Reinforcement Learning Basics

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Special thanks

https://github.com/Feryal/rl_mlss_2020

Section 1

Introduction to reinforcement learning

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What is reinforcement learning?

- Learning from reward, “trial-and-error”
- A general framework/formalism for deciding how to act in an environment
- Can be divided into 2 components
  - 1) prediction
  - 2) control

Reward/value prediction (classical conditioning)

Ivan Pavlov, 1897

Reward/value prediction (classical conditioning)

Ivan Pavlov, 1897

Reward/value prediction (classical conditioning)

Ivan Pavlov, 1897

Reward prediction error

RPE = **Actual reward** - **Expected**

Reward prediction error

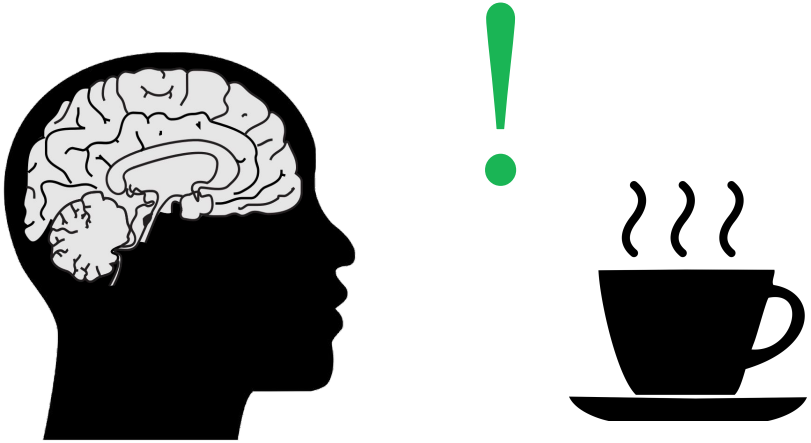
RPE = **Actual reward** - **Expected**

Learning happens when there's prediction error

$$\textbf{Actual reward} \xleftarrow{\alpha} \textbf{Expected}$$

With learning rate α

Reward prediction error



RPE = **Actual reward** - **Expected**

Learning happens when there's prediction error

$$\textbf{Actual reward} \xleftarrow{\alpha} \textbf{Expected}$$

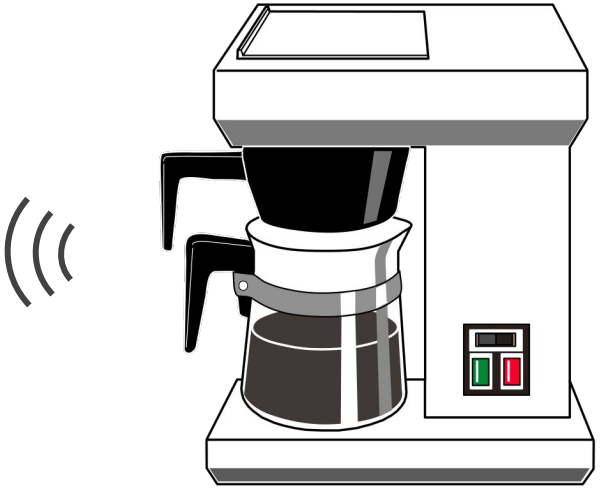
With learning rate α

Reward prediction error

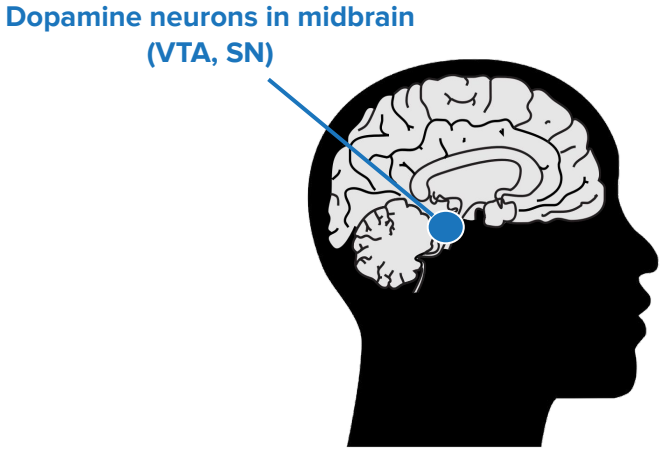
Actual reward = **Expected**

RPE = **0**

Reward prediction error

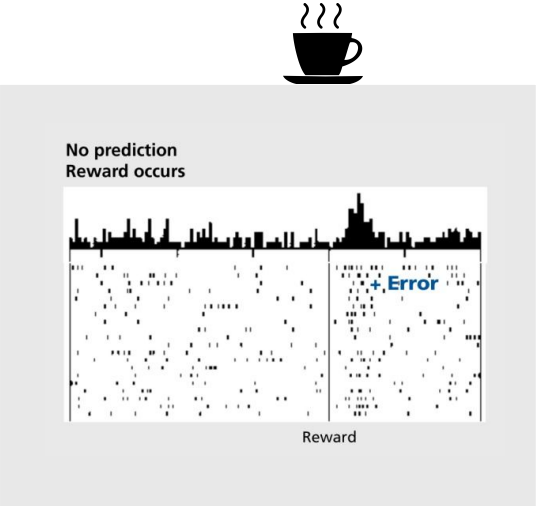


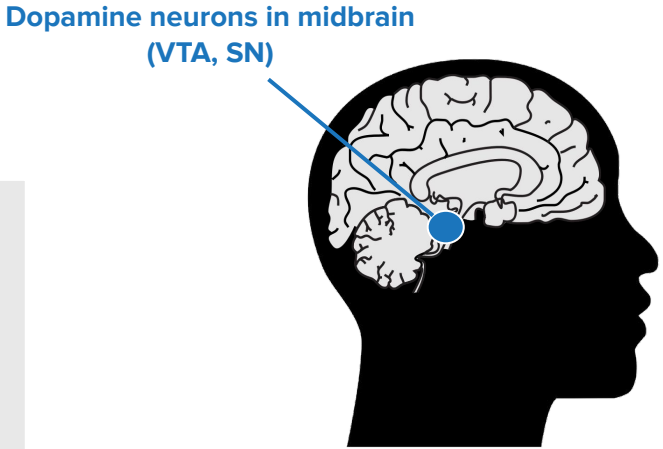
Reward prediction in the brain



Schultz, Dayan, Montague, 1997, Science.
Schultz, 2016, Dialogues Clin Neurosci.

Reward prediction in the brain





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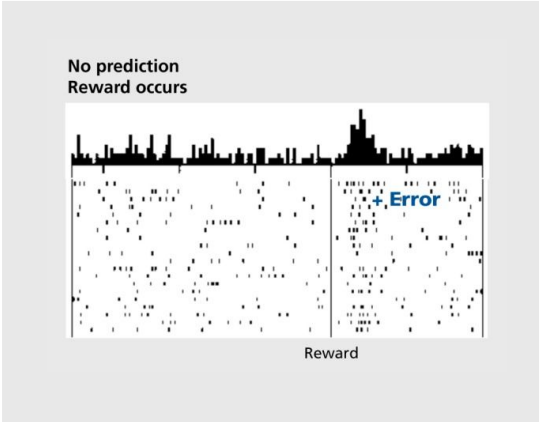
Reward prediction in the brain

Before learning



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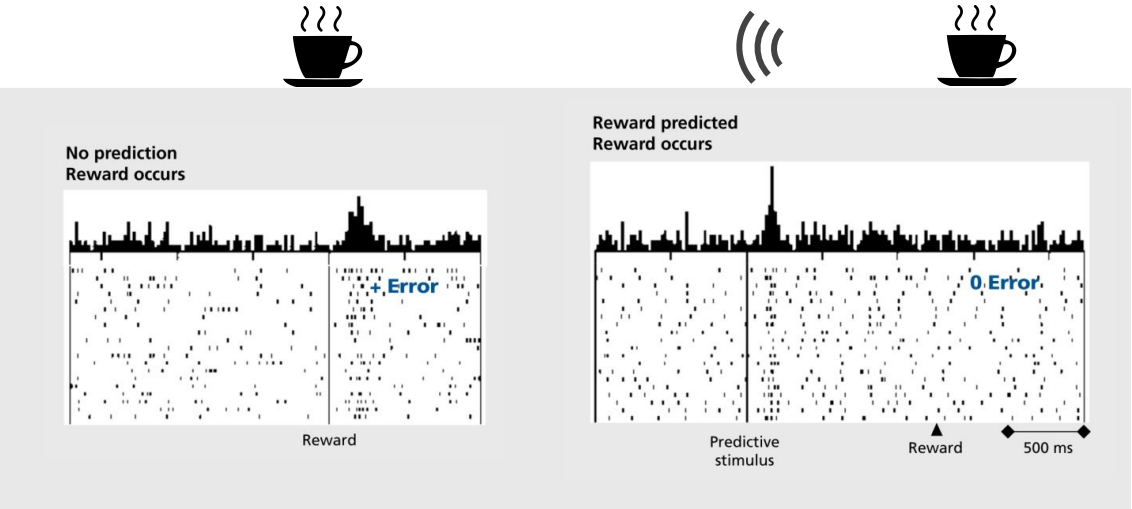
Reward prediction in the brain

