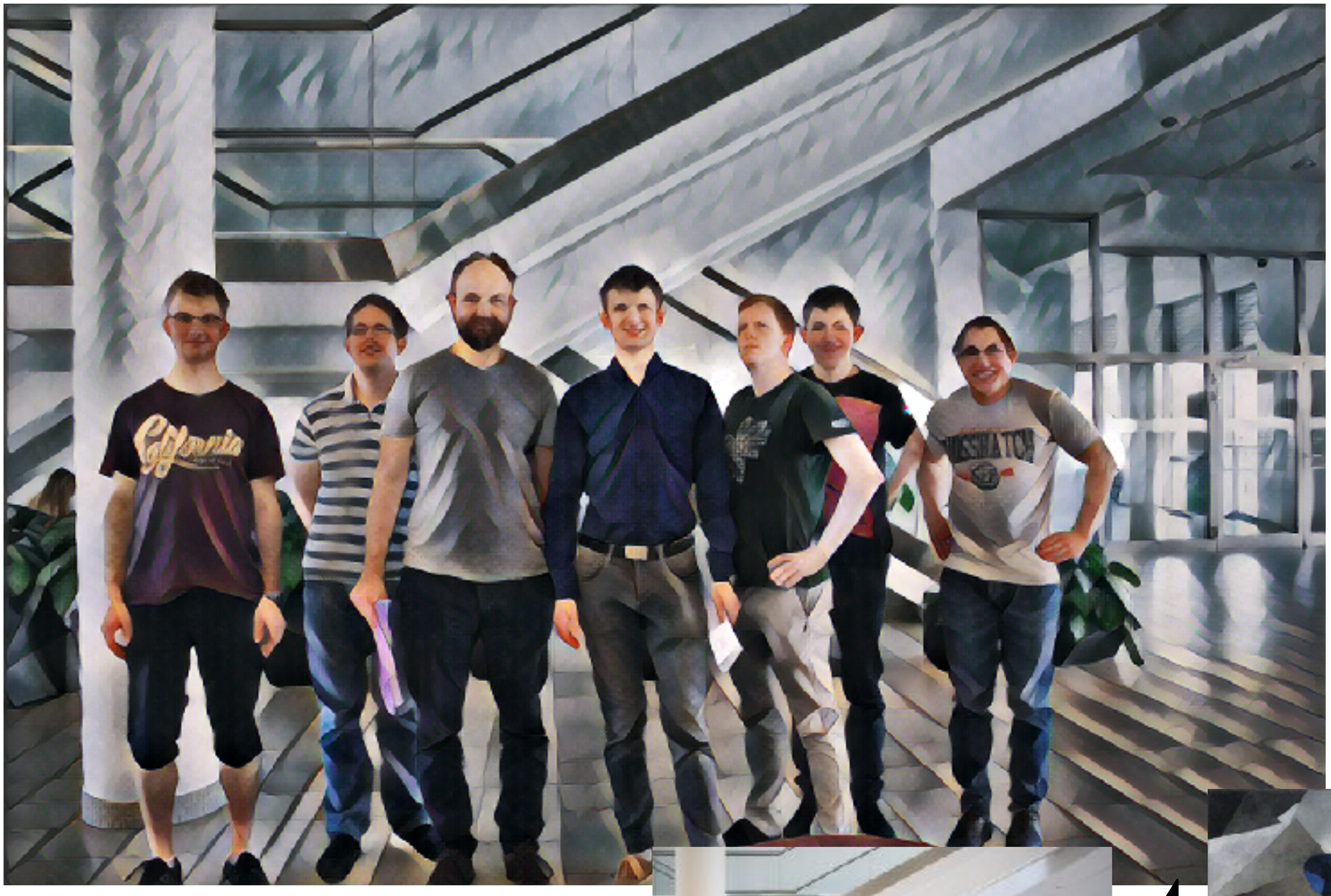
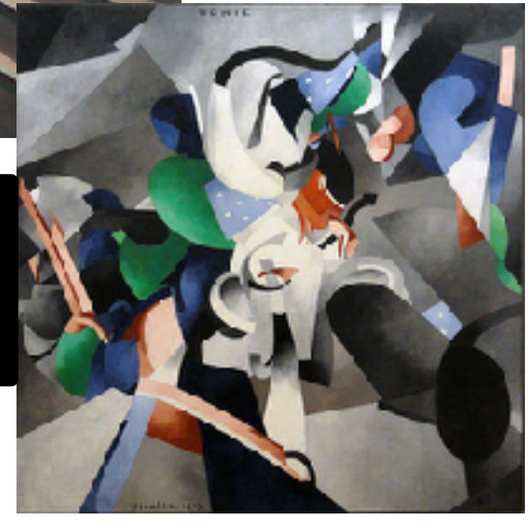
Intel Software Innovator

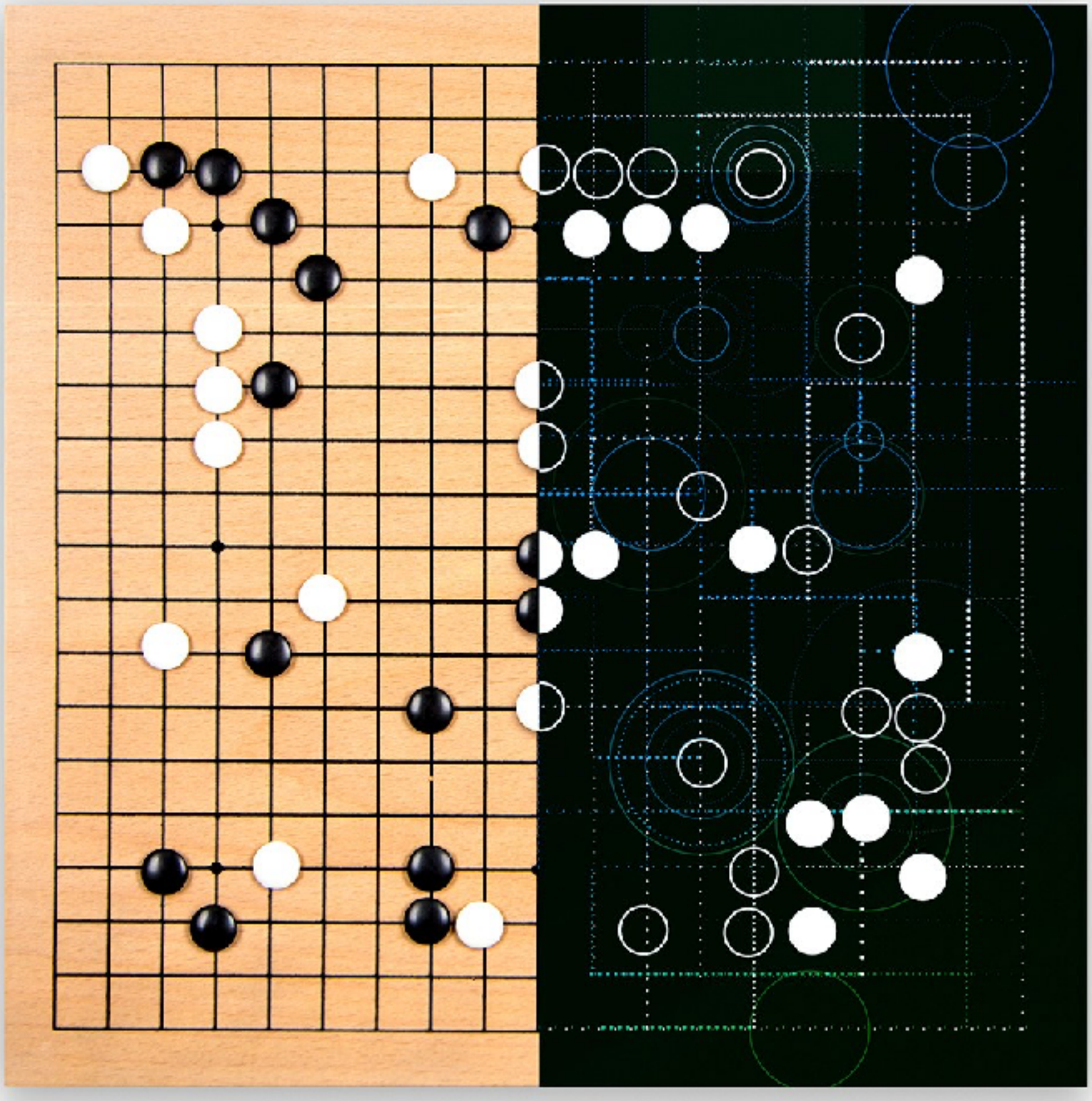
GDAŃSK UNIVERSITY OF TECHNOLOGY

Deep Reinforcement Learning on AlphaZero example 🤖

Piotr Januszewski

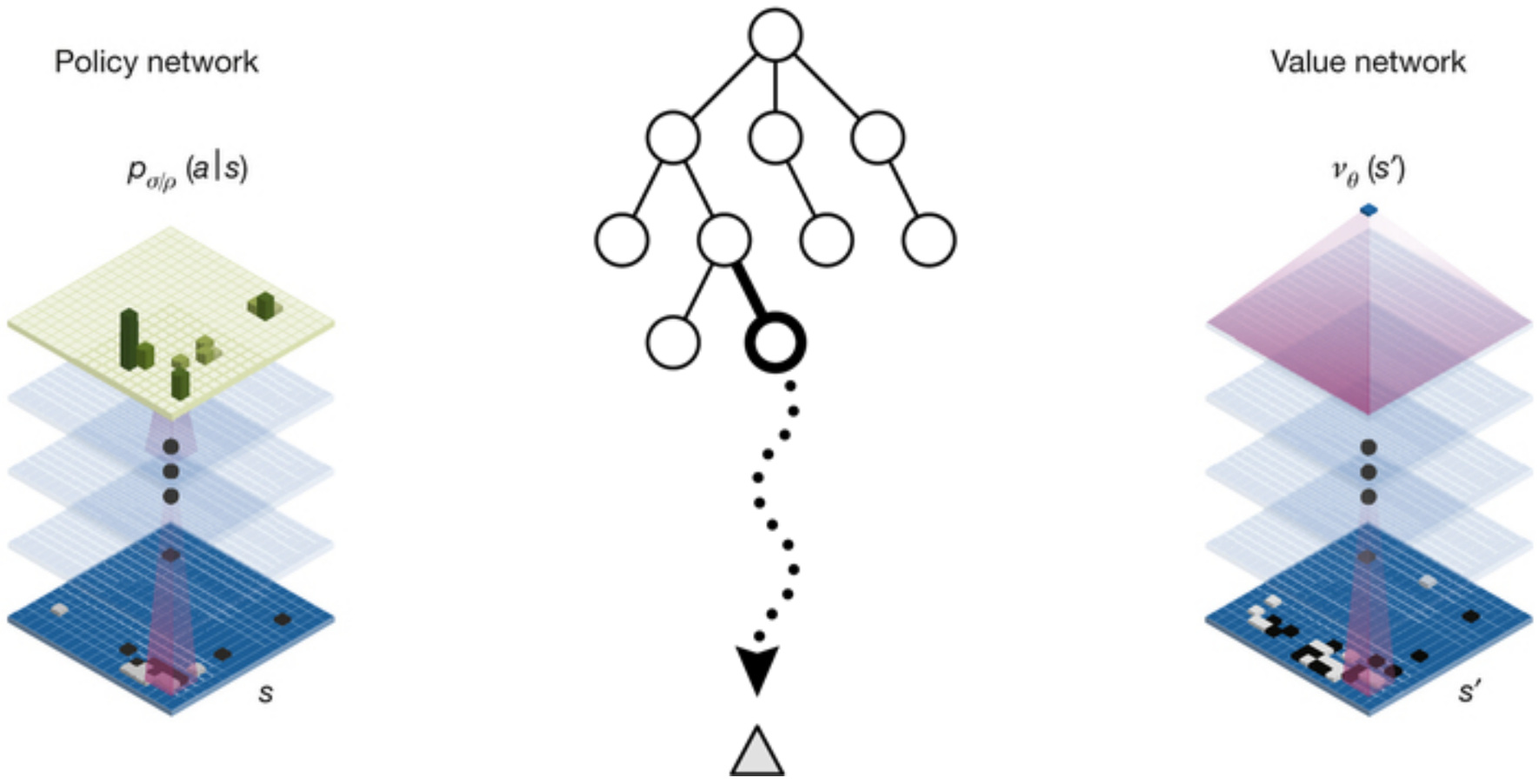






Source: https://www.wired.com/2016/01/in-a-huge-breakthrough-googles-ai-beats-a-top-player-at-the-game-of-go/

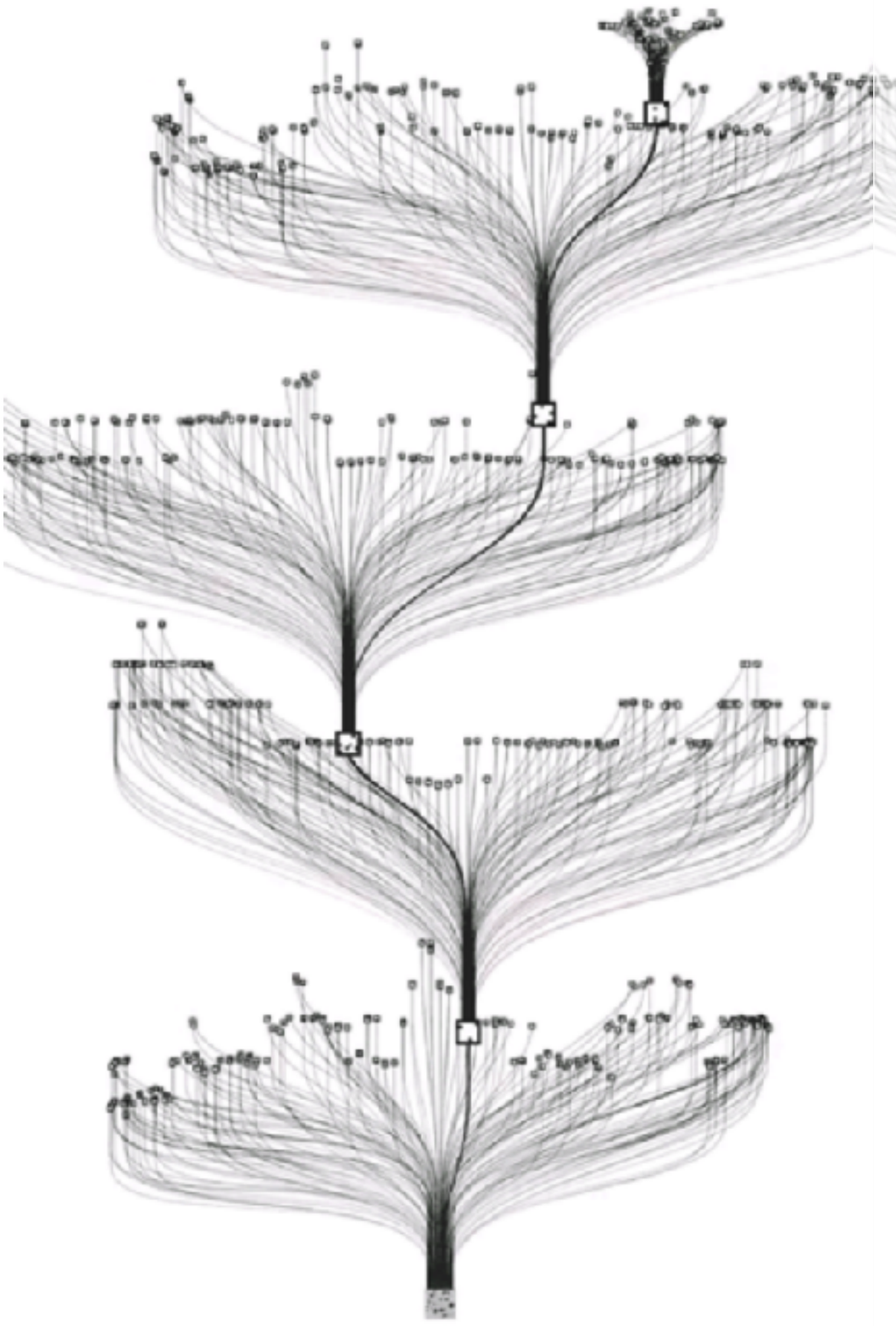
AlphaZero architecture



DeepMind's AlphaGo Lee

became the first AI to beat a human grandmaster of Go.

