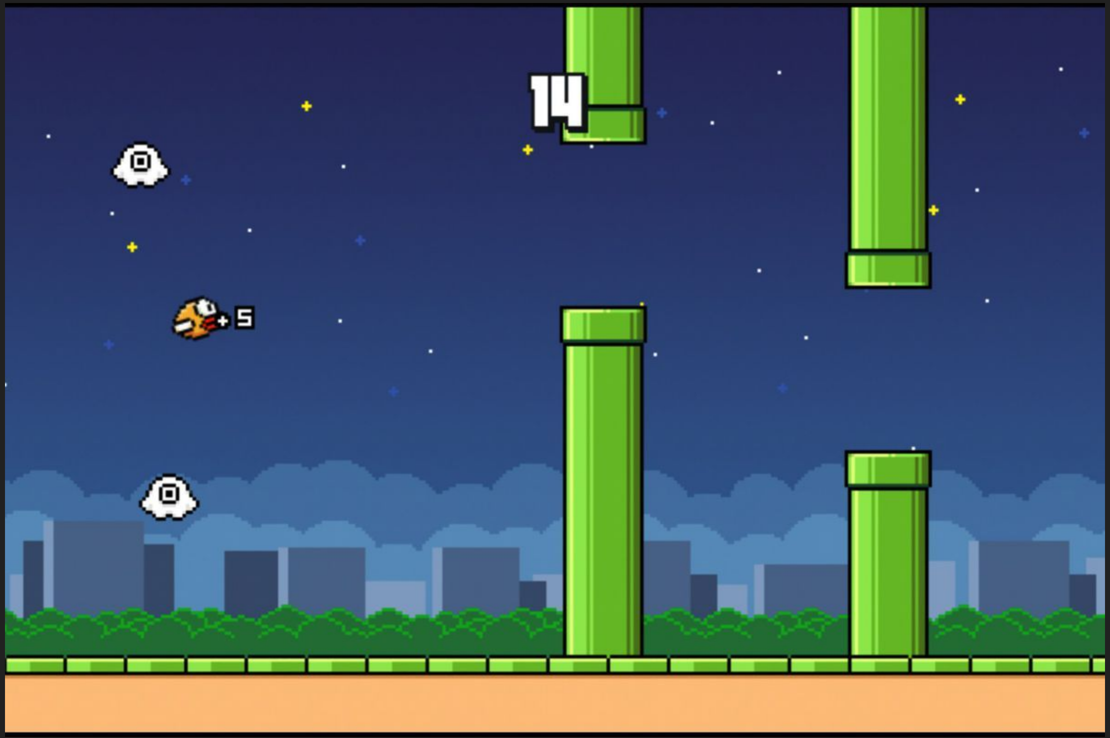
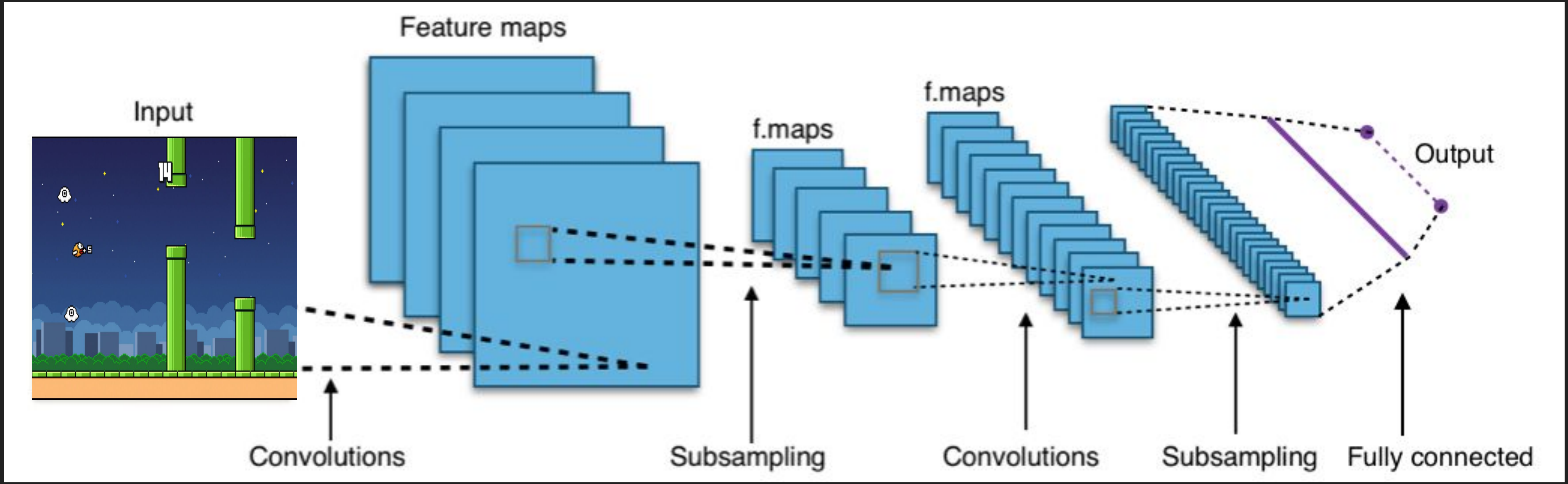
1. Requires domain knowledge
2. Prone to human bias
3. Could limit learning!