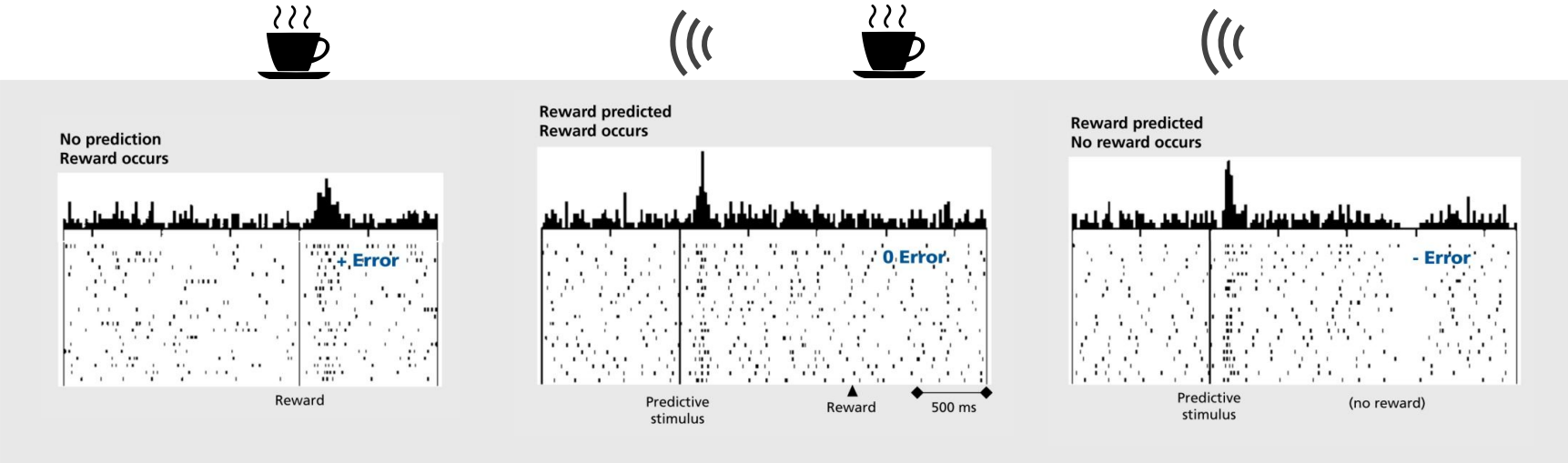
After learning



Schultz, 2016, Dialogues Clin Neurosci.

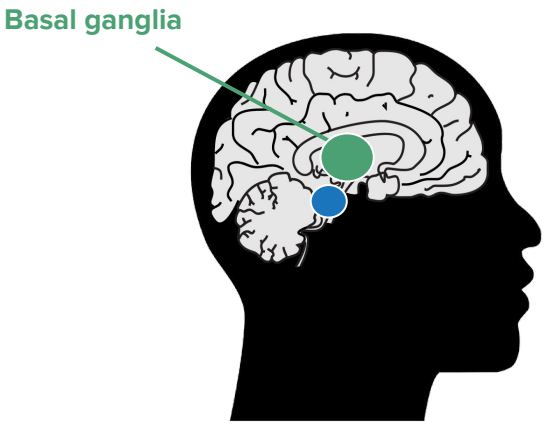
Reward prediction in the brain

Prediction incorrect - more learning



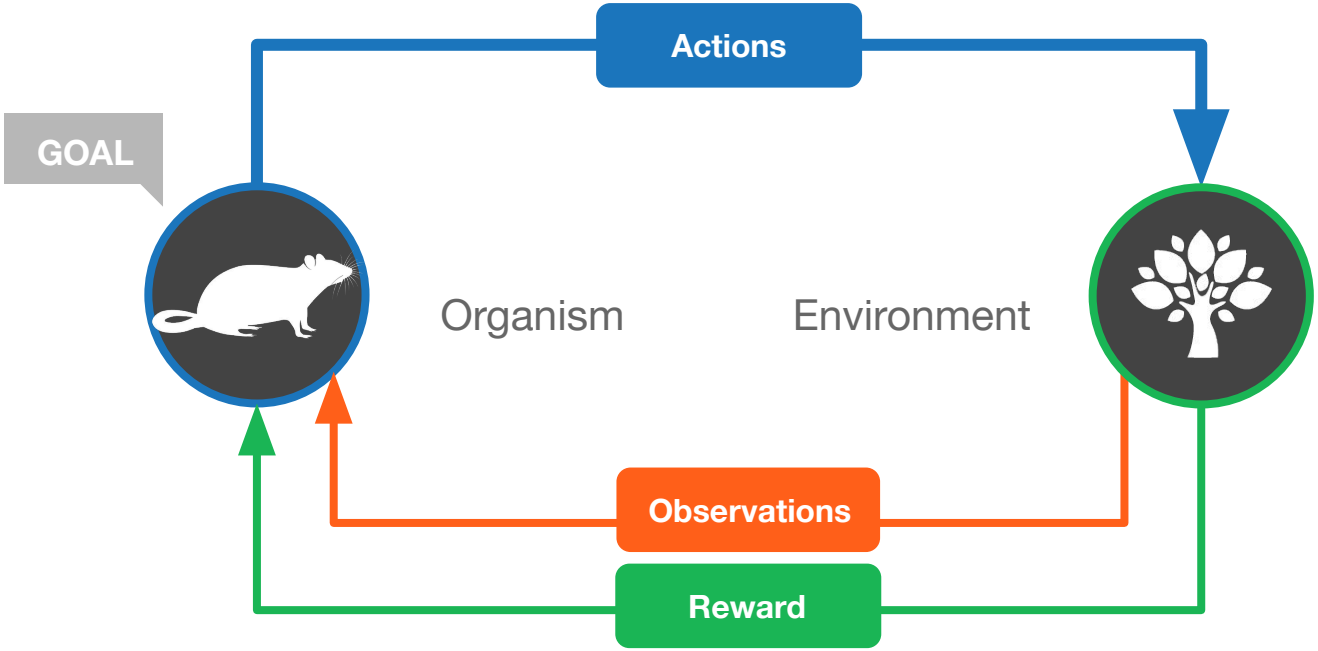
Schultz, 2016, Dialogues Clin Neurosci.

Control and action selection (instrumental conditioning)



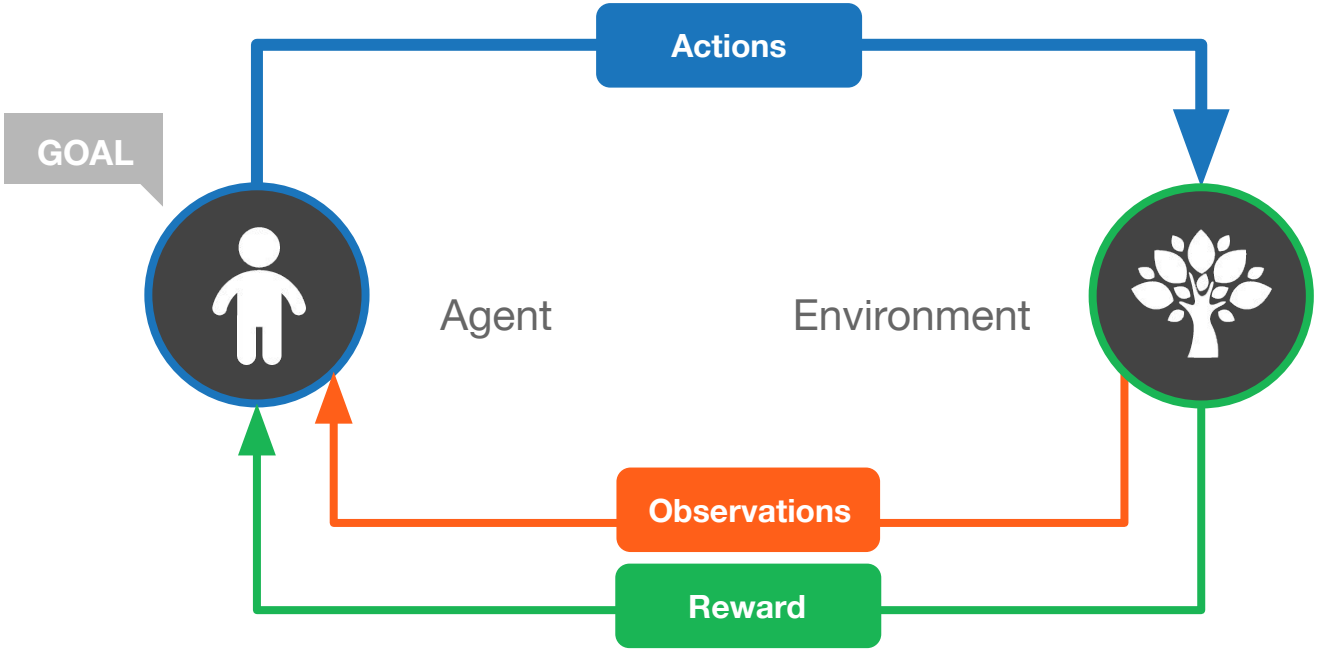
Wang et al, 2014, Neurobiol. Learn. Mem.