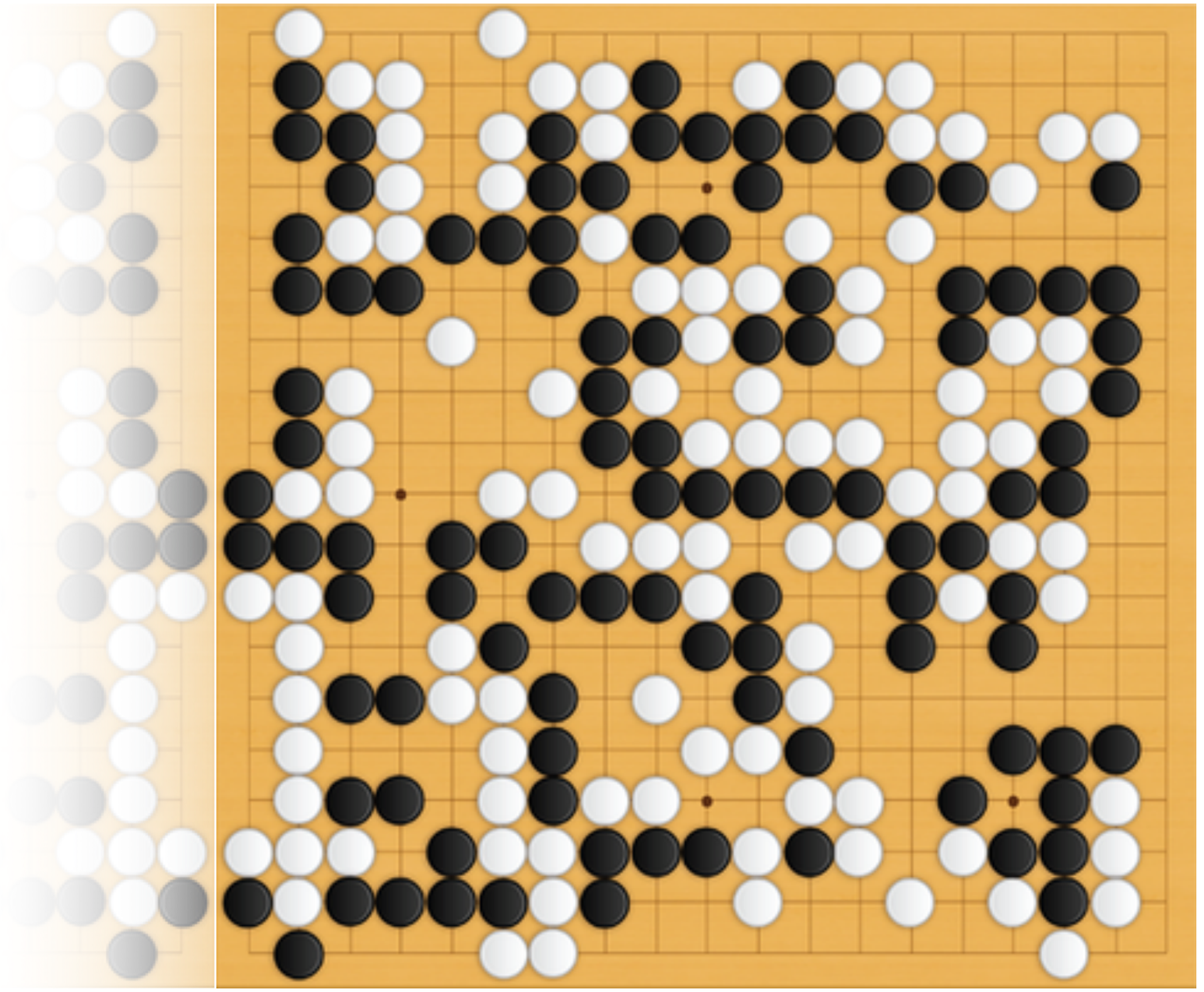
Up to 361 legal moves



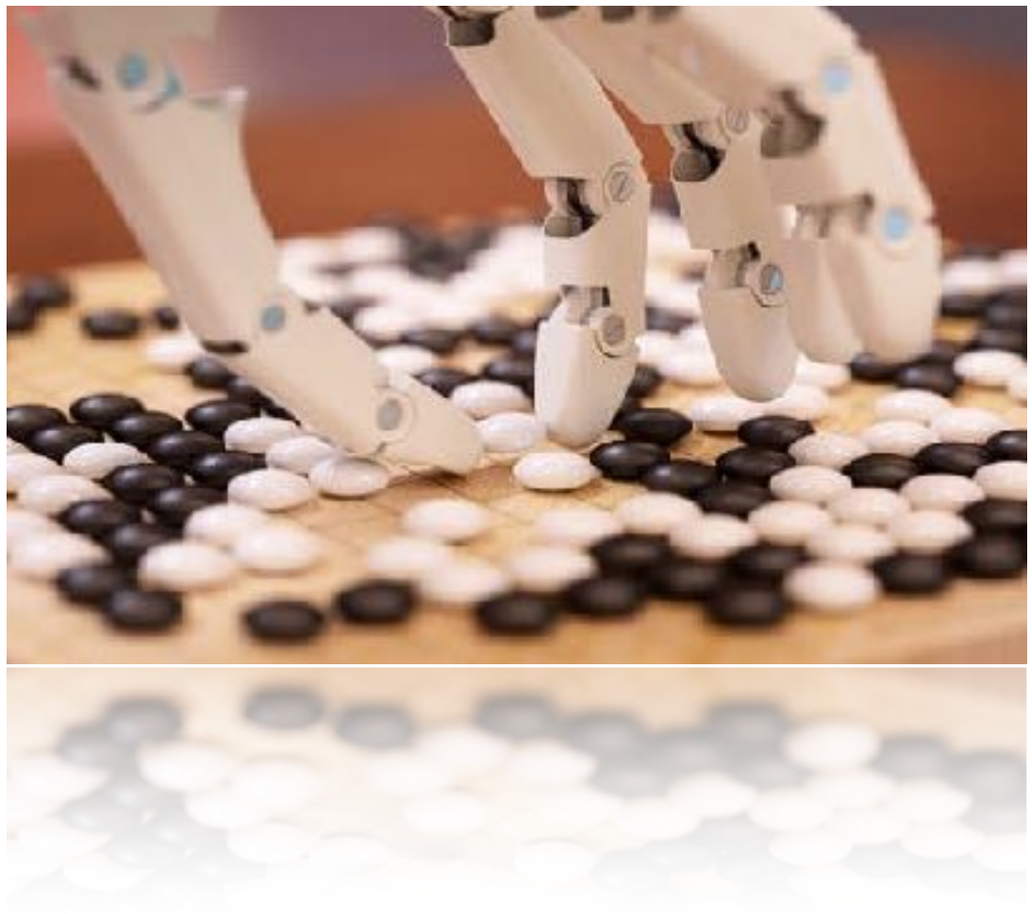
Around 10^{80} atoms

Around 10^{170} states

Black is winning?...



...or white is winning?



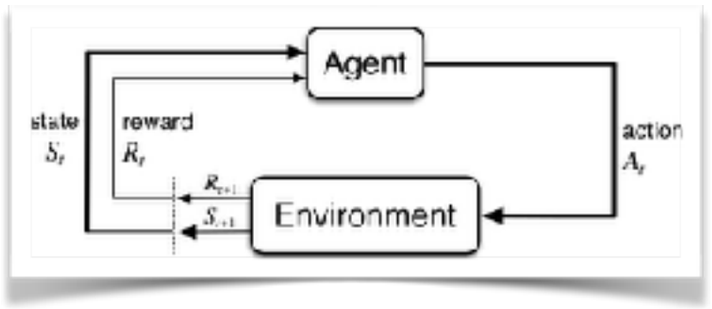
Learning procedure

DeepMind's AlphaZero

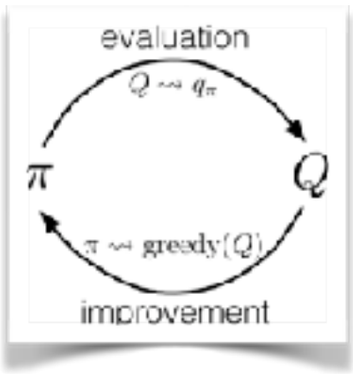
can play other games like Chess and Shogi.

Agenda

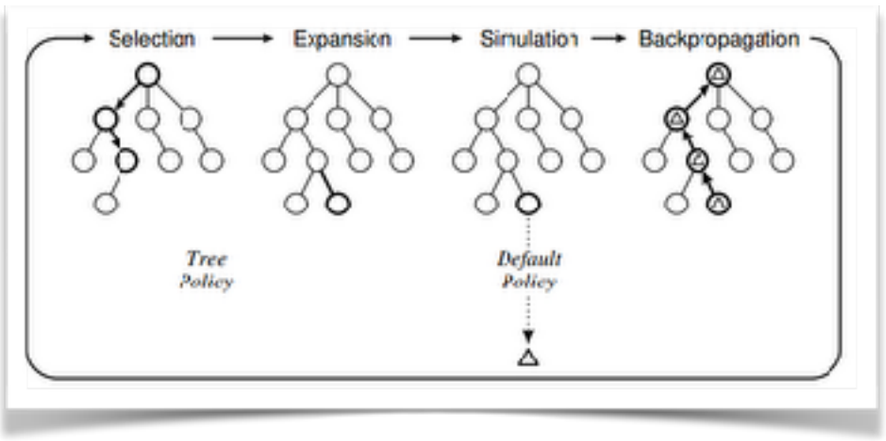
Reinforcement Learning

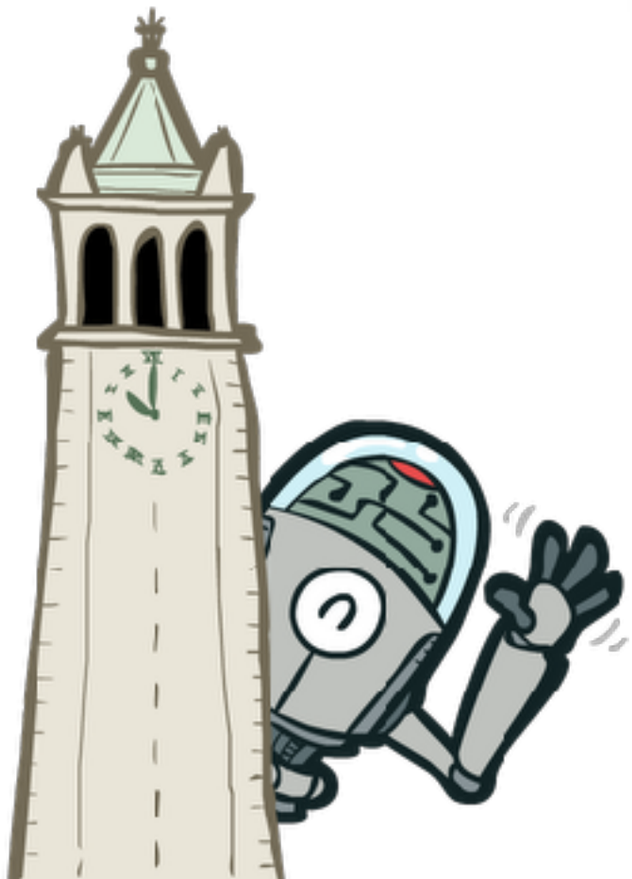


Policy iteration



Simulation-based search and AlphaZero





Reinforcement Learning 🍬

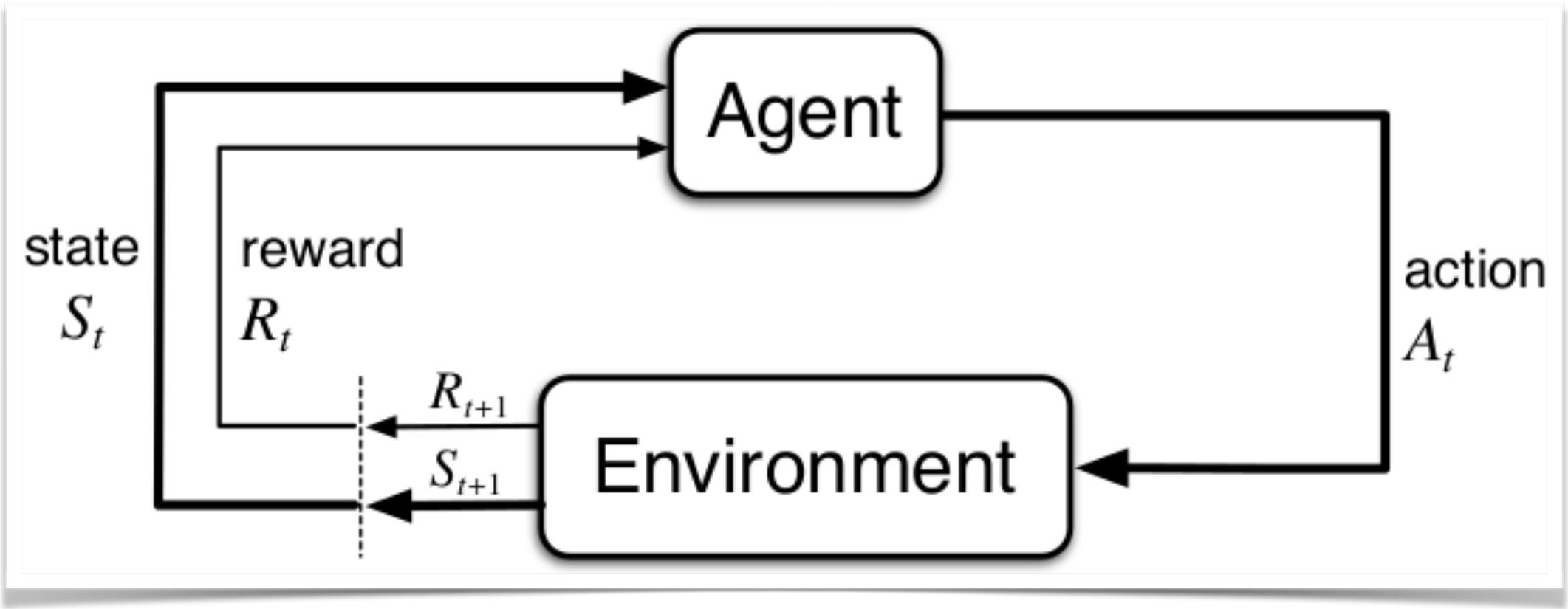
Where is it used?

- Robotics
- Video games
- Conversational systems
- Medical intervention
- Algorithm improvement
- Improvisational theatre
- Autonomous driving
- Prosthetic arm control
- Financial trading
- Query completion

RL is a natural way of learning for animals and humans

E.g. playing video games:

1. You start with exploration, what is possible?
2. You learn what gives you high rewards.
3. And finally, you exploit gained knowledge to win.



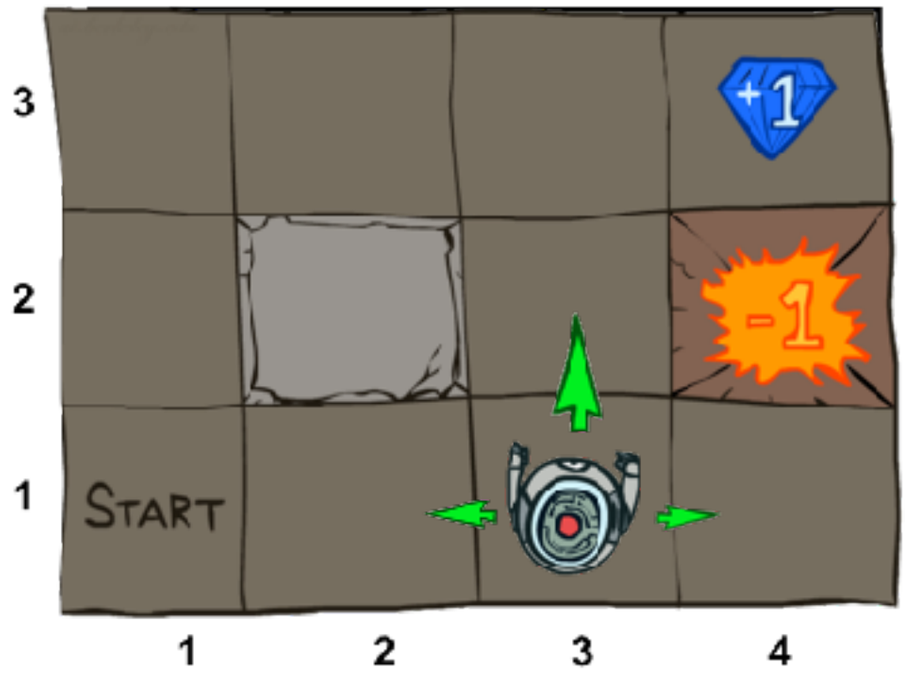
- Inspired by psychology – Agent + Environment
  – Agent selects actions to maximise total reward (return).
- Learning by trial-and-error, in real-time.
- Improves with experience.