# Solution?



# Deep Learning!



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*(Known as Experience Replay!)*

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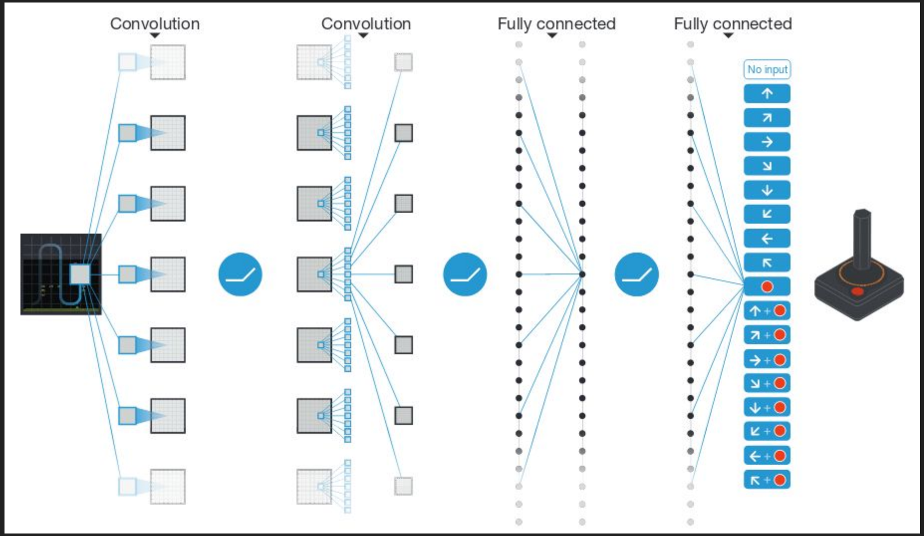
# The Deep Q-Network!

| Automatic feature extraction | Experience Replay | Main & Target Networks |
|---|---|---|
| \| | \| | \| |
| CNN | Dataset D | $Q(s,a;\theta)$ $Q(s,a;\theta_{target})$ |



# Does it work?

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    - *50M training **frames** (timesteps)*
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- 43/49 games - *Outperformed best algorithms for each individual game*

- 29/49 games - *Human level or above*
  - *15/29 games - Superhuman control!*


180 2 1

# Cool resources to check out:

- OpenAI Baselines - Tensorflow implementation of SOTA algorithms:
  - *https://github.com/openai/baselines*

- Stable Baselines - Fork from openai/baselines with refactored code:
  - *https://github.com/hill-a/stable-baselines*

- Tensorflow Agents - Full Deep RL library with good abstractions, written in tensorflow:
  - *https://github.com/tensorflow/agents*

- Deep Reinforcement Learning that Matters - Really cool paper on statistical significance and reproducibility of Deep RL work:
  - *https://arxiv.org/abs/1709.06560*

- Deep RL Hands on - Really practical book on DRL with code examples written in PyTorch:
  - https://github.com/aibooks/aibooks.github.io


Throttle: 0.00, Steering: 0.00
Use arrow keys to move, q or ESCAPE to exit.
space key: toggle recording – m: change mode
Mode:
MANUAL
Training Status:
X8 Speed