Reinforcement learning formalism



Learning to achieve **goals** via **trial and error** by **interacting** with an **environment**

Reinforcement learning in agents



Learning to achieve **goals** via **trial and error** by **interacting** with an **environment**

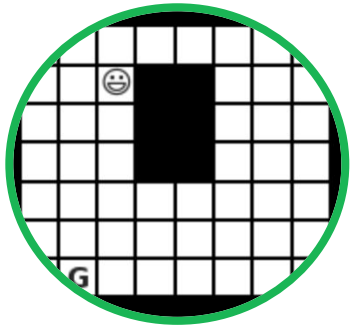
What is an environment?

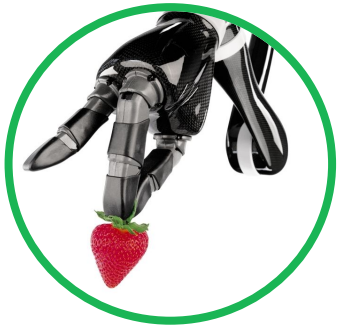
Environment receives **actions** and in turn provides **observations** and **rewards** to the agent.

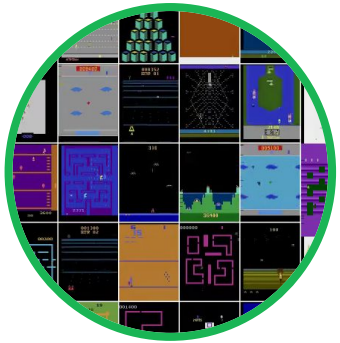
It can be stochastic, complex and not fully observable to the agent.

Learning to achieve **goals** via **trial and error** by **interacting** with an **environment**

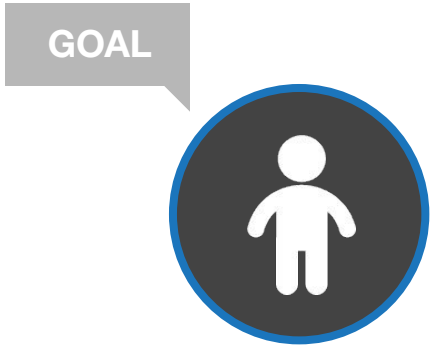
What is an environment?







What is an agent?

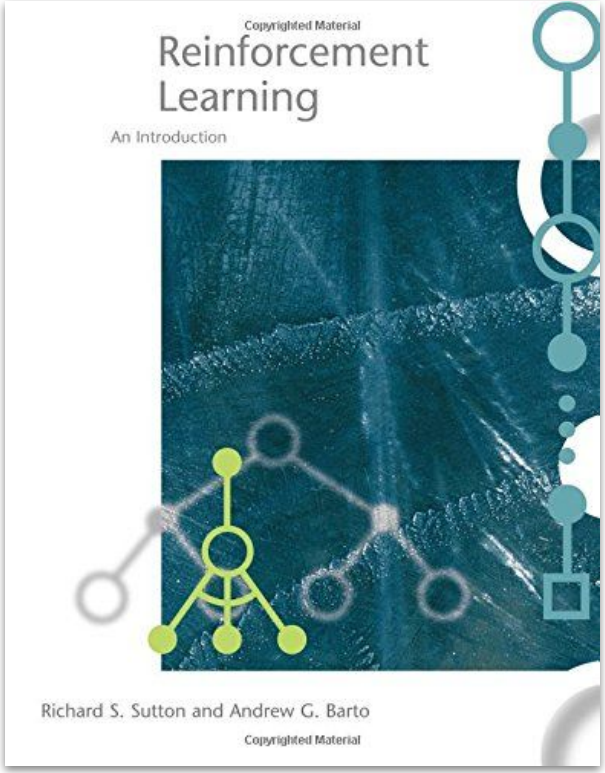


Agent learns a policy mapping **observations** to **actions**.

The agent's **goal** is to maximize its cumulative **reward**.

Learning to achieve **goals** via **trial and error** by **interacting** with an **environment**

Reinforcement Learning: An Introduction



Section 2

General formulation and MDPs

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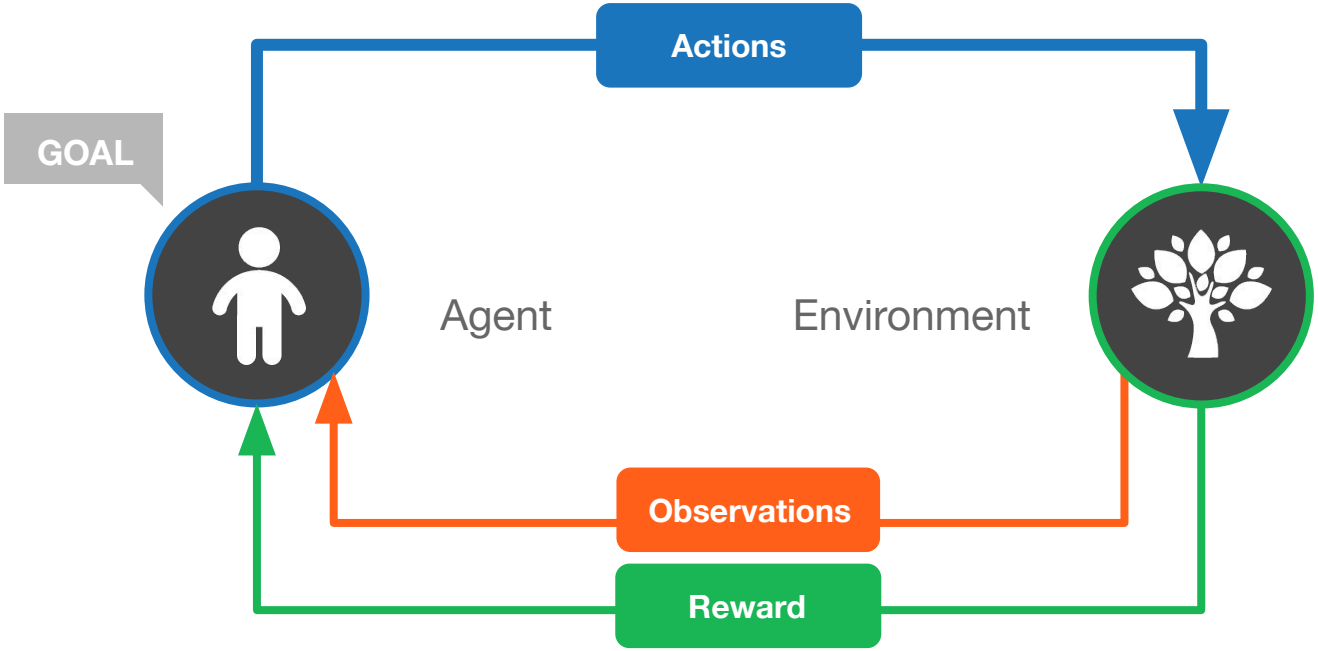
Reinforcement learning in agents



Learning to achieve **goals** via **trial and error** by **interacting** with an **environment**

Where do rewards come from?

Reward is typically a scalar feedback signal.

- Extrinsic
  - Environmental
  - Typically hard-coded by the environment designer
- Intrinsic
  - Curiosity/Surprise/Novelty
  - Learning progress
  - Empowerment
  - Explanation
  - Compression

Why is RL hard?

RL = exploration to gather experience + learning from experience

Supervised Learning = ? + learning from experience

In **supervised learning**, data is often gathered and filtered by humans, which alleviates the **exploration problem**.

Why is RL hard?

- **Sequential** decision making
- **Exploration** might not be trivial
- **High-dimensional** continuous states & actions
- The **environment** is often **unknown**
- **Rewards** are **unknown**, **delayed** and possibly **sparse**
- **Non-stationarity**

Markov Decision Process (MDP)

Finite set of **states**

Transition function

Discount factor

$$\langle \mathcal{S}, \mathcal{A}, P, R, \gamma \rangle$$

Finite set of **actions**

Reward function

We often solve the **RL problem** by modelling it as an **MDP.**

Markov Decision Process (MDP)

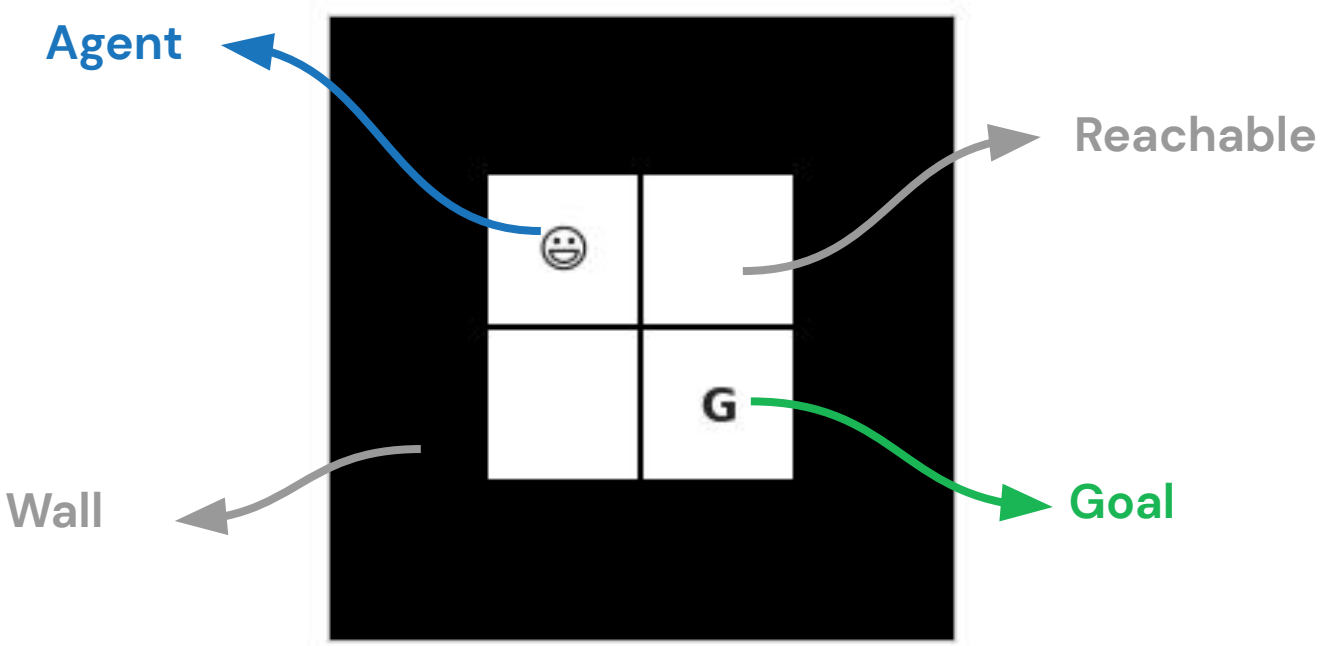
$$\langle \mathcal{S}, \mathcal{A}, P, R, \gamma \rangle$$