Example: Grid World

- A maze-like problem
  - The agent lives in a grid
  - Walls block the agent's path
  - States are robot positions

- The agent receives rewards each time step
  - Small "living" reward each step (can be negative)
  - Big rewards come at the end (good or bad)

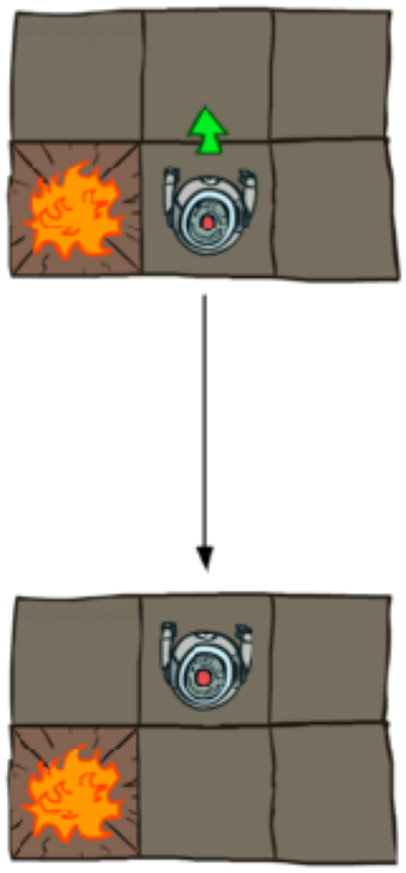
- Goal: maximise sum of rewards



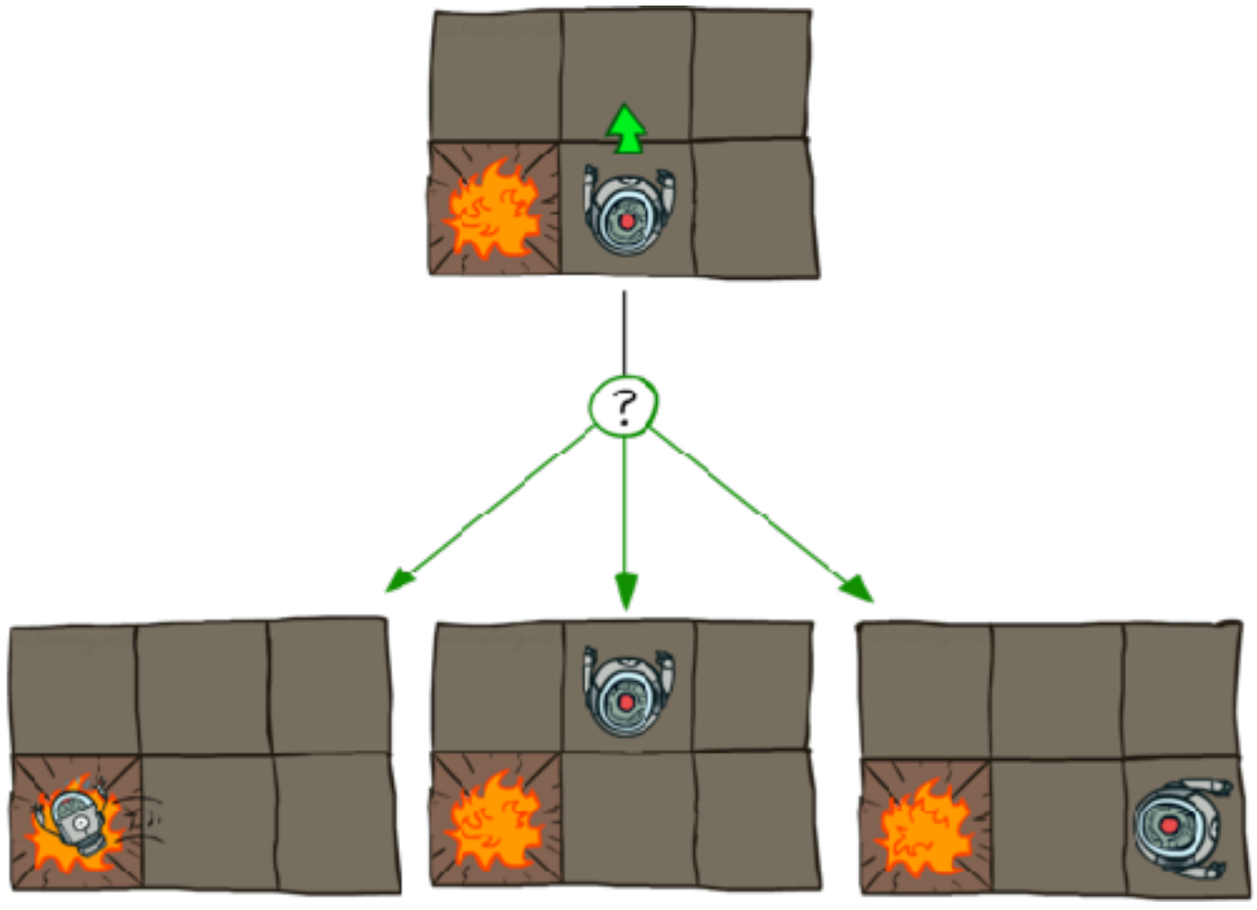
Source: UC Berkeley CS188 Intro to AI

Grid World Actions

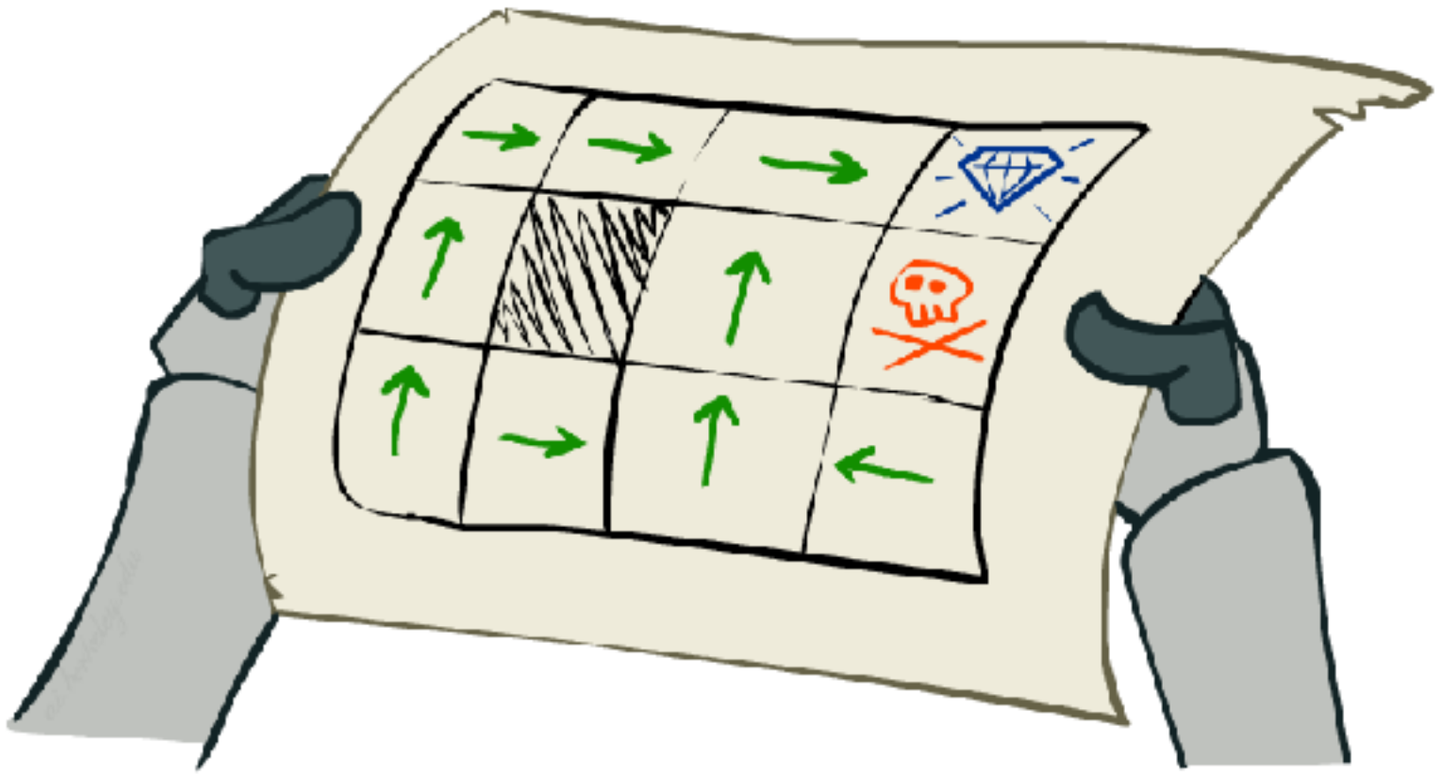
Deterministic Grid World



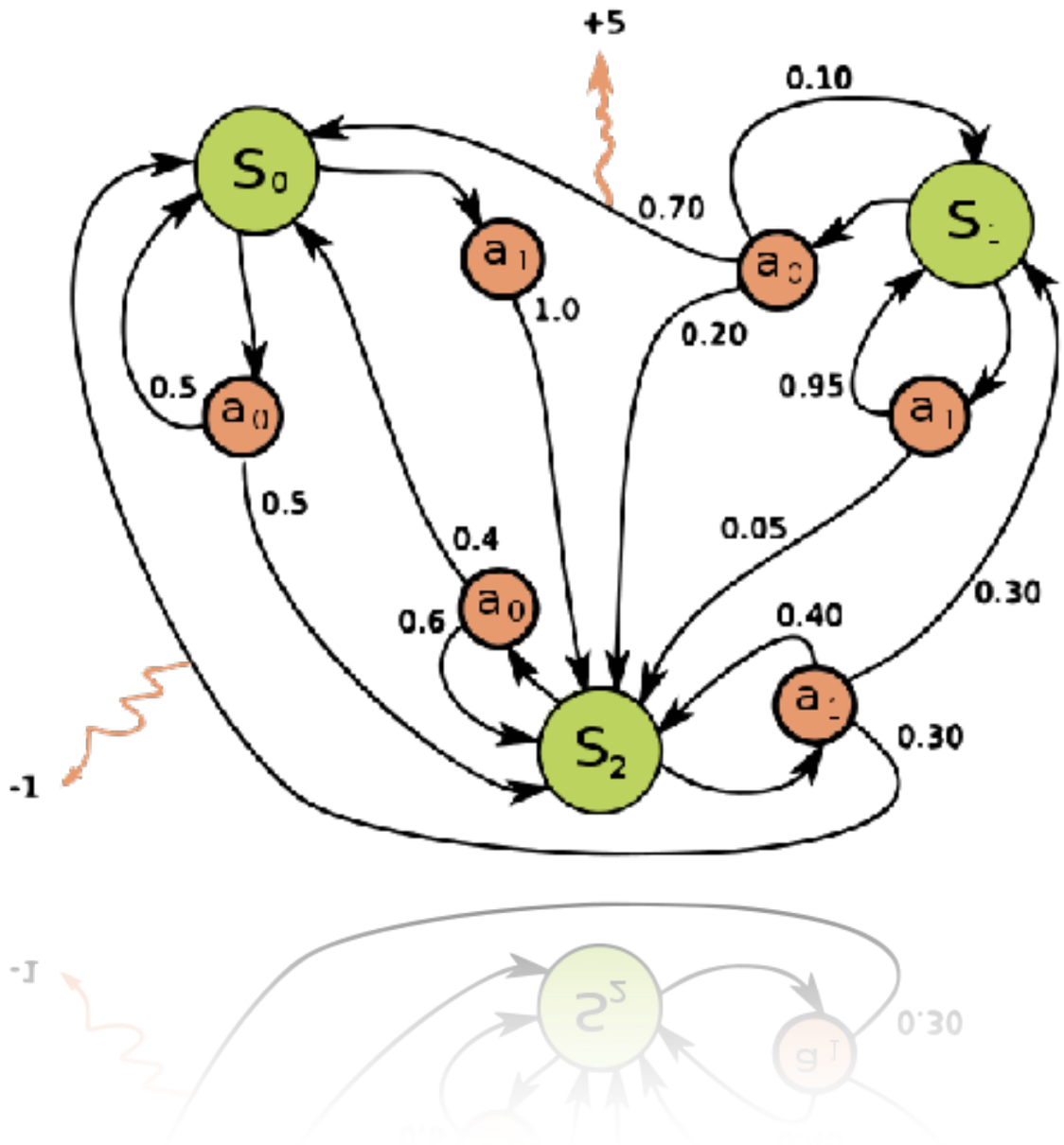
Stochastic Grid World



Policy tells an agent how it should behave



Markov Decision Process



- Set of states: S with initial s_0
- Set of actions: A
- The dynamics of the MDP or transition probabilities:

$$P^a_{ss'} = Pr(S_{t+1} = s' \,|\, S_t = s, A_t = a)$$

- Reward function:

$$R^a_{ss'} = R(s, a, s')$$

- Policy: $\pi(s, a) = Pr(A_t = a \,|\, S_t = s)$
- Discounting factor: γ

Markov property

$$P^{a}_{ss'} = Pr(S_{t+1} = s' | S_t = s, A_t = a)$$

The probability of reaching s’ from s depends only on s and a and not on the history of earlier states.

Andrey A. Markov was a Russian mathematician best known for his work on stochastic processes.

Expected return

G_t – **future expected (discounted) return from time t**

R_t – **random variable, reward at time t**

Continuous environment

$$G_t \doteq \mathbf{E}[r_t + r_{t+1} + r_{t+2} + \dots] = \sum_{i=0}^{\infty} R_{t+i}$$

$$G_t \doteq \mathbf{E}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \dots] = \sum_{i=0}^{\infty} \gamma^i R_{t+i}$$

Episodic environment

$$G_t \doteq \mathbf{E}[r_t + r_{t+1} + r_{t+2} + \dots + r_T] = \sum_{i=0}^{T-t} R_{t+i}$$

$$G_t \doteq \mathbf{E}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \dots + \gamma^{T-t} r_T] = \sum_{i=0}^{T-t} \gamma^i R_{t+i}$$

1

Worth Now

γ

Worth Next Step

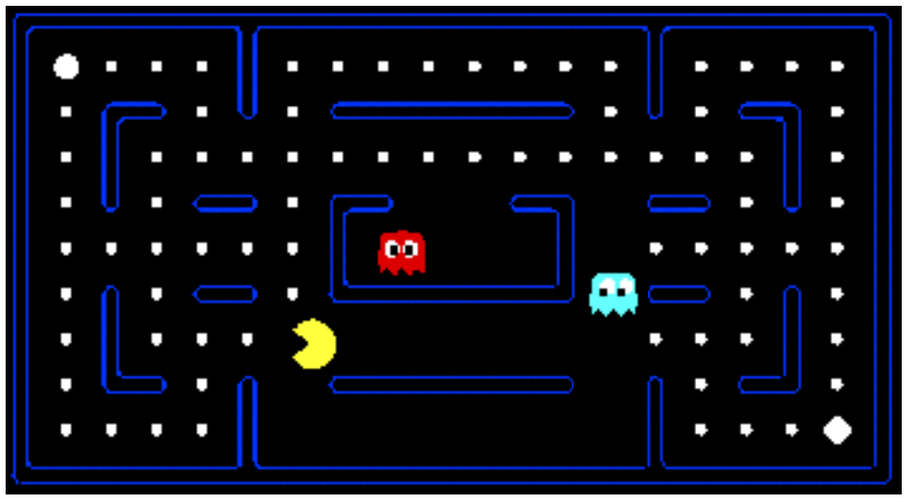
γ^2

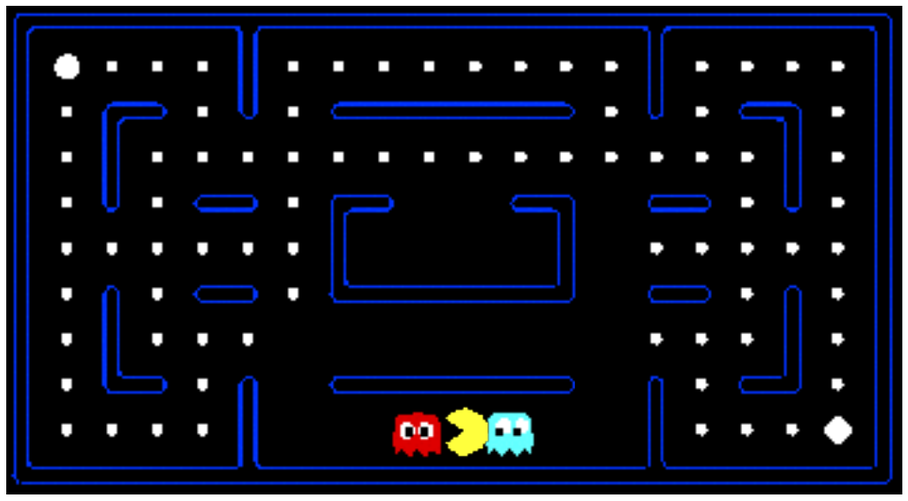
Worth In Two Steps

Value Function

Which state has higher “value”?

…or which state is better to be at, if you want to maximise the total sum of the collected white dots?

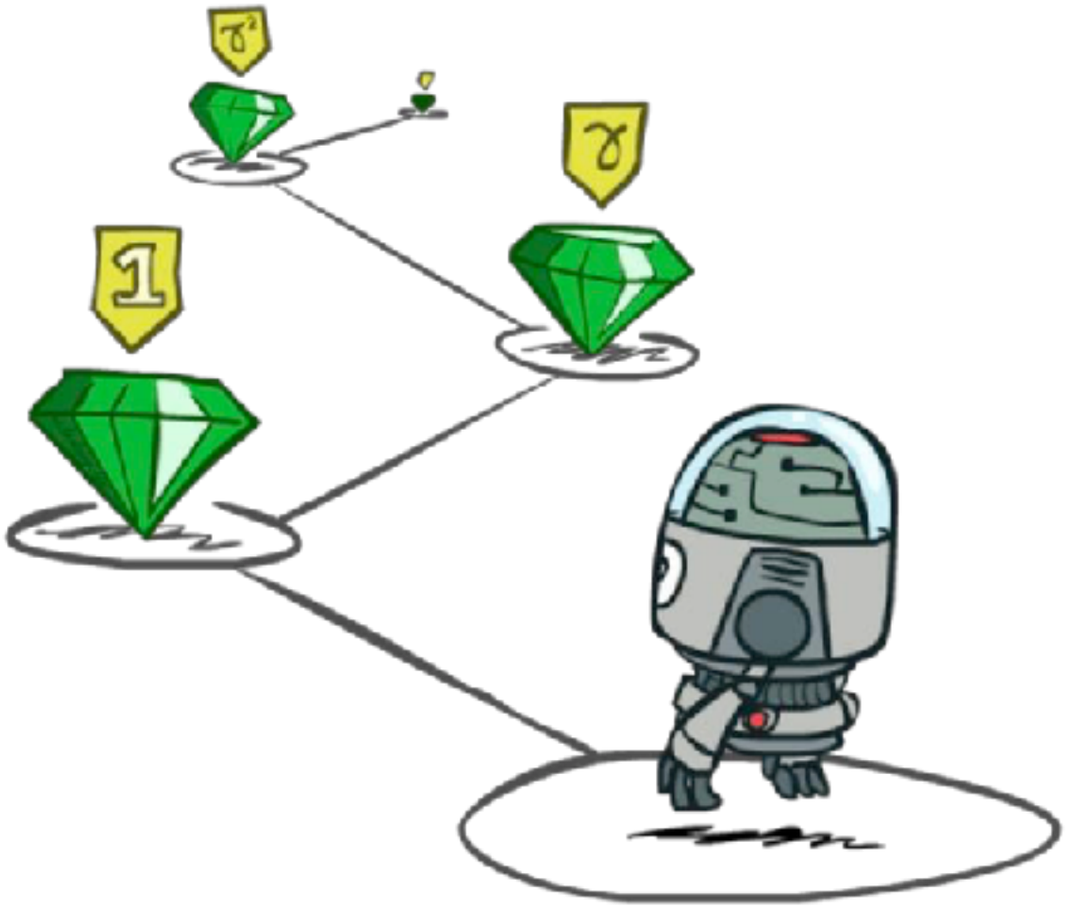




But why?

Value function

$$v_\pi(s) = \mathbf{E}_\pi[G_t \,|\, S_t = s] = \mathbf{E}_\pi[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots] = \mathbf{E}_\pi[R_{t+1} + \gamma v_\pi(S_{t+1})]$$

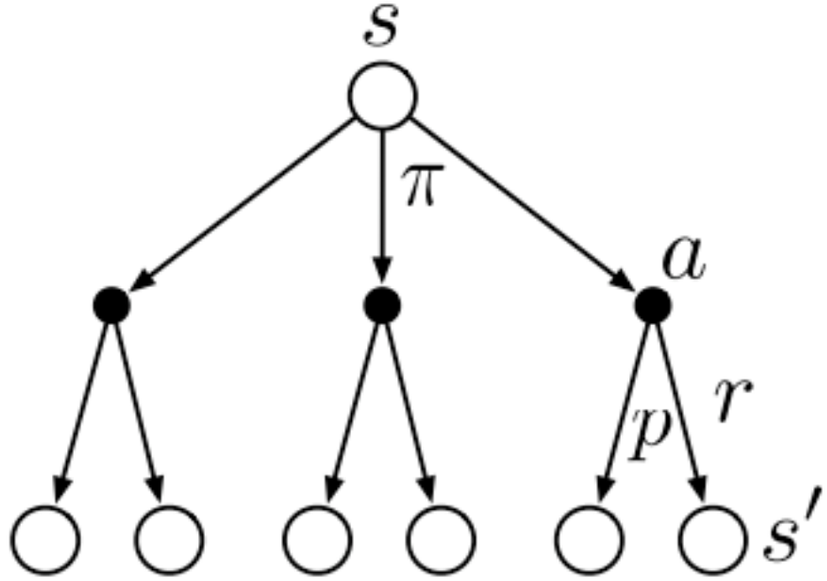


Value function estimates how good it is for the agent to be in a given state. The notion of “how good” here is defined in terms of **future rewards that can be expected**, or to be precise, in terms of **expected return from a given state following agent’s policy**.

Value function

$$v_\pi(s) = \mathbf{E}_\pi[R_{t+1} + \gamma v_\pi(S_{t+1})] = \sum_a \pi(s,a) \sum_{s'} Pr(S_{t+1} = s' \,|\, S_t = s, A_t = a)[r_{t+1} + \gamma v_\pi(s')]$$

The value of the state must equal the (discounted) value of the expected next state, plus the reward expected along the way.



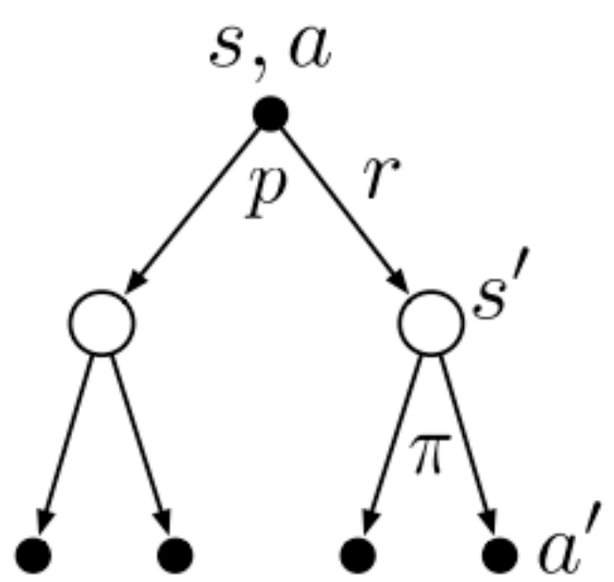
Backup diagram for value of state “s”

Quality function

$$q_\pi(s,a) = \mathbf{E}_\pi[G_t \,|\, s_t = s, a_t = a] = \mathbf{E}_\pi[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots] = \mathbf{E}_\pi[R_{t+1} + \gamma v_\pi(s')]$$

$$v_\pi(s) = \sum_a \pi(s,a) q_\pi(s,a)$$

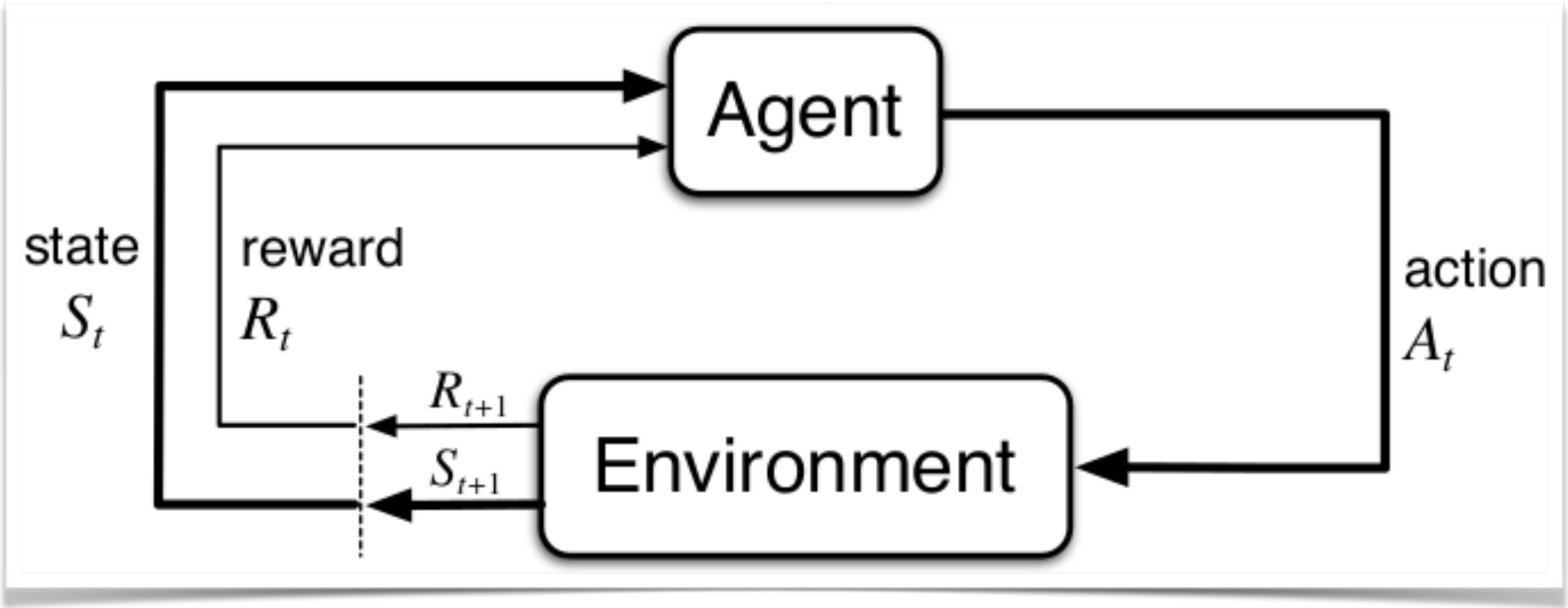
The quality of the state-action pair is expected return when taking the given action in the given state and following agent's policy afterwards.



Backup diagram for quality of state-action pair "s,a"

Policy Evaluation 

Reminder



You can only take actions and receive a feedback from the environment

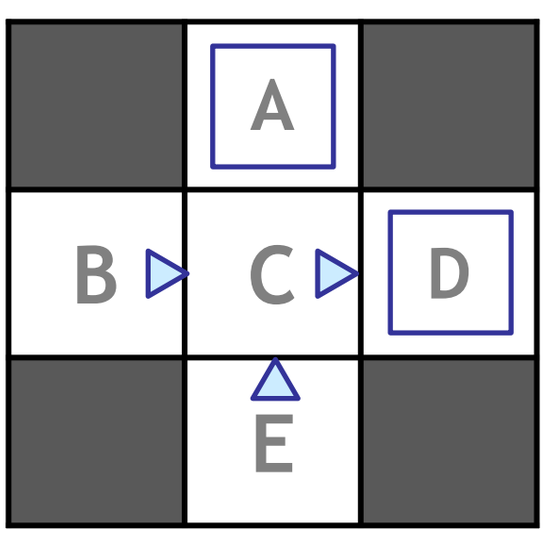
Monte Carlo!

Monte-Carlo prediction

1. Rollout a given policy to gather experience.
2. Average the returns observed after visiting each state.
3. As more returns are observed, the average will converge to the expected value.

Monte-Carlo prediction

Input Policy π



Assume: $\gamma = 1$

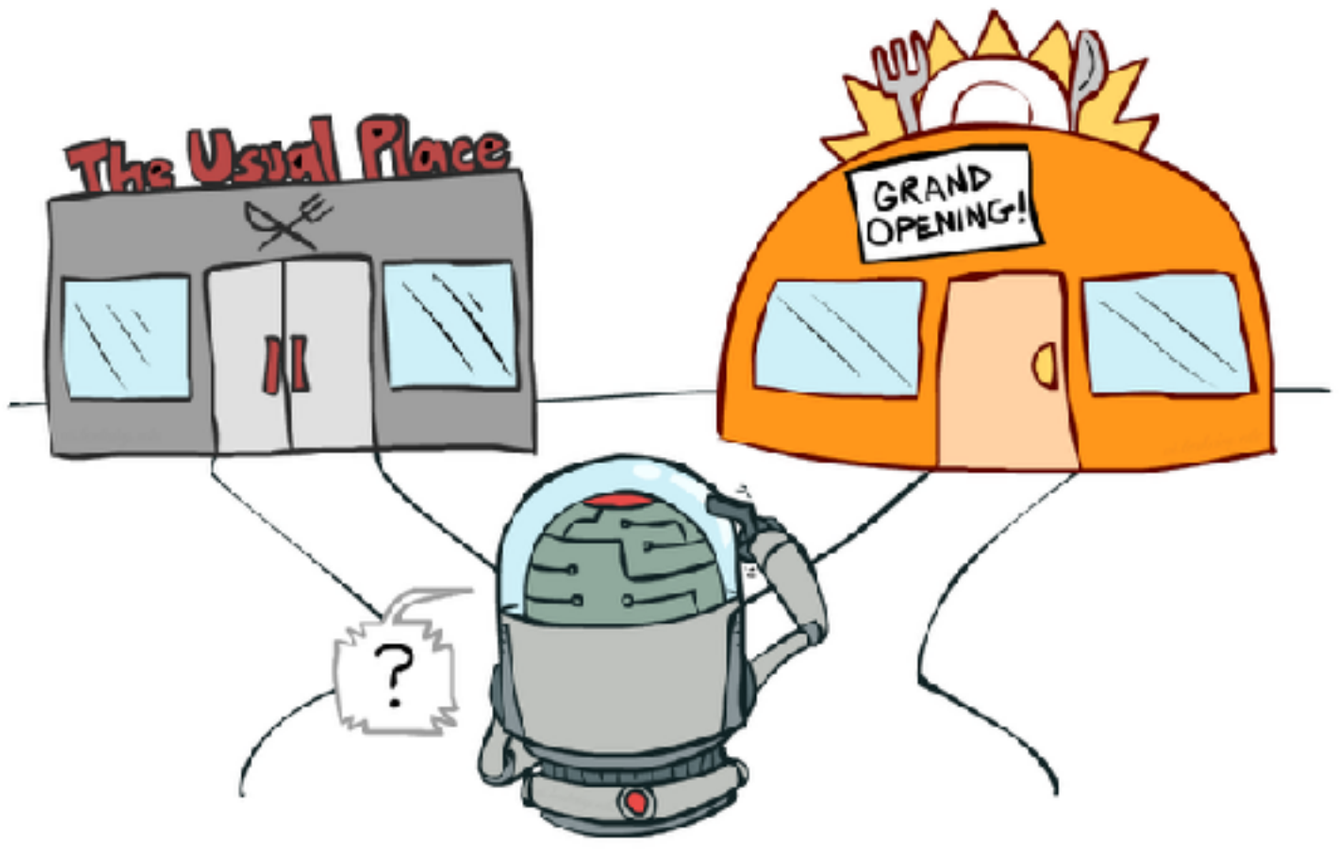
Episodes:

1. B -> East -> -1 -> C -> East -> -1 -> D -> exit -> +10
2. B -> East -> -1 -> C -> East -> -1 -> D -> exit -> +10
3. E -> North -> -1 -> C -> East -> -1 -> D -> exit -> +10
4. E -> North -> -1 -> C -> East -> -1 -> A -> exit -> -10

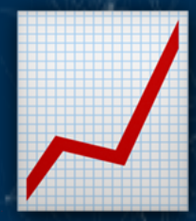
Monte-Carlo estimation of quality function

- Track the return after visiting each state-action pair.
- Many state–action pairs may never be visited if a policy is deterministic.
- This means no information about how good are other actions and no way to improve our policy.