Markov property: the next state depends only on the current state, and not all of the states that came before it.

$$\mathbf{P}(\underbrace{\mathbf{s_{t+1}}}_{\text{Future}} | \underbrace{\mathbf{s_t}, \mathbf{a_t}}_{\text{Present}}, \underbrace{\mathbf{s_{t-1}}, \mathbf{a_{t-1}}, \ldots, \mathbf{s_0}}_{\text{Past}}) = \mathbf{P}(\underbrace{\mathbf{s_{t+1}}}_{\text{Future}} | \underbrace{\mathbf{s_t}, \mathbf{a_t}}_{\text{Present}})$$

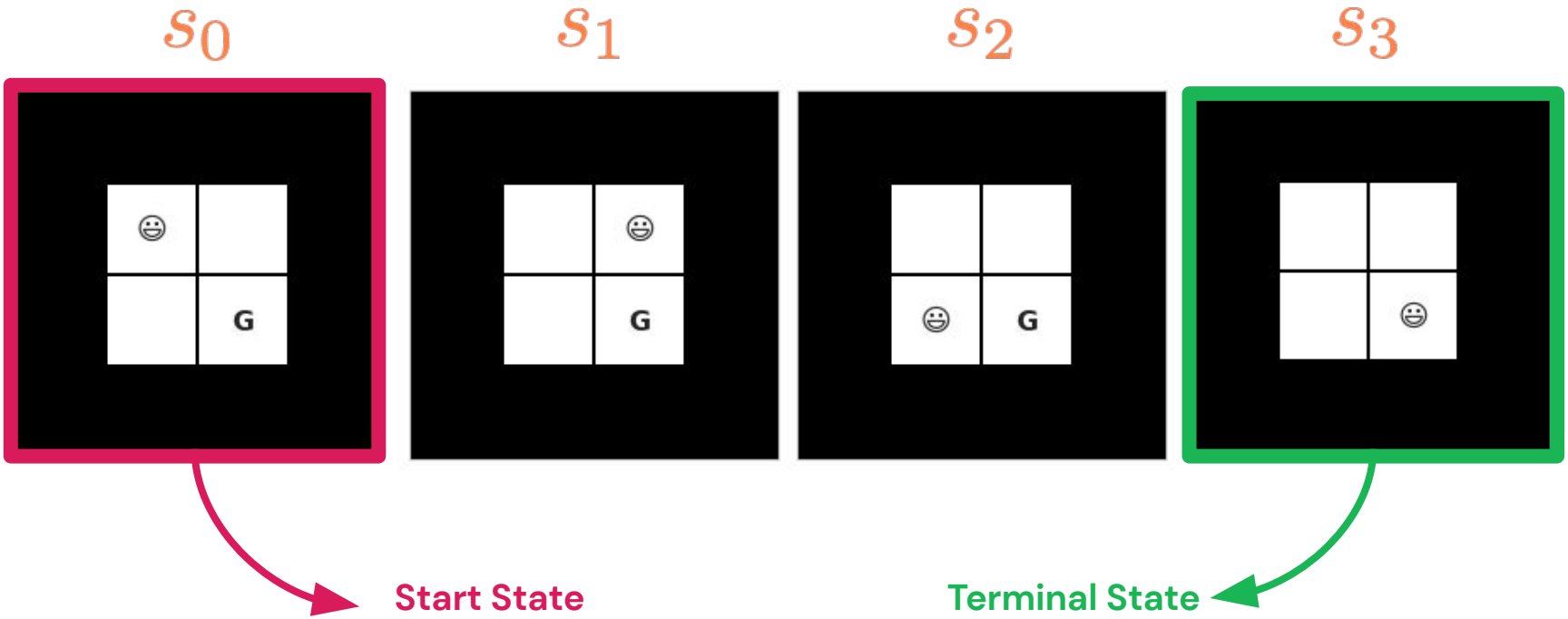
Grid World Environment

Size of the world: [2 X 2]

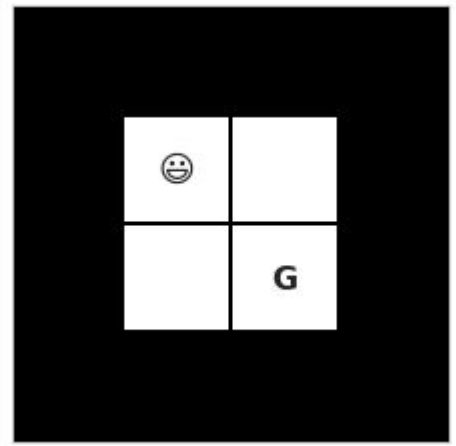


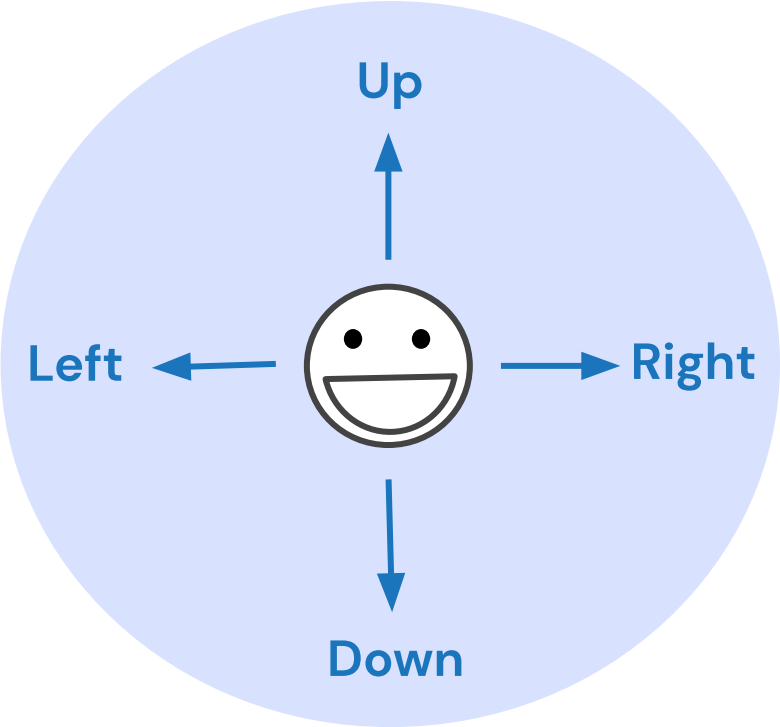
State space $\mathcal{S}$

There are **4 unique states** in this environment.

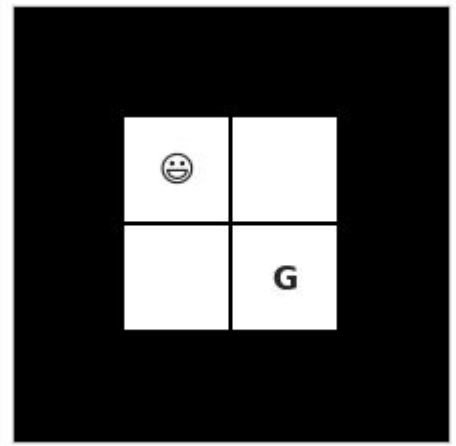


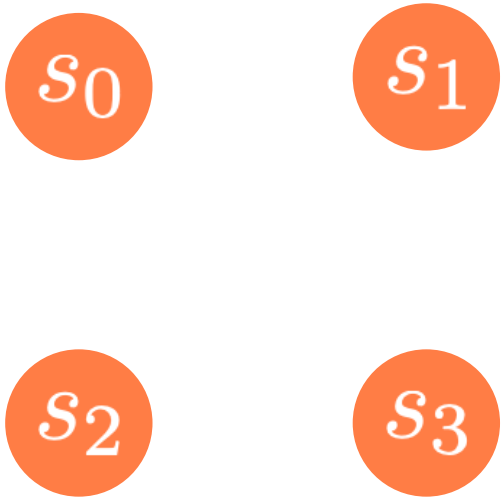
Action Space $\mathcal{A}$





Transition model P





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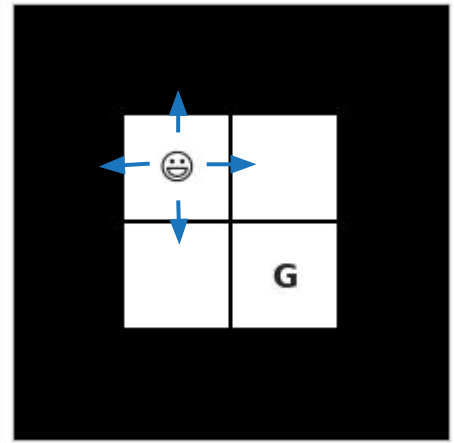