Exploration-exploitation



Policy Improvement

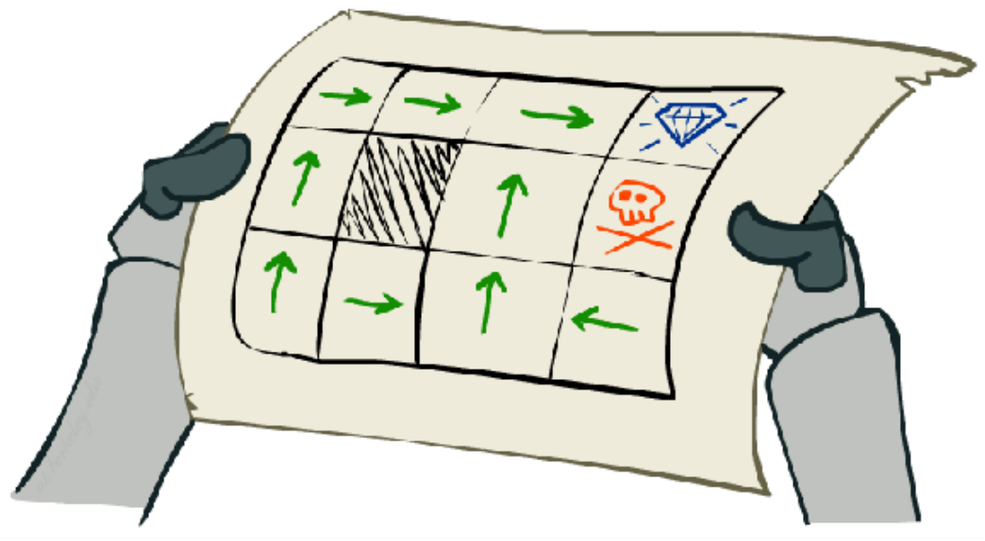


Choose best action now and follow your policy from next state onwards

One step look-ahead

$$\pi'(s) \doteq \operatorname*{argmax}_a q_\pi(s, a)$$

$$\forall_s \pi'(s) \geq \pi(s)$$



ε-greedy policy

With probability *(1 - epsilon)*:

$$a \leftarrow \pi(s) \doteq \underset{a}{\text{argmax}} q_\pi(s, a)$$

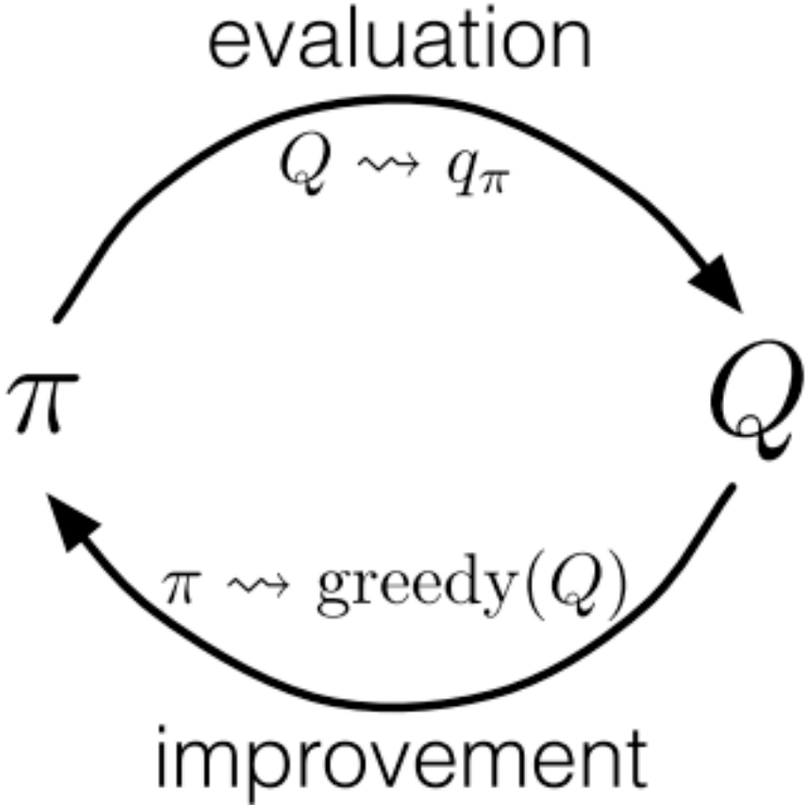
With probability *epsilon*:

$$a \leftarrow random\ action$$

Policy Iteration 🔁

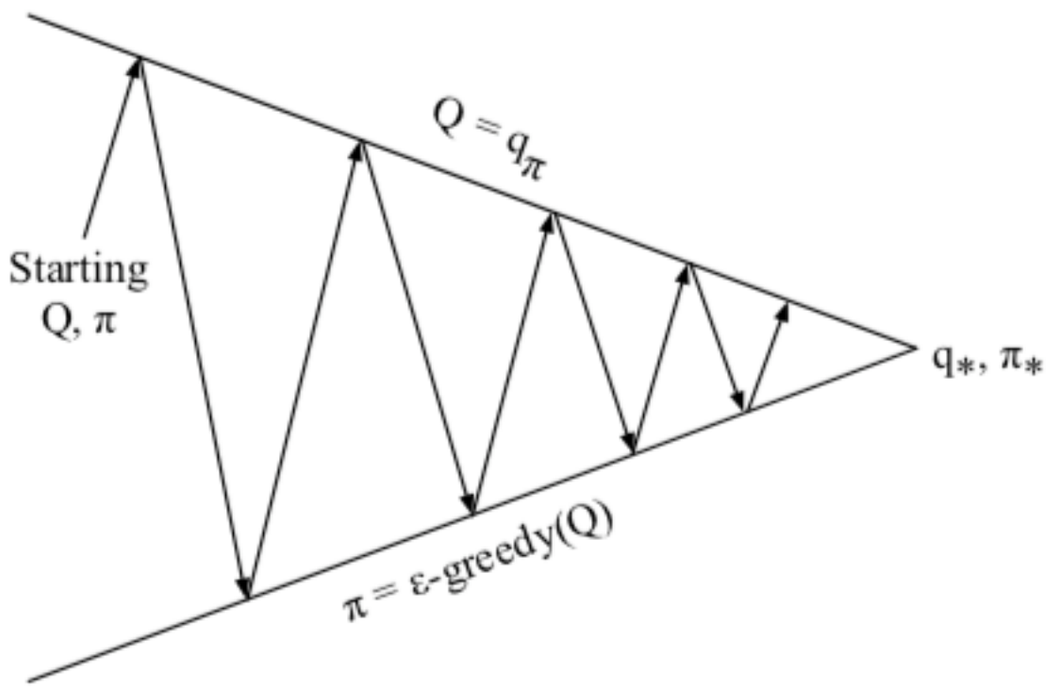
Evaluate your current policy

then improve it and start over!



Monte-Carlo control

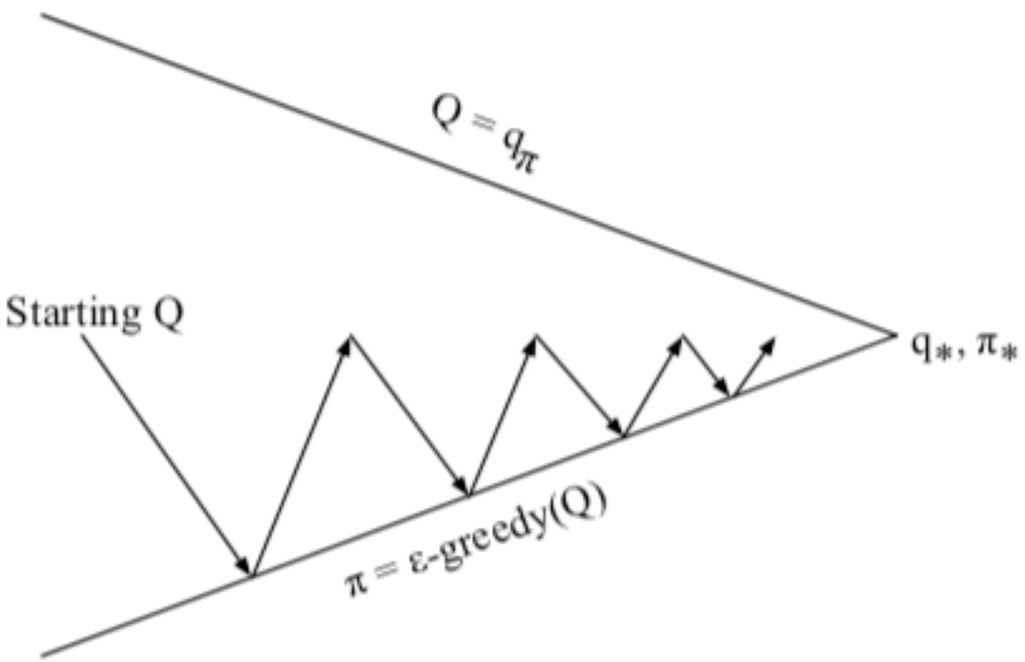
1. Start with an arbitrary policy and Q-values.
2. Alternate between policy evaluation and policy improvement.
3. When the policy doesn't change anymore, you've reached the optimal point.



$$q_\pi(s,a) = \mathbf{E}[R_{t+1} + \gamma \max_{a'} q_\pi(S_{t+1}, a') \,|\, S_t = s, A_t = a] \iff \pi = \pi^*$$

Bellman optimality equation

Iterative implementation

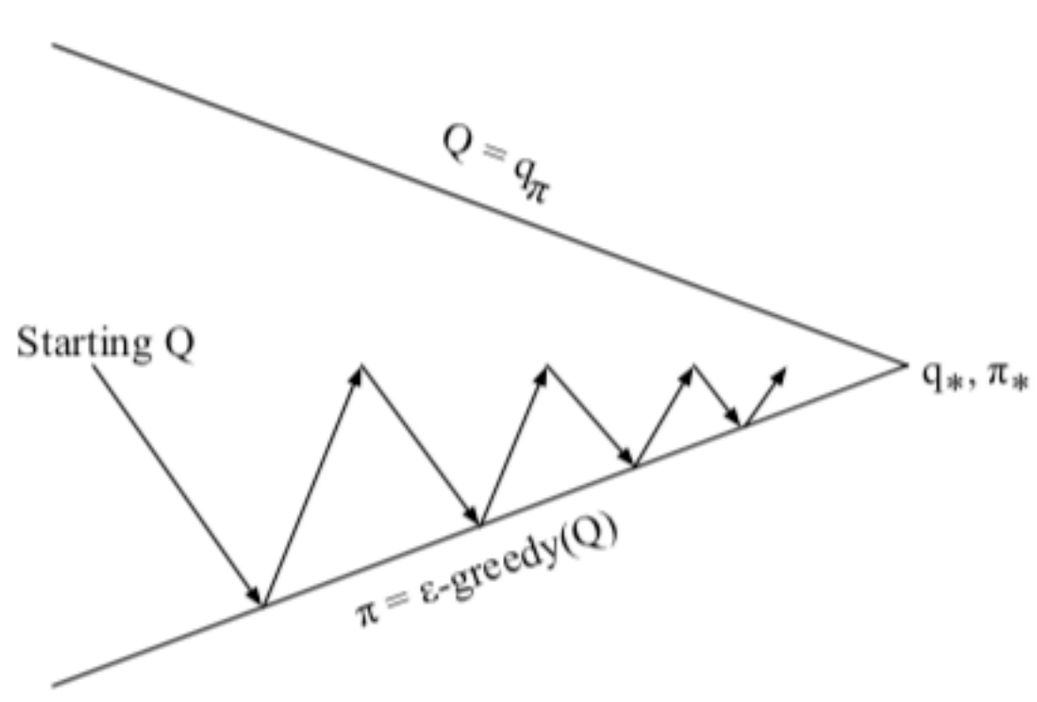


Interleave policy evaluation and policy improvement on an episode-by-episode basis.

Policy iteration will converge, regardless of evaluation and improvement steps arrangement.

One last problem

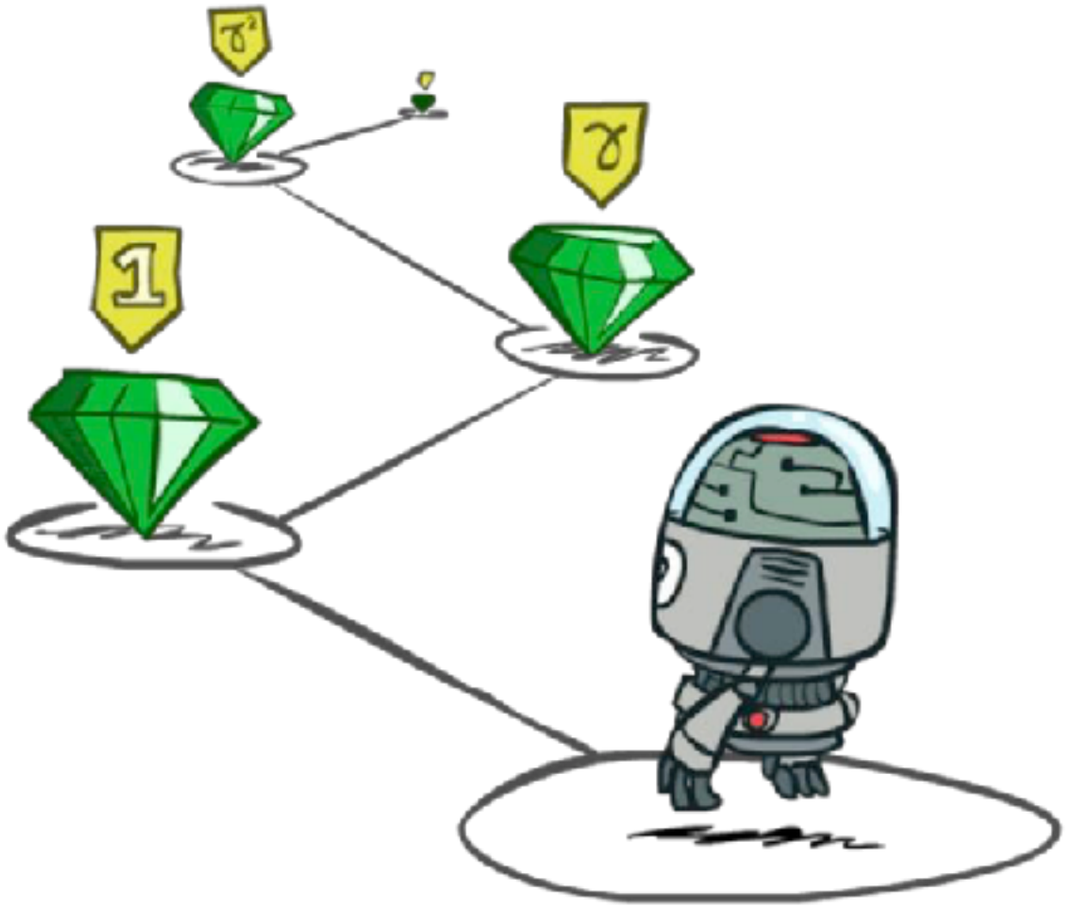
Q-values of what policy do we learn?



Policy Evaluation (differently) 🧮

(Recap) Value function

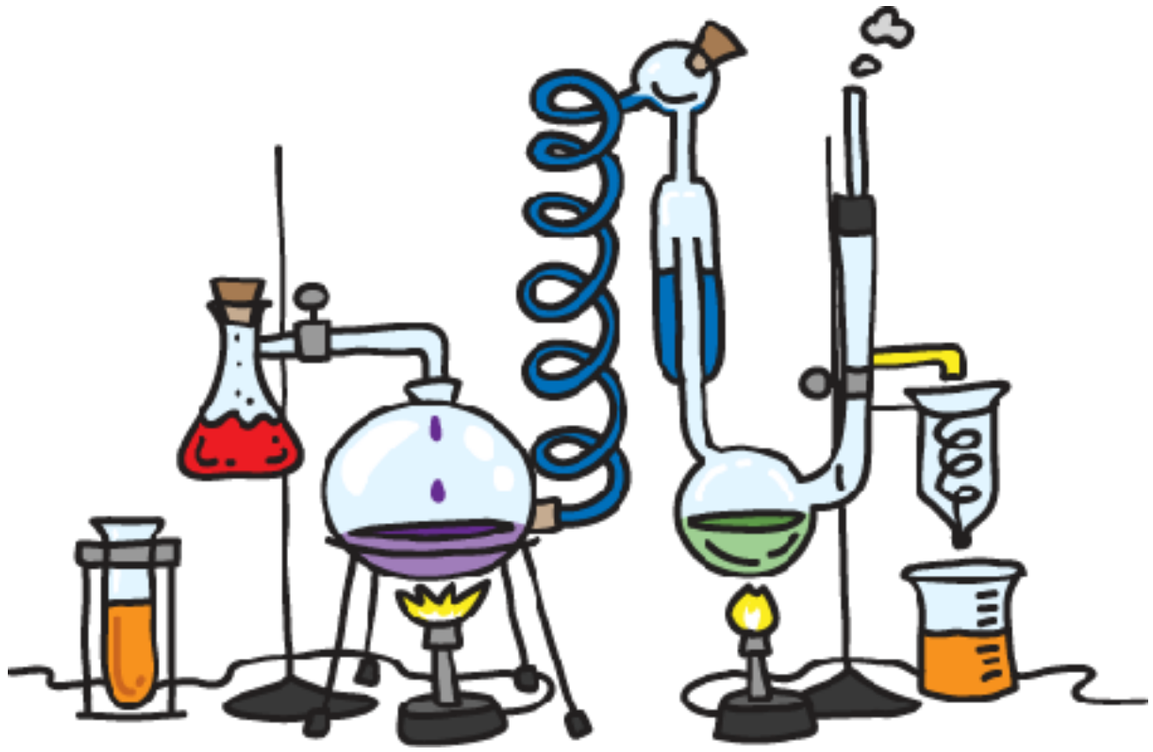
$$v_\pi(s) = \mathbf{E}_\pi[G_t \,|\, S_t = s] = \mathbf{E}_\pi[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots] = \mathbf{E}_\pi[R_{t+1} + \gamma v_\pi(S_{t+1})]$$



Value function estimates how good it is for the agent to be in a given state. The notion of “how good” here is defined in terms of **future rewards that can be expected**, or to be precise, in terms of **expected return from a given state following agent’s policy**.

Temporal-Difference Learning

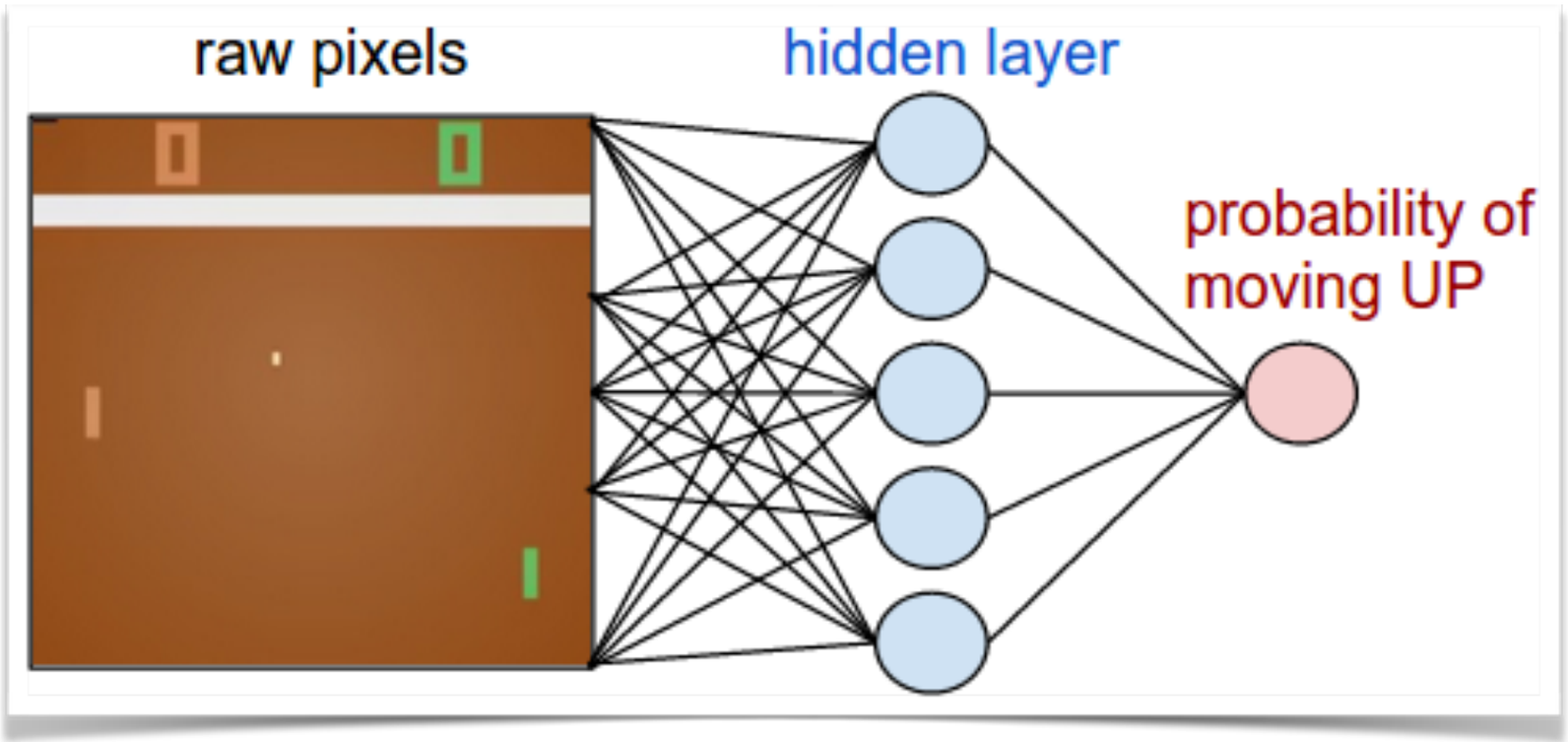
$$v_{k+1}(s) \doteq \mathbb{E}_\pi[R_{t+1} + \gamma v_k(S_{t+1}) \mid S_t = s]$$



Do it yourself!

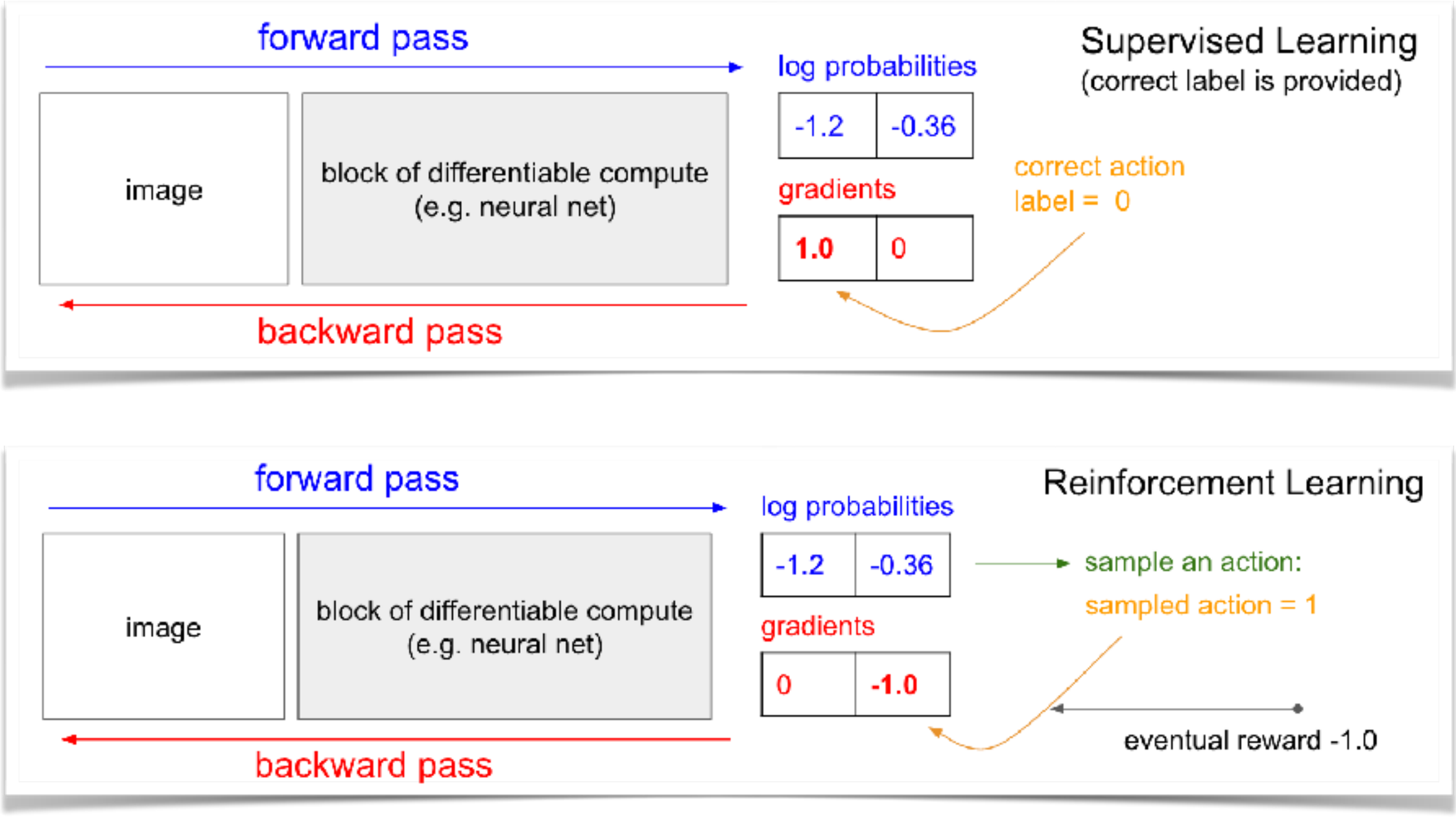
Policy Gradients 🎯

Why to learn some values, if all we care about is policy?

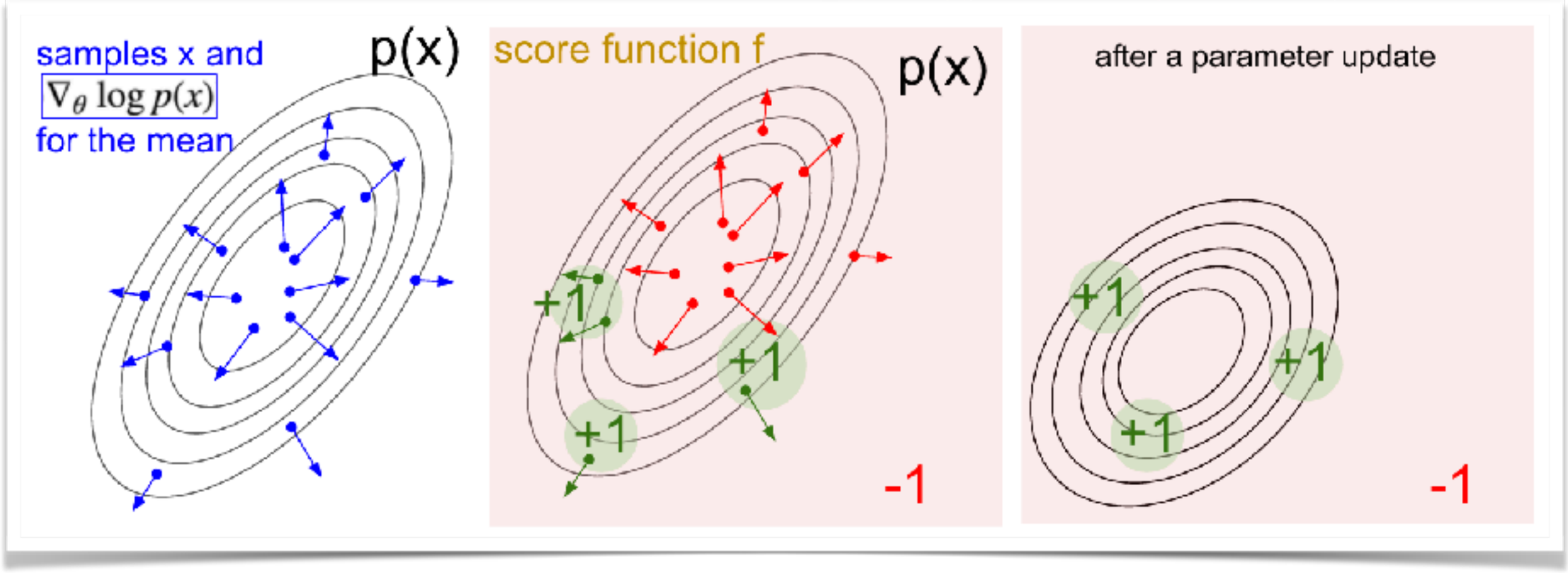


Our NN takes a current game state, processes it and returns probabilities of particular actions (it's the parametrised distribution over actions). Then we sample from this distribution to decide what action to take.

How is RL related to SL?



Plug-in reward as a label



What happens is we shift action distribution (which depends on current state) to areas where actions result in higher rewards. We encourage NN to take “good” actions and discourage it to take “bad” actions.

Policy Gradients: pros and cons

We train NN policy directly, that’s great! But also we learn on-policy, from current policy experience. It means that what we do has high impact on what we learn.

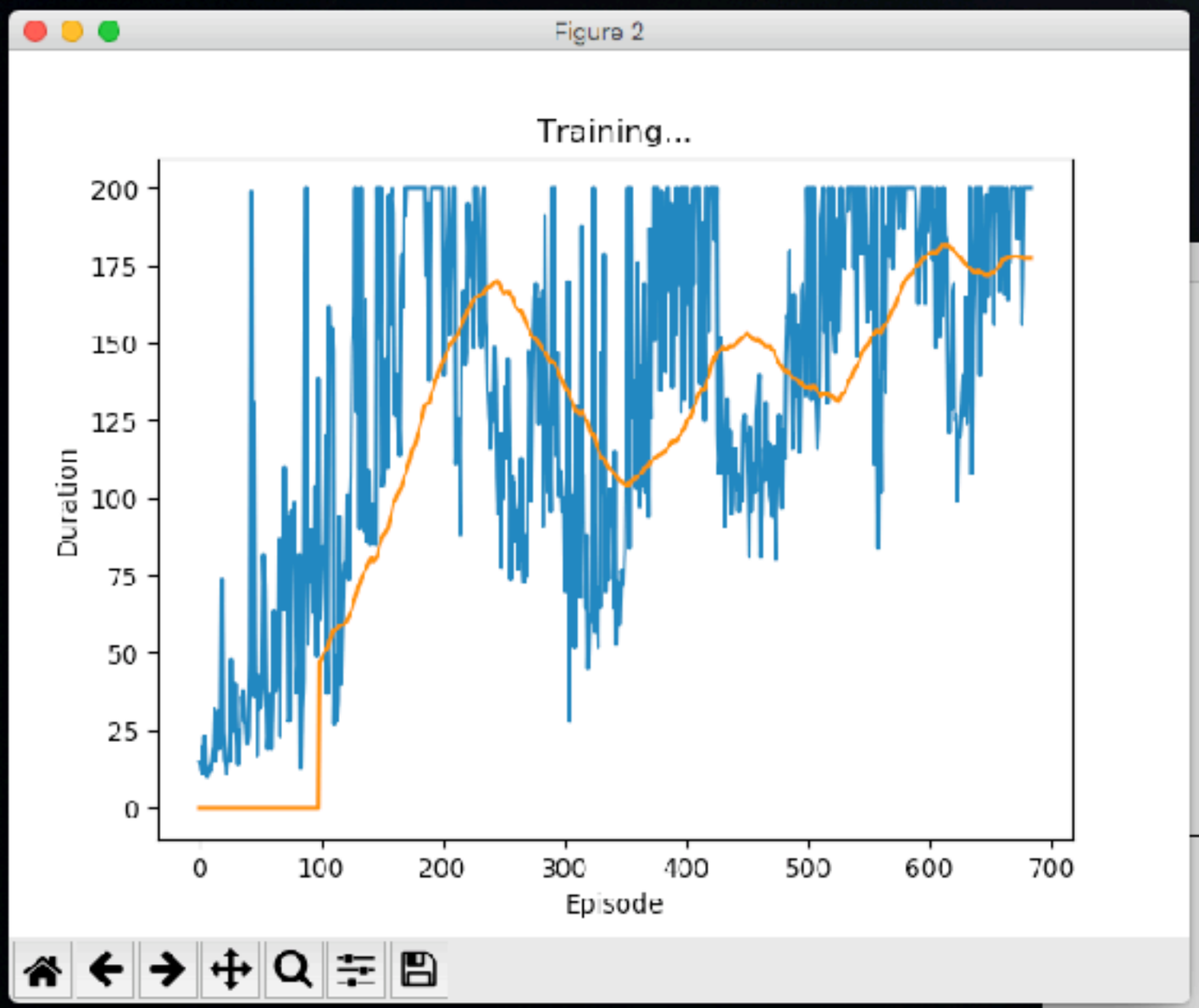


Figure 2
Training...
Duration
Episode
0
25
50
75
100
125
150
175
200
0
100
200
300
400
500
600
700