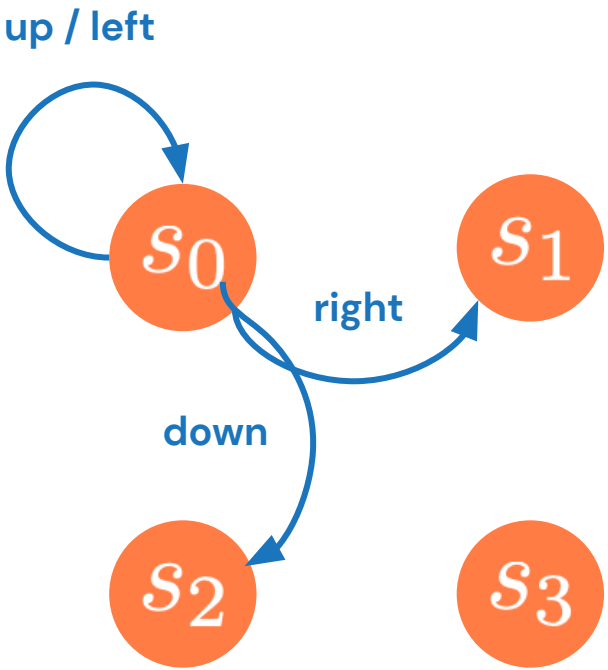

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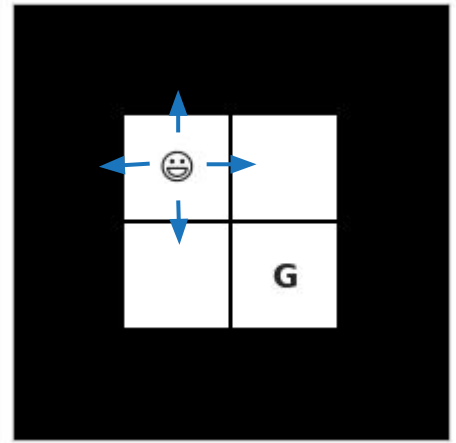
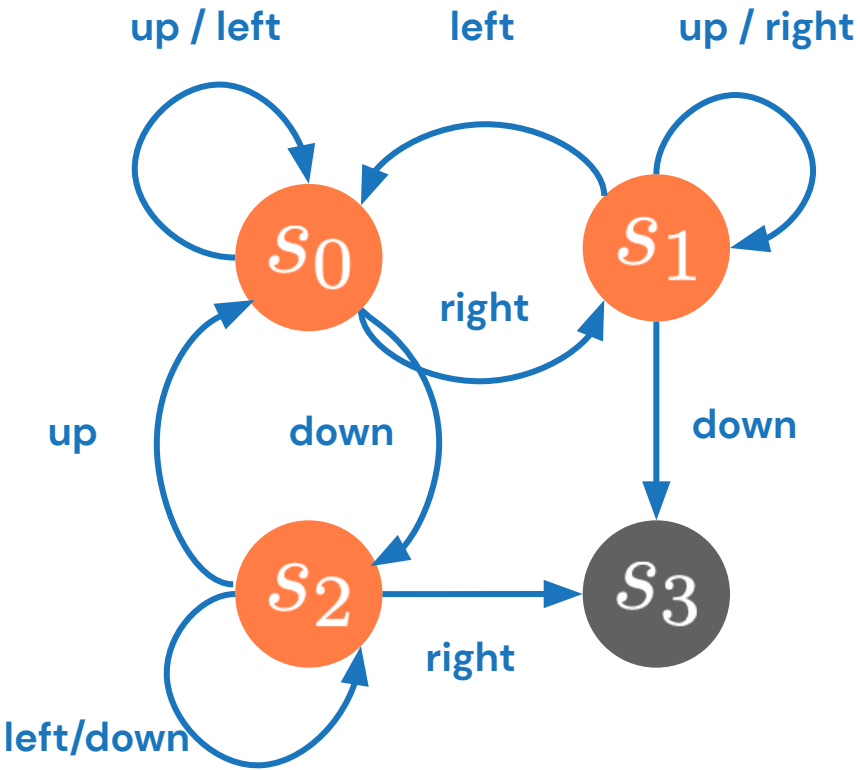
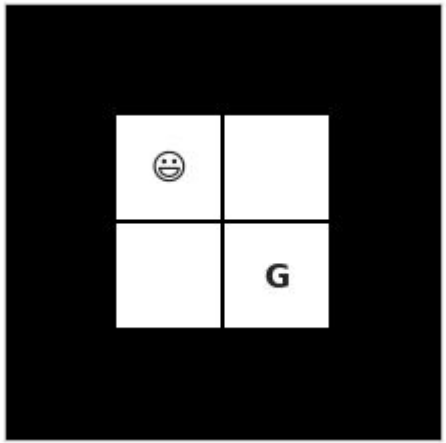
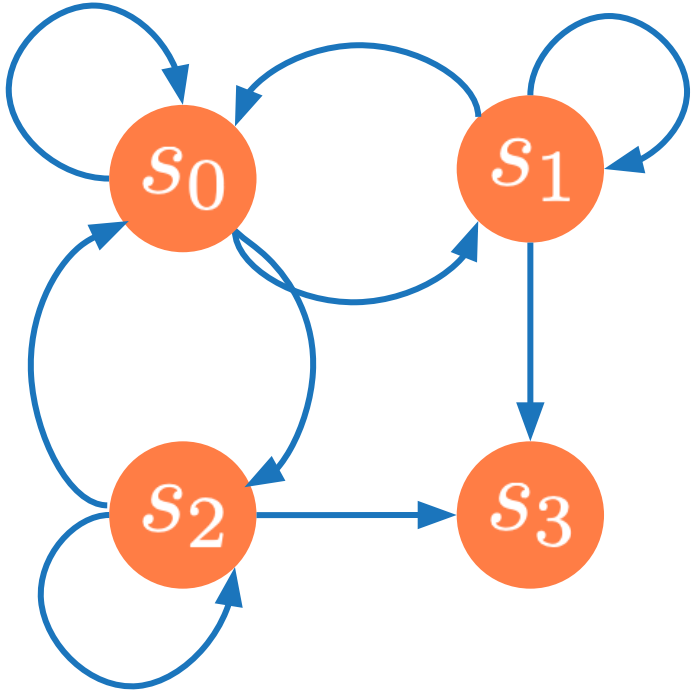




Rewards R

Empty cell $\mathbf{r} = 0$
Hit the wall $\mathbf{r} = -5$
Goal reached $\mathbf{r} = 10$





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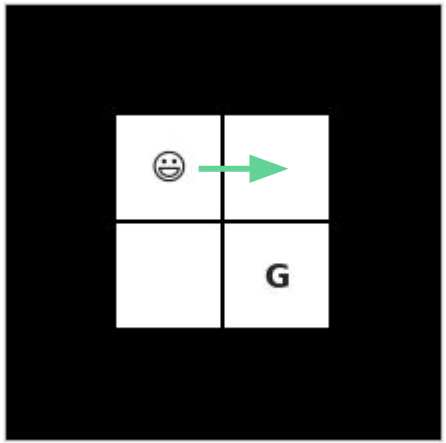

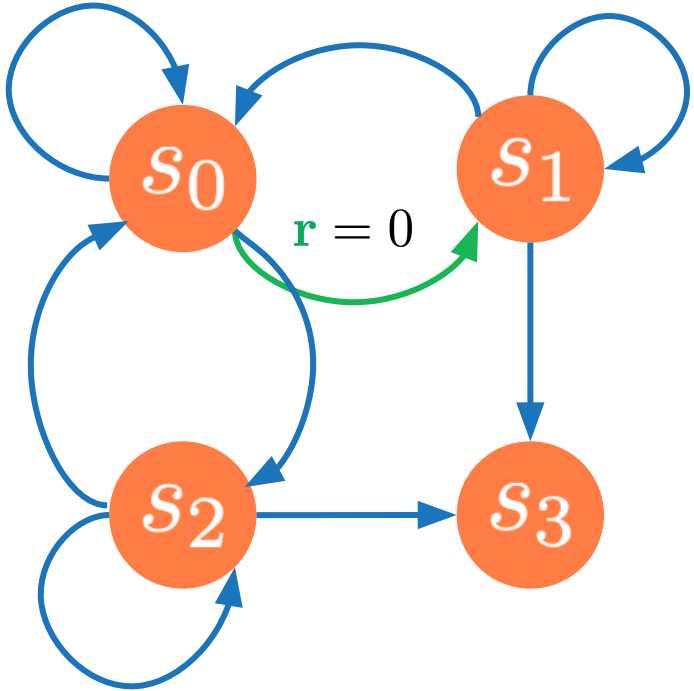

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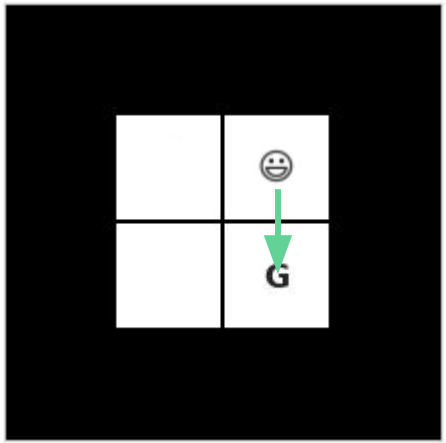

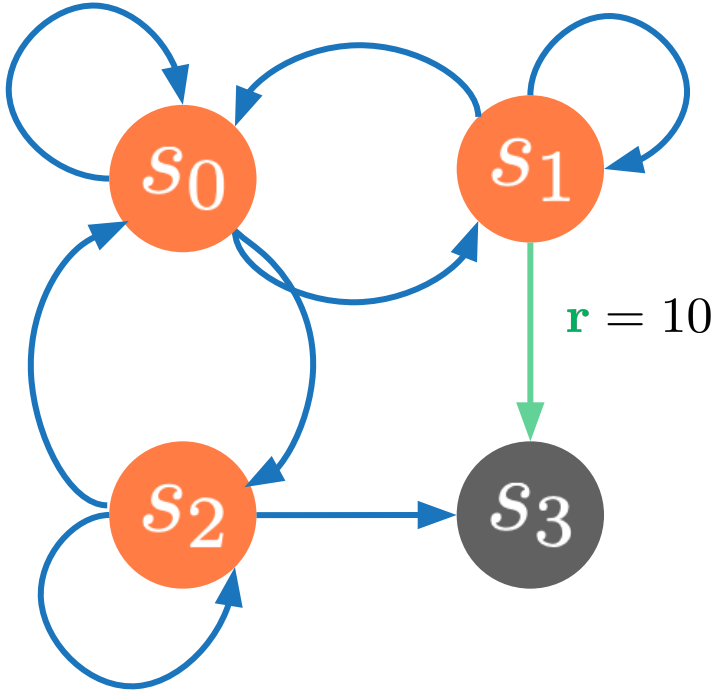

Agent's Goal

The agent's **goal** is to maximize the **discounted** **sum of future rewards**.

$$\mathbf{G_t} = \underbrace{\mathbf{r_t} + \gamma \mathbf{r_{t+1}} + \gamma^2 \mathbf{r_{t+2}} +}_{\textbf{Return}} \ldots$$

Discount γ specifies how much **future rewards** are worth compared to **immediate reward**.

Policy

Policy maps **states** to **actions**.

$$\mathbf{a_t} \sim \pi(\mathbf{a_t} | \mathbf{s_t})$$

Typically in RL we are searching for the **optimal policy**, which will maximize the **discounted** **sum of future rewards**.

Section 3

The Bellman equation

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State Value Function

State value function maps **states** to **expected rewards**.

$$V^{\pi}(s_t) = \mathbb{E}_{\pi}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots | s_t\right]$$

It is equal to **expected total discounted reward** for an agent starting from that **state** and following its **policy**. It specifies how **good** it is to be in a given **state**.

State-Action Value Function

State-action value function maps an **action** in a given **state** to **expected rewards**.

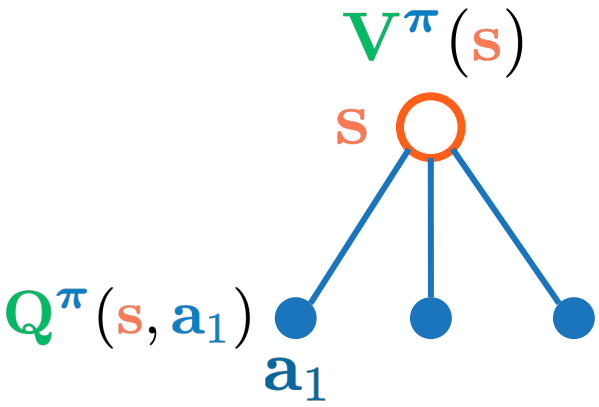
$$\mathbf{Q}^{\pi}(\mathbf{s_t}, \mathbf{a_t}) = \mathbb{E}_{\pi}\left[\mathbf{r_t} + \gamma \mathbf{r_{t+1}} + \gamma^2 \mathbf{r_{t+2}} + \ldots \middle| \mathbf{s_t}, \mathbf{a_t}\right]$$

It is equal to **expected total discounted reward** for an agent starting from state **s** and performing action **a** and following its **policy**.

State-Action Value vs State Value

The relationship between $\mathbf{V}^{\boldsymbol{\pi}}$ and $\mathbf{Q}^{\boldsymbol{\pi}}$

$$\mathbf{V}^{\boldsymbol{\pi}}(\mathbf{s}) = \sum_{\mathbf{a} \in \mathcal{A}} \boldsymbol{\pi}(\mathbf{a}|\mathbf{s}) \mathbf{Q}^{\boldsymbol{\pi}}(\mathbf{s}, \mathbf{a})$$



Bellman Expectation Equation

Return at time t

$$V^{\pi}(s_t) = \mathbb{E}_{\pi}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots | s_t\right]$$

Return at time t+1

$$V^{\pi}(s_t) = \mathbb{E}_{\pi}\left[r_t + \gamma(r_{t+1} + \gamma r_{t+2} + \ldots) | s_t\right]$$

$$V^{\pi}(s_t) = \mathbb{E}_{\pi}\left[r_t + \gamma V(s_{t+1}) | s_t\right]$$

Bellman Expectation Equation

Return at time t

$$V^{\pi}(s_t) = \mathbb{E}_{\pi}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots | s_t\right]$$

Return at time t+1

$$V^{\pi}(s_t) = \mathbb{E}_{\pi}\left[r_t + \gamma(r_{t+1} + \gamma r_{t+2} + \ldots) | s_t\right]$$

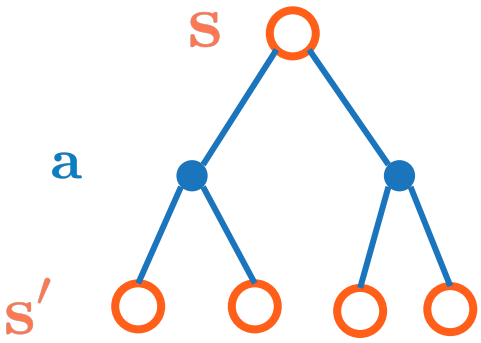
$$V^{\pi}(s_t) = \mathbb{E}_{\pi}\left[r_t + \gamma V(s_{t+1}) | s_t\right]$$

The **state-action value function** can be similarly decomposed to:

$$Q^{\pi}(s_t, a_t) = \mathbb{E}_{\pi}\,\mathbb{E}_{s_{t+1}}\left[r_t + \gamma Q^{\pi}(s_{t+1}, a_{t+1}) | s_t, a_t\right]$$

Bellman's principle of optimality

The **value** of a **state** under an **optimal policy** is equal to the **expected return** from the **best action** from that **state**.



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

$$\mathbf{Q}^*(\mathbf{s}, \mathbf{a}) = \mathbf{R}(\mathbf{s}, \mathbf{a}) + \gamma \sum_{\mathbf{s}' \in \mathcal{S}} \mathbf{P}(\mathbf{s}' | \mathbf{s}, \mathbf{a}) \max_{\mathbf{a}'} \mathbf{Q}^*(\mathbf{s}', \mathbf{a}')$$

Optimal policy

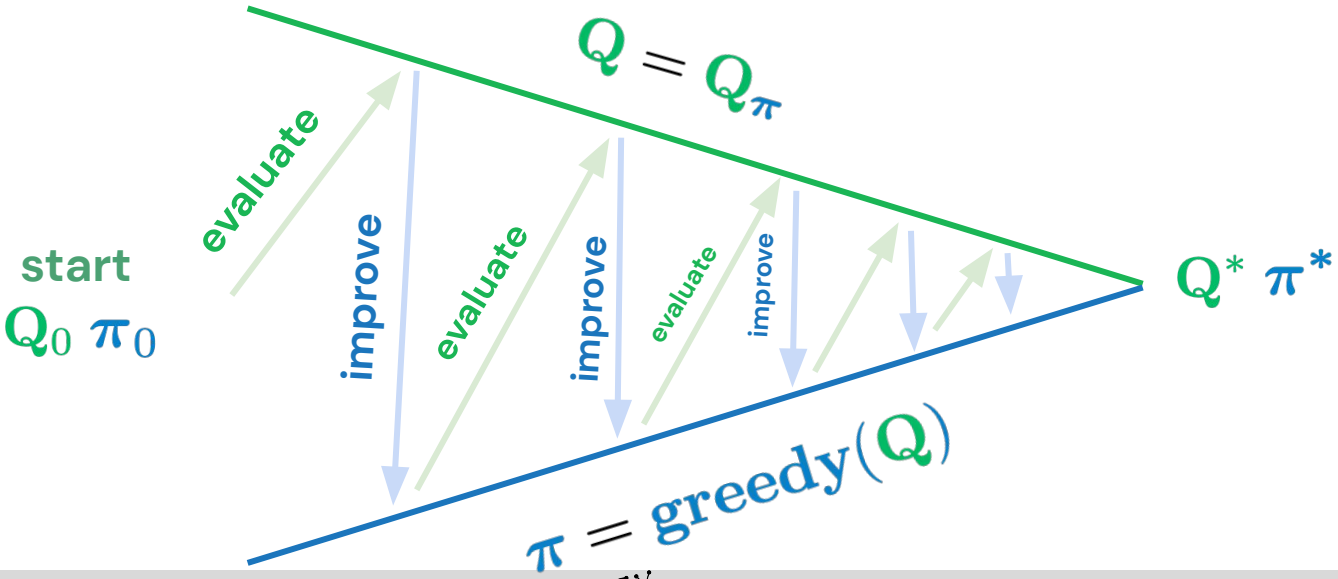
An **optimal policy** can be found by maximising over the **optimal state-action value function**. If we know the $\mathbf{Q}^*(\mathbf{s}, \mathbf{a})$ we immediately have the optimal policy $\boldsymbol{\pi}^*(\mathbf{s})$.

$$\boldsymbol{\pi}^*(\mathbf{s}) = \max_{\mathbf{a}} \mathbf{Q}^*(\mathbf{s}, \mathbf{a})$$

We say that the **optimal policy** is **greedy** with respect to the **optimal value function**.