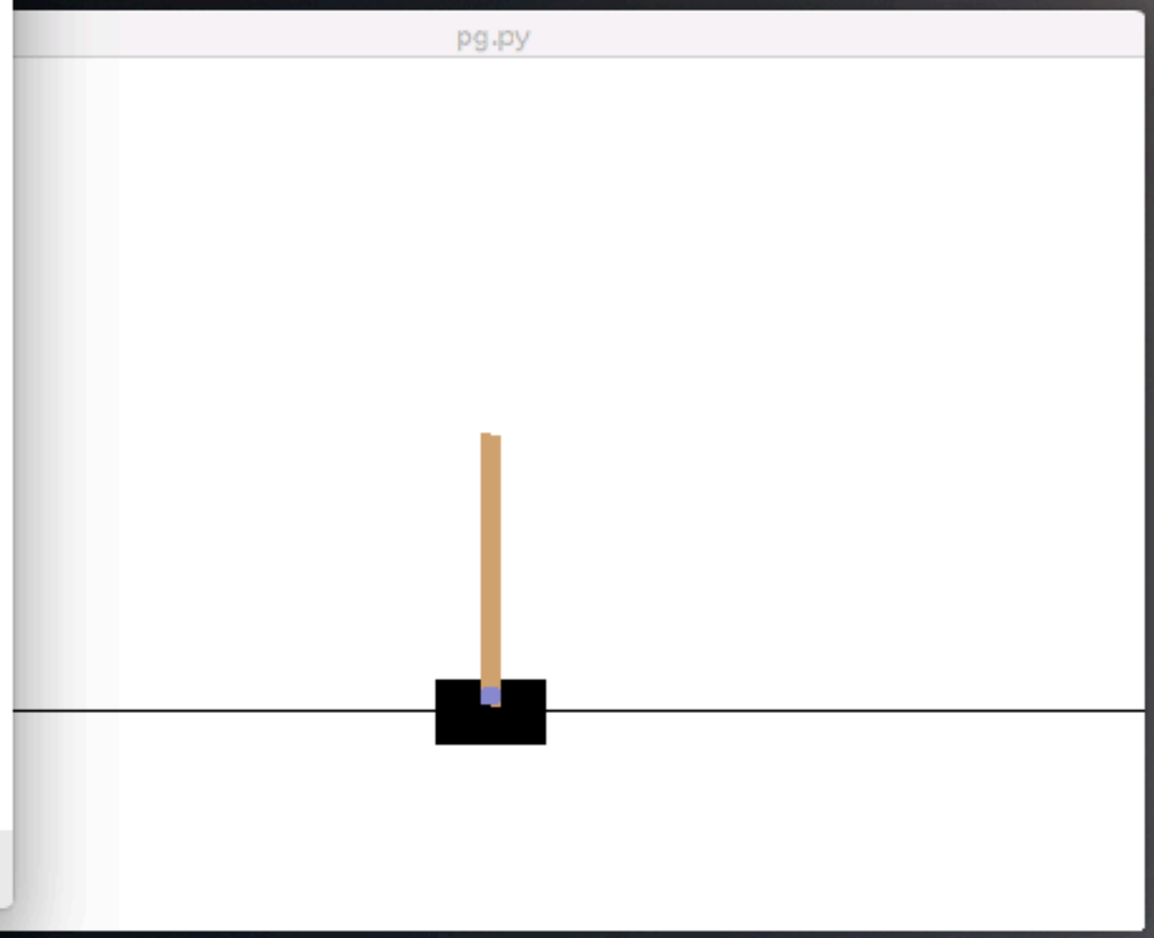
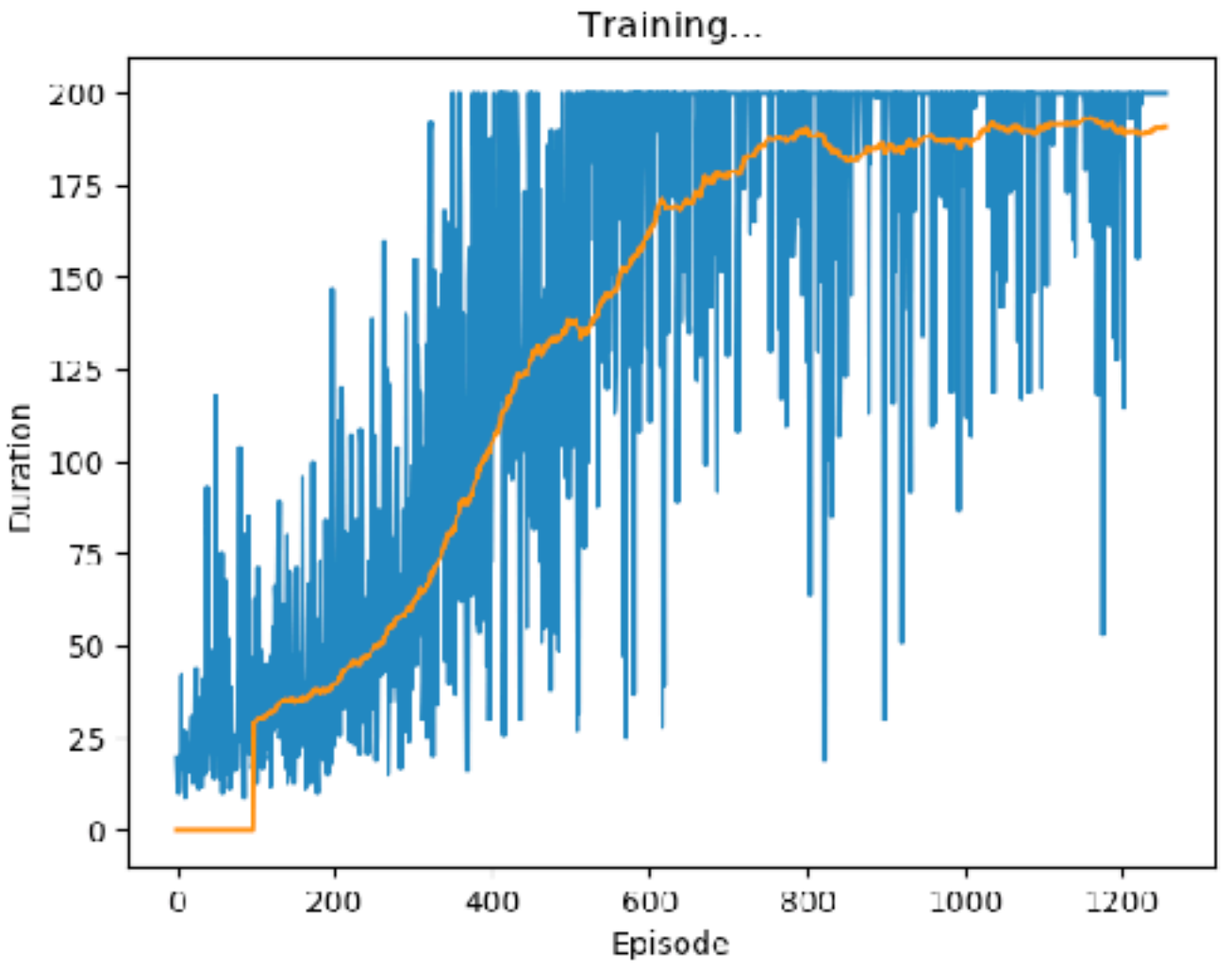

pg.py

Figure 2

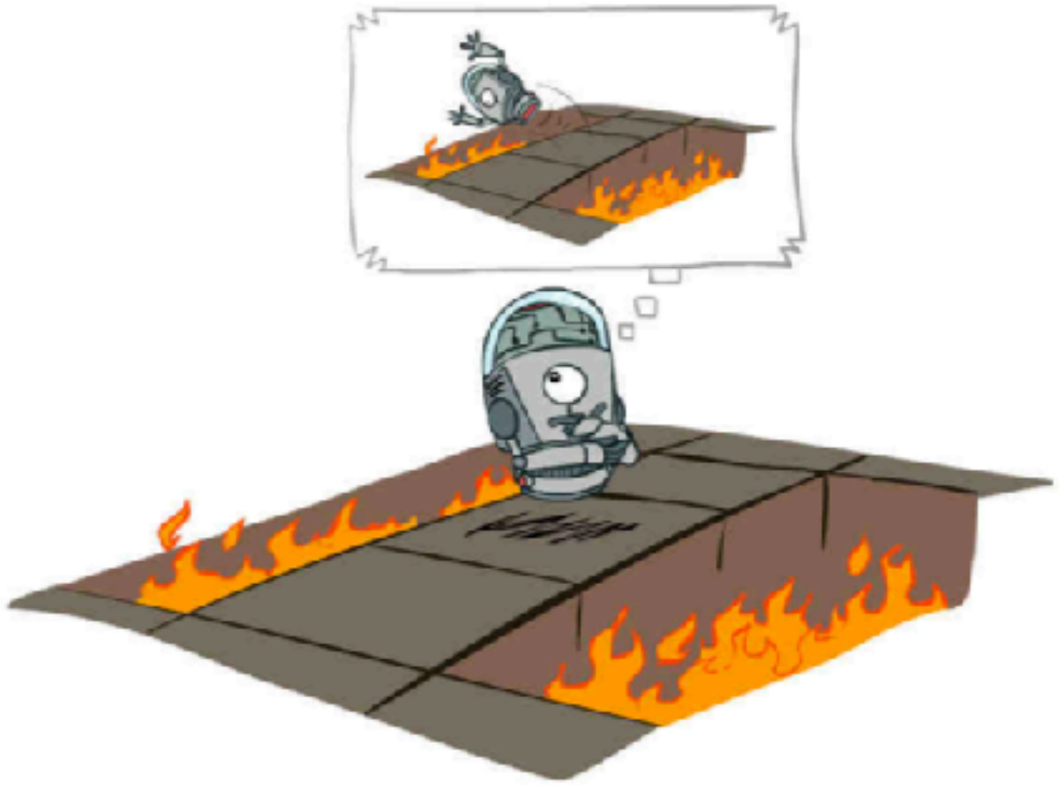


x=301.533 y=131.657

pg.py

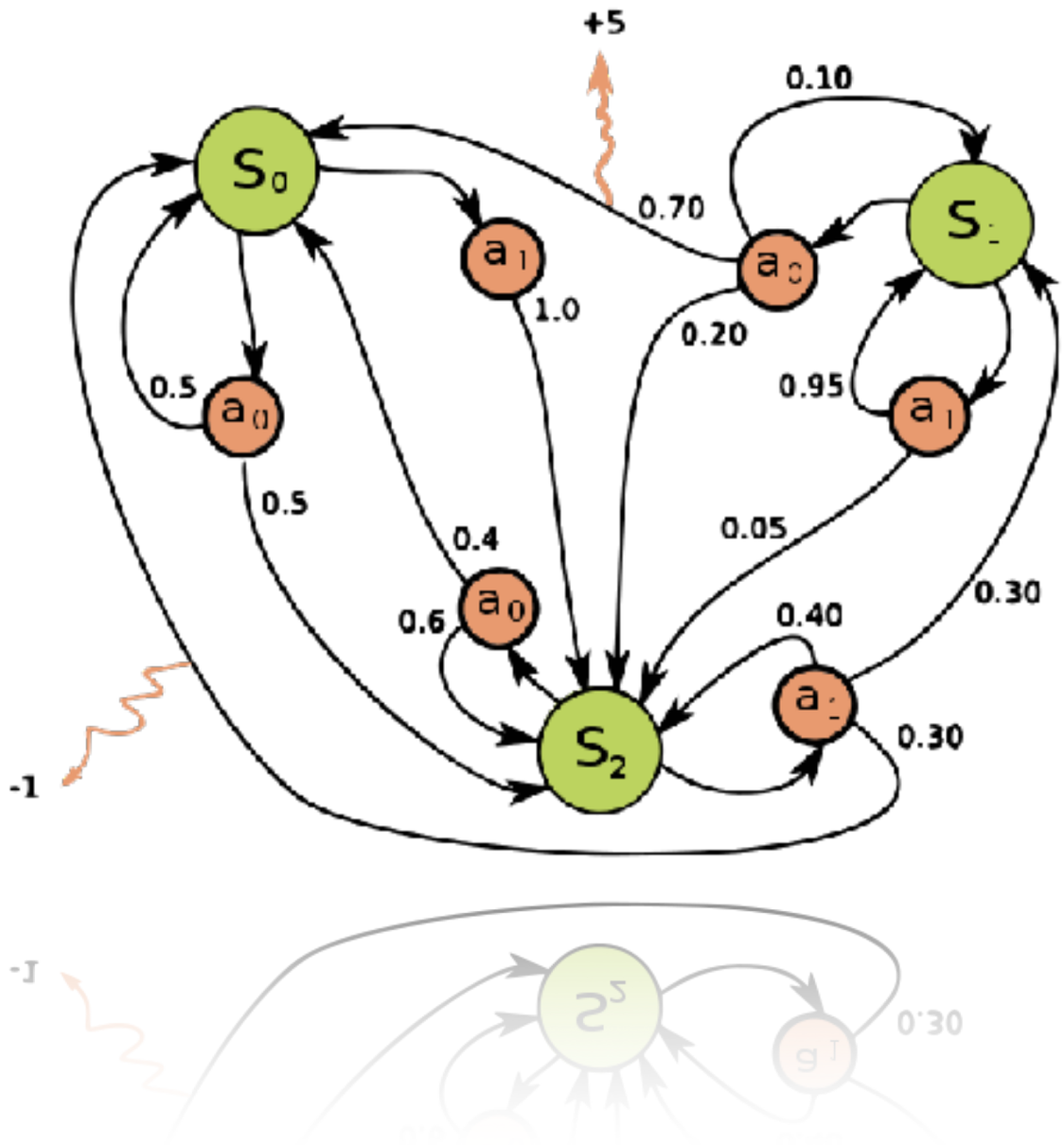
Simulation-based search 🌳

Planning vs. learning



Temporality

sub-MDP



- Set of states: S with initial s_t
- Set of actions: A
- The dynamics of the MDP or transition probabilities:

$$P^a_{ss'} = Pr(S_{t+1} = s' \,|\, S_t = s, A_t = a)$$

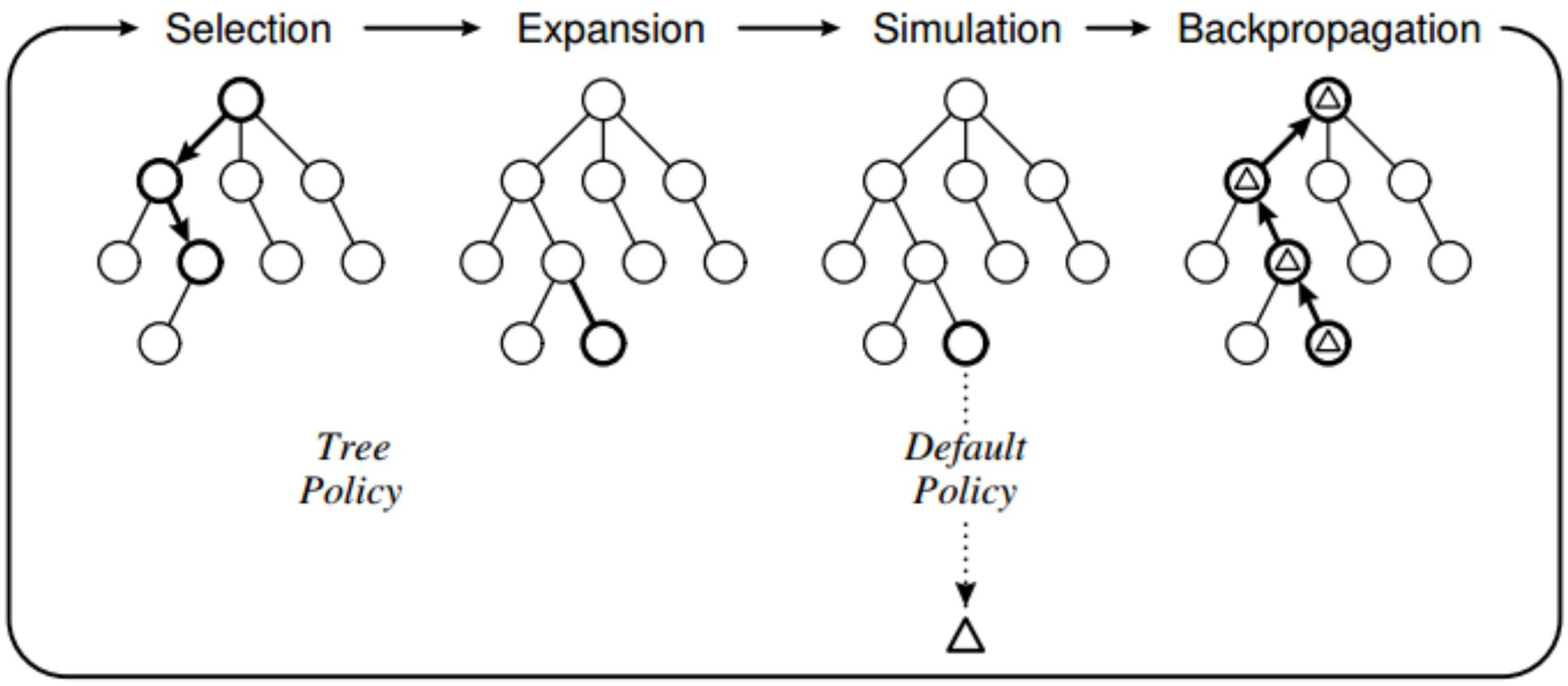
- Reward function:

$$R^a_{ss'} = R(s, a, s')$$

- Policy: $\pi(s, a) = Pr(A_t = a \,|\, S_t = s)$
- Discounting factor: γ

Monte-Carlo Tree Search

in policy iteration framework



Each node keeps track of:

$N(s)$ – **a total count for the state**

$N(s, a)$ – **a total count for the action in the state**

$Q(s, a)$ – **value of the action in the state**

What about exploration?