How to find the optimal policy? (Policy Iteration)

We can start from a random policy and random value function and find the optimal policy and value function through the following iterative process:



Why does this work? (Policy Iteration Theorem)

Given the **true** **value function** $Q_\pi(s, a)$ for any **policy** π for $s \in \mathcal{S}$ and $a \in \mathcal{A}$ it can always be **greedified** to obtain a **better policy**:

$$\pi' = \arg\max_a Q^\pi(s, a)$$

Where "**better**" means:

$$Q^{\pi'}(s, a) \geq Q^\pi(s, a)$$

Equality happens when we find the **optimal** **value function** and **policy**.

Section 4

Policy evaluation

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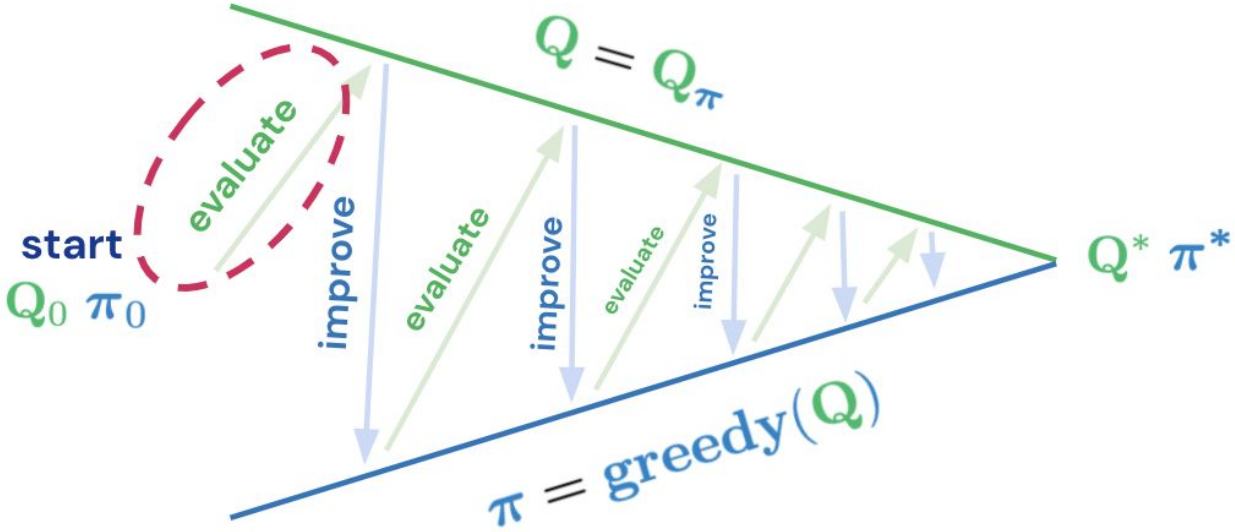
Iterative policy evaluation

During policy evaluation we are making the value function consistent with the current policy, also through an **iterative process**.



Iterative policy evaluation

Evaluate a given policy π iteratively to find its **true value function**:

$$\mathbf{Q}_0 \rightarrow \mathbf{Q}_1 \rightarrow \ldots \rightarrow \mathbf{Q}^{\pi}$$

At each iteration **k:**

For all states $\mathbf{s} \in \mathcal{S}$ and $\mathbf{a} \in \mathcal{A}$

Update $\mathbf{Q}_k(\mathbf{s}, \mathbf{a})$ from $\mathbf{Q}_{k-1}(\mathbf{s}', \mathbf{a}')$

Model-based policy evaluation: **Dynamic Programming**

Dynamic programming finds the **optimal policy** given a perfect **model of the environment**.

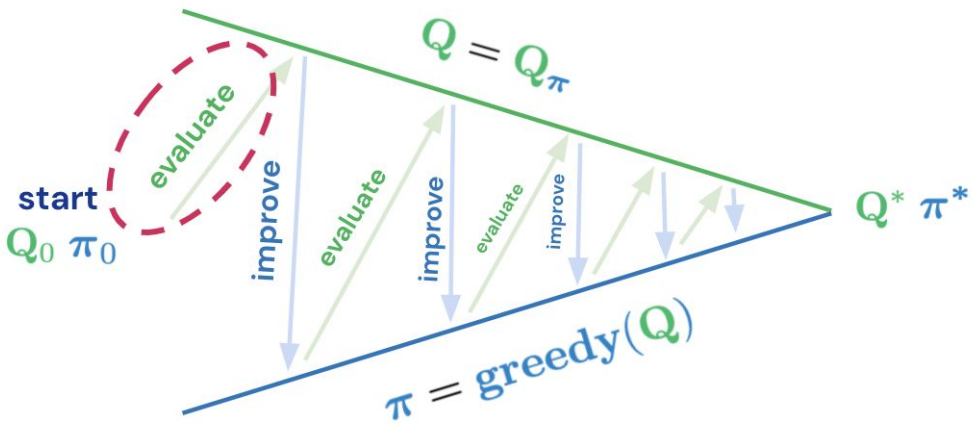
DP algorithms turn Bellman equations into update rules and iterate until convergence:

$$\mathbf{Q}_k(\mathbf{s}, \mathbf{a}) \leftarrow \mathbf{R}(\mathbf{s}, \mathbf{a}) + \gamma \sum_{\mathbf{s}' \in \mathcal{S}} \mathbf{P}(\mathbf{s}'|\mathbf{s}, \mathbf{a}) \sum_{\mathbf{a}' \in \mathcal{A}} \boldsymbol{\pi}_{k-1}(\mathbf{a}'|\mathbf{s}') \mathbf{Q}_{k-1}(\mathbf{s}', \mathbf{a}')$$

Policy Iteration

We can start from a random policy and random value function and find the optimal policy and value function through the following iterative process:

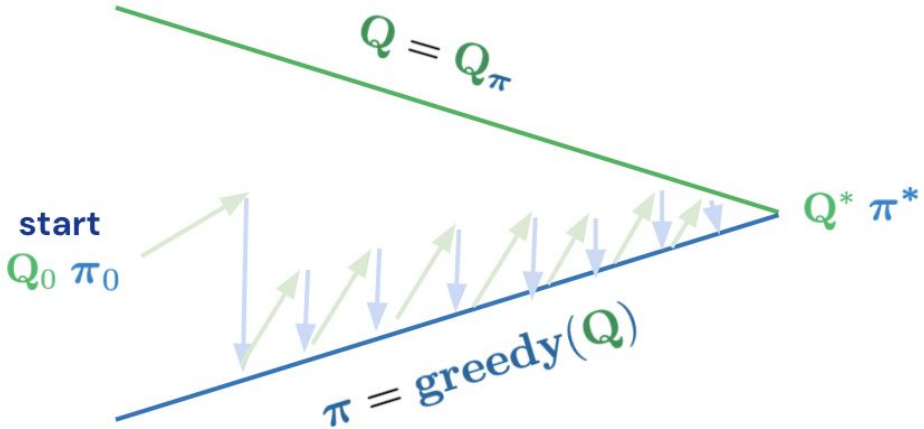
$$\mathbf{Q}_k(\mathbf{s},\mathbf{a}) \leftarrow \mathbf{R}(\mathbf{s},\mathbf{a}) + \gamma \sum_{\mathbf{s}' \in \mathcal{S}} \mathbf{P}(\mathbf{s}'|\mathbf{s},\mathbf{a}) \sum_{\mathbf{a}' \in \mathcal{A}} \boldsymbol{\pi}_{k-1}(\mathbf{a}'|\mathbf{s}')\mathbf{Q}_{k-1}(\mathbf{s}',\mathbf{a}')$$



Value Iteration

We can iteratively improve our estimation of the value function by directly using the **Bellman optimality equation**.

$$\mathbf{Q}_k(\mathbf{s},\mathbf{a}) \leftarrow \mathbf{R}(\mathbf{s},\mathbf{a}) + \gamma \sum_{\mathbf{s}' \in \mathcal{S}} \mathbf{P}(\mathbf{s}'|\mathbf{s},\mathbf{a}) \max_{\mathbf{a}'} \mathbf{Q}_{k-1}(\mathbf{s}',\mathbf{a}')$$



Model-free policy evaluation

If we **do not have access to the true model of the environment**, we can instead learn directly from episodes of experience.

- **Monte Carlo Methods**
- **Temporal Difference Learning**

Monte Carlo Policy Evaluation

The goal is to update the value function towards the **actual return**.

We have to wait until the end of the episode to start learning.

$$\mathbf{Q}_k(\mathbf{s_t}, \mathbf{a_t}) \leftarrow \mathbf{Q}_{k-1}(\mathbf{s_t}, \mathbf{a_t}) + \overset{\text{Learning rate}}{\alpha} \big(\underbrace{\mathbf{G_t}}_{\text{TD Target}} - \mathbf{Q}_{k-1}(\mathbf{s_t}, \mathbf{a_t})\big)$$

Reminder $\mathbf{G_t} = \mathbf{r_t} + \gamma \mathbf{r_{t+1}} + \ldots + \gamma^{T-1} \mathbf{r}_T$

Monte Carlo Policy Evaluation

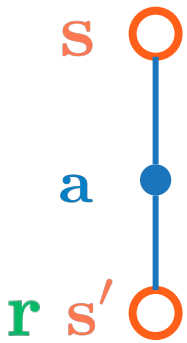
The goal is to update the value function towards the **actual return**.

We have to wait until the end of the episode to start learning.

$$\mathbf{Q}_k(\mathbf{s_t}, \mathbf{a_t}) \leftarrow \mathbf{Q}_{k-1}(\mathbf{s_t}, \mathbf{a_t}) + \alpha \overbrace{(\underbrace{\mathbf{G_t}}_{\text{TD Target}} - \mathbf{Q}_{k-1}(\mathbf{s_t}, \mathbf{a_t}))}^{\text{RPE}}$$

Reminder $\mathbf{G_t} = \mathbf{r_t} + \gamma \mathbf{r_{t+1}} + \ldots + \gamma^{T-1} \mathbf{r}_T$

Temporal Difference Learning



Instead of waiting until the end of the episode, TD can learn from incomplete episodes via **bootstrapping**, updating a guess from a guess.

$$\mathbf{Q}_k(\mathbf{s},\mathbf{a}) \leftarrow \mathbf{Q}_{k-1}(\mathbf{s},\mathbf{a}) + \alpha\,\overbrace{\Big(\underbrace{\mathbf{r} + \mathbf{Q}_{k-1}(\mathbf{s}',\boldsymbol{\pi}(\mathbf{s}'))}_{\text{TD Target}} - \mathbf{Q}_{k-1}(\mathbf{s},\mathbf{a})\Big)}^{\text{RPE}}$$

TD vs MC

- TD learns **after each step** while MC has to wait for the **end of episode** when **return** is known.
- TD can learn in **non-episodic** environments while MC cannot.

Bias/Variance Tradeoff

- **Return** is an **unbiased estimation** of the value function while TD target is a **biased estimation** (a guess from a guess).
- TD target is much **lower variance** than the **return**
  - **Return** depends on sequences of random **actions**, **transitions**, and **rewards**.
  - TD target depends on **one random action**.

Section 5

Model-free learning

Jane Wang

neuromatch academy

Model-free policy evaluation

If we **do not have access to the true model of the environment**, we can instead learn directly from episodes of experience.

- **Monte Carlo Methods**
- **Temporal Difference Learning**

Model-free learning

When we don't have access to the model of environment, we learned how to do **model-free evaluation**, now we focus on **model-free learning** where we want to learn to optimise the **value function** of an **unknown MDP**.

On-policy learning "Learning on the job"

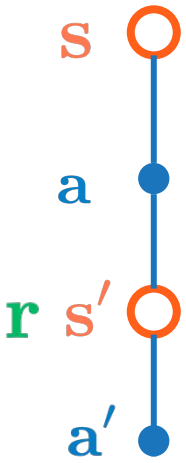
Off-policy learning "Look over someone's shoulder"

Exploration

- **ε-Greedy** is a simple **policy improvement** method that allows for continual exploration.
- **Exploit:** with probability 1-ε we select a **greedy action** wrt the **value function**.
- **Explore:** with probability ε a **random action** is uniformly selected instead.

SARSA: On-policy TD Control

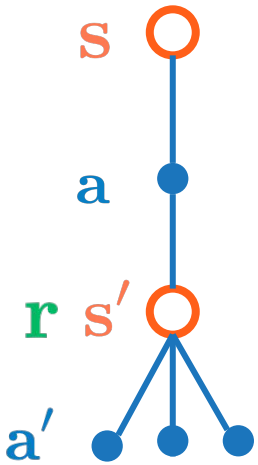
- **SARSA** learns the **policy** by executing it in the environment to gather experiences.
- We often use **ε-Greedy policy** to gather experiences and each update needs access to $(\mathbf{s}, \mathbf{a}, \mathbf{r}, \mathbf{s}', \mathbf{a}')$.



$$\mathbf{Q}(\mathbf{s}, \mathbf{a}) \leftarrow \mathbf{Q}(\mathbf{s}, \mathbf{a}) + \alpha(\mathbf{r} + \gamma \mathbf{Q}(\mathbf{s}', \mathbf{a}') - \mathbf{Q}(\mathbf{s}, \mathbf{a}))$$

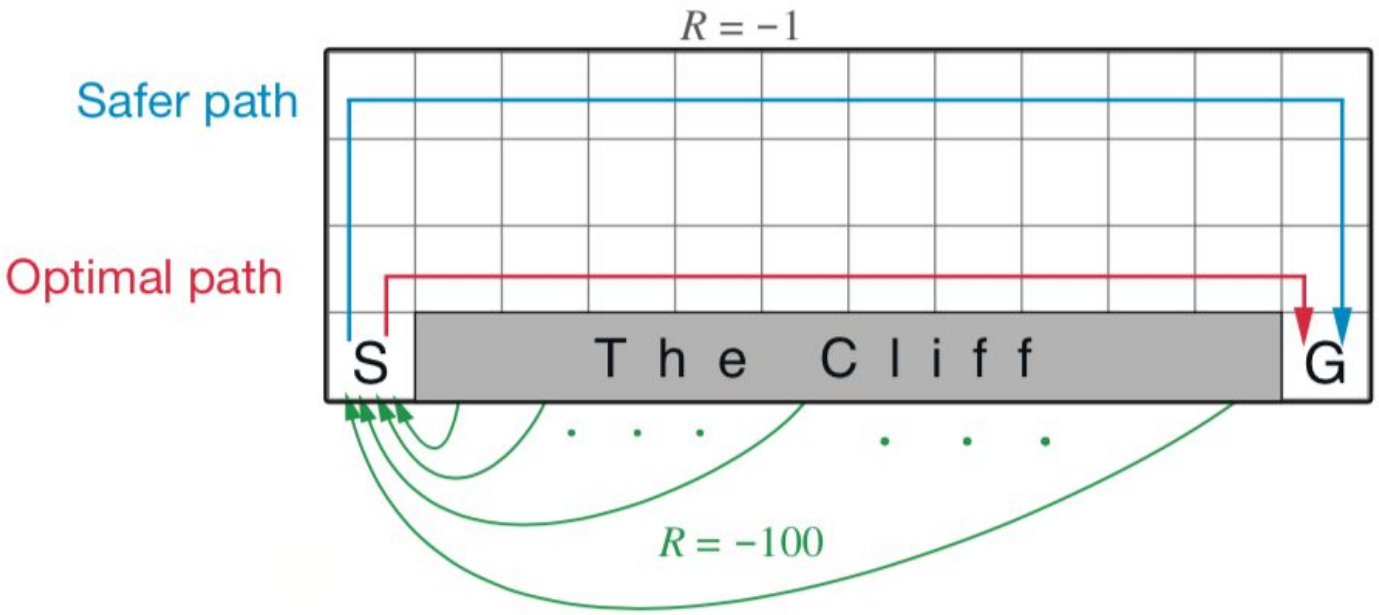
Q Learning: Off-policy TD Control

- **Q-learning** learns about the **value** of its **greedy policy** from experiences gathered by a **different policy** (e.g. **ε-Greedy**).
- We use **max** of the Q-value for $\mathbf{a}'$ instead of executing the policy for an extra step.



$$\mathbf{Q}(\mathbf{s},\mathbf{a}) \leftarrow \mathbf{Q}(\mathbf{s},\mathbf{a}) + \alpha(\mathbf{r} + \gamma \max_{\mathbf{a}'} \mathbf{Q}(\mathbf{s}',\mathbf{a}') - \mathbf{Q}(\mathbf{s},\mathbf{a}))$$

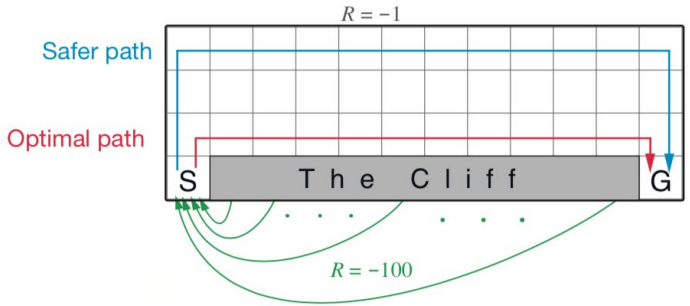
SARSA vs Q-Learning: The Cliff-walking Example