Tree policy in Monte-Carlo Tree Search (MCTS)

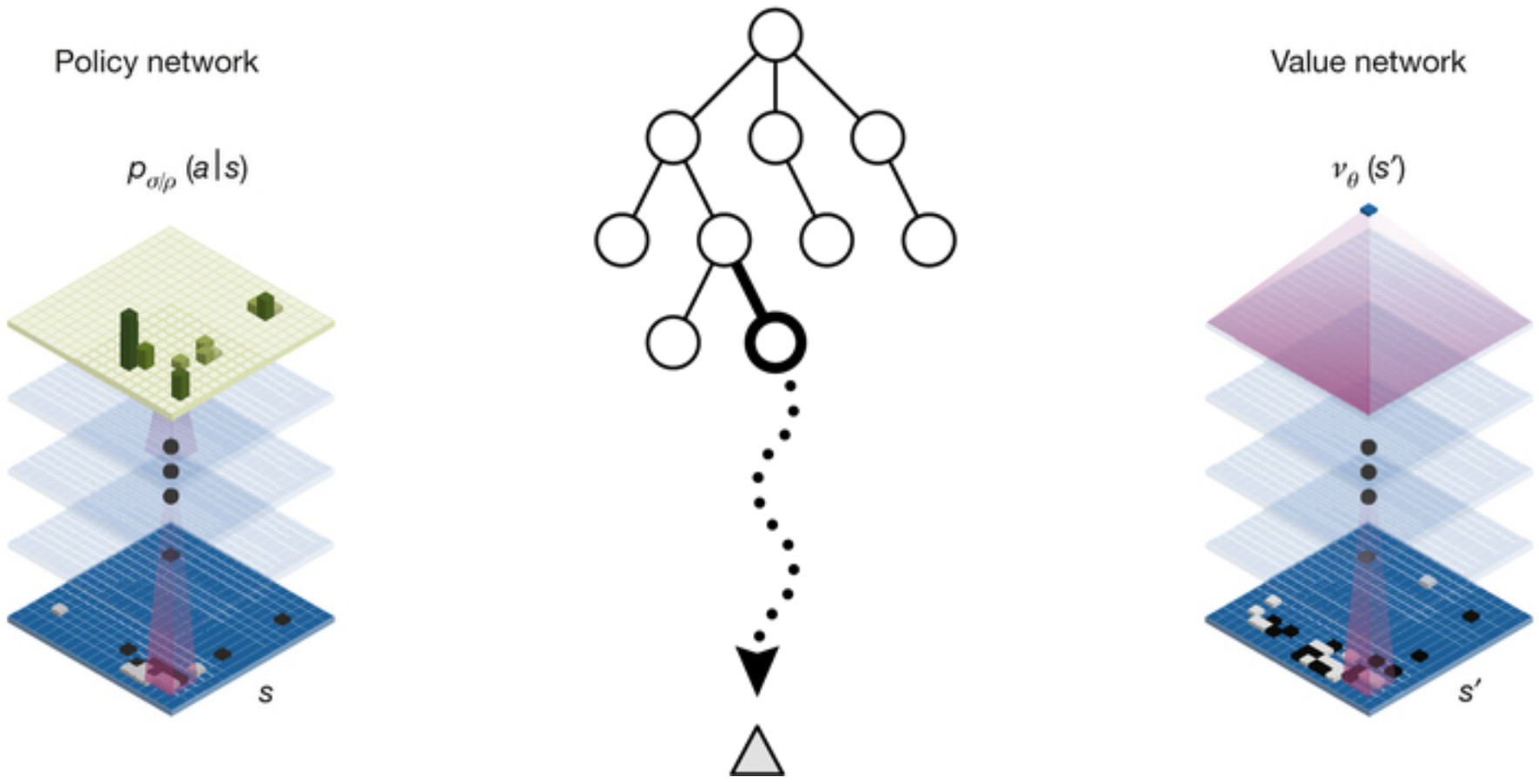
$$\pi_{tree}(s) \doteq \text{argmax}_a Q(s,a)$$

Tree policy in Upper Confidence Tree (UCT)

$$\pi_{tree}(s) \doteq \text{argmax}_a \left[Q(s,a) + c\sqrt{\frac{\ln N(s)}{N(s,a)}} \right]$$

AlphaZero demystified

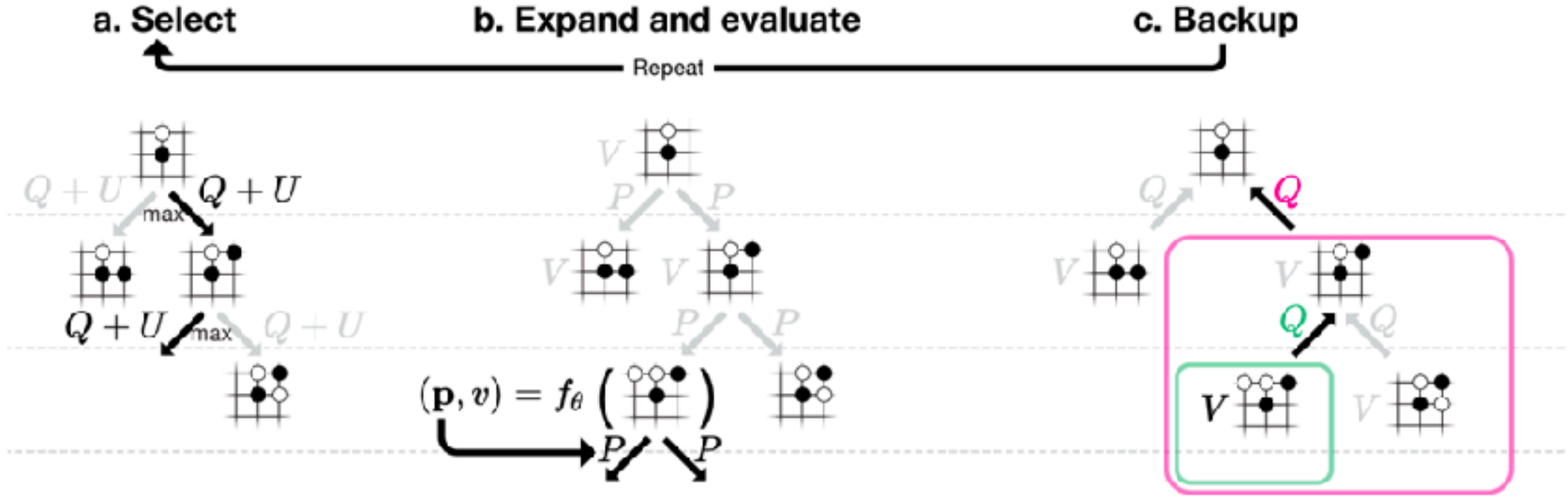
AlphaZero architecture



Requirements on problem kind

- discrete - states and actions sets form a discontinuous sequences, put simply they are discrete.
- deterministic - every move has one possible outcome.
- with perfect information - both players have perfect knowledge about current game state.
- access to game rules - there need to be some sort of environment simulator.

AlphaZero Tree Search



Efficiency Through Value Function

Games like chess ♛ and Go ⚪ have very (in Go I mean VERY) large state space - legal board game positions.

Any ideas how to obtain the value function?

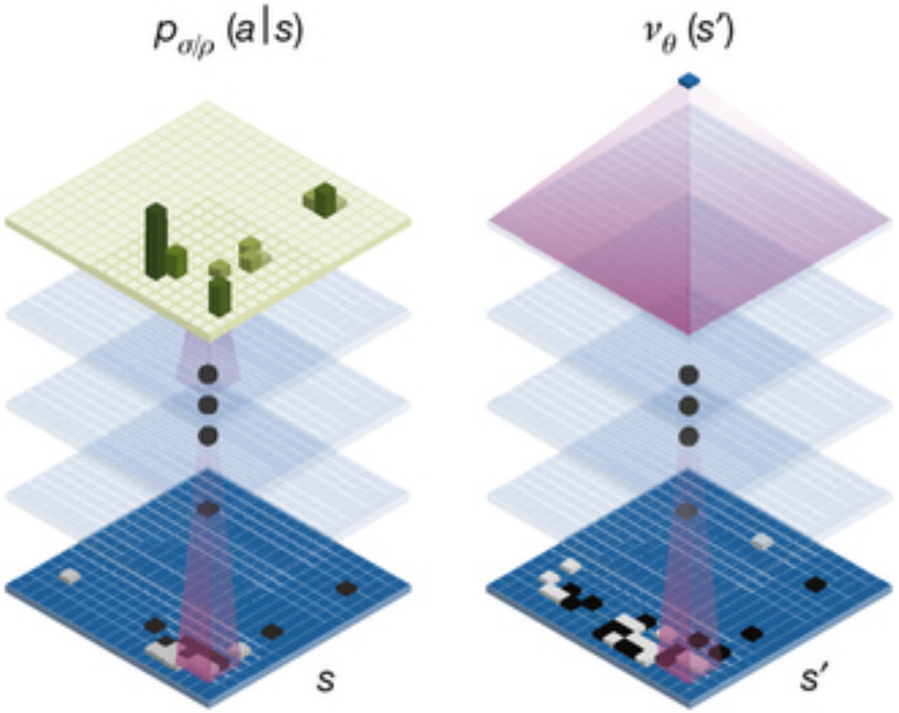
Efficiency Through Expert Policy

Also, games like chess ♛ and Go ⚪ have very (in Go I mean VERY) large branching factor - possible moves in each state.

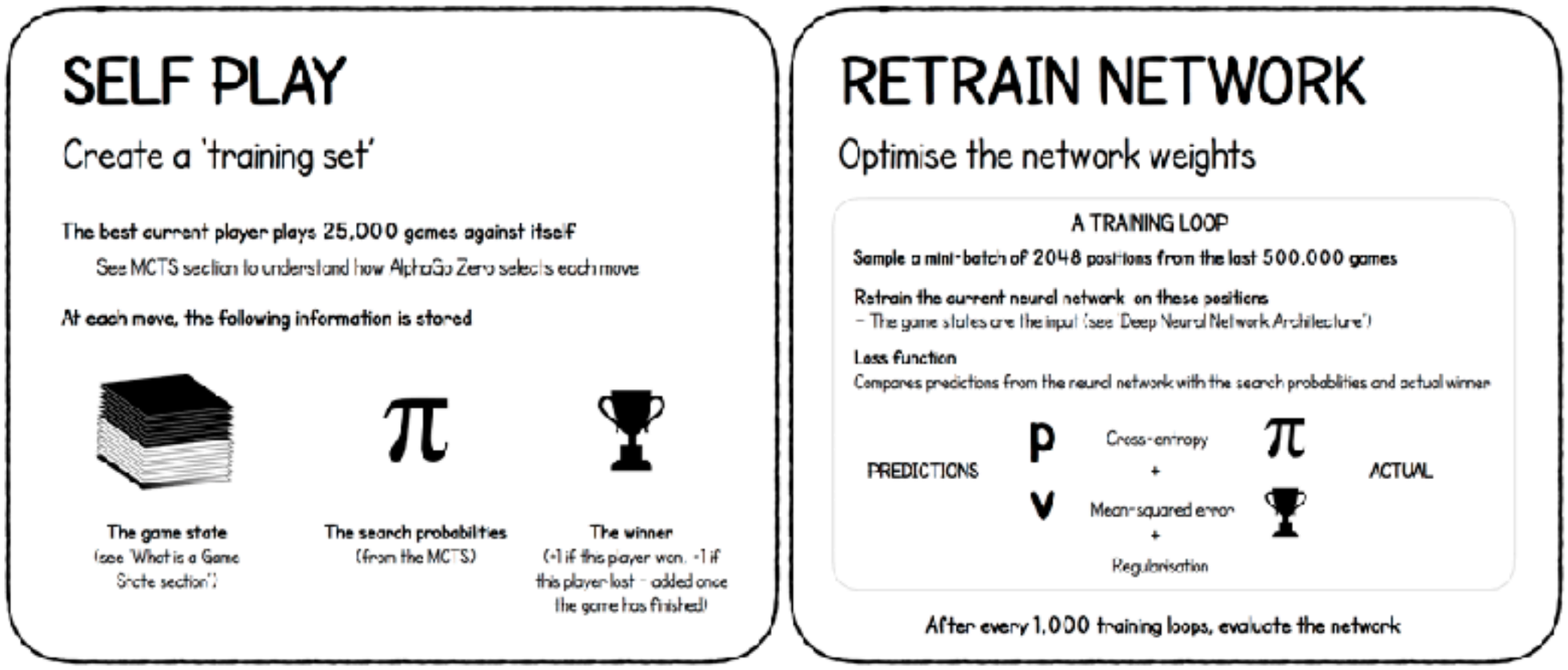
$$\pi_{tree}(s) \doteq \underset{a}{\operatorname{argmax}} \left[Q(s,a) + c \cdot P(s,a) \cdot \frac{\sqrt{N(s)}}{1 + N(s,a)} \right]$$

Any ideas how to obtain the expert policy?

How to model the value function and the expert policy?



Train through Policy Iteration



Full infographic in references, highly recommend to give a look

Case Study

Summary

- We’ve learned the basics of how to train an agent to make optimal decisions in an environment.

- Reinforcement Learning is mostly theoretical field because of time and space complexities of presented algorithms.

- Deep Reinforcement Learning is “more practical” thanks to advances in Deep Learning (function approximation).

- Deep Reinforcement Learning is under heavy research and development and doesn’t really work yet.

Thank you 😊

You can find this presentation and AlphaZero implementation (along other projects) on my GitHub: https://github.com/piojanu

Sources and Good Reads

- A Simple Alpha(Go) Zero Tutorial by Surag Nair
- **AlphaGo Zero cheatsheet by David Foster**
- **AlphaGo Zero - How and Why it Works by Tim Wheeler**
- Deep Reinforcement Learning: Pong from Pixels by Andrej Karpathy
- UC Berkeley AI course
- Mastering the game of Go without Human Knowledge by David Silver et al.
- UCL Course on RL by David Silver
- The Multi-Armed Bandit Problem and Its Solutions by Lilian Weng
- Deep Learning and Reinforcement Learning Summer School, Montreal 2017
- Reinforcement Learning: An Introduction 2nd edition
- **AlphaGo movie on Netflix** 📽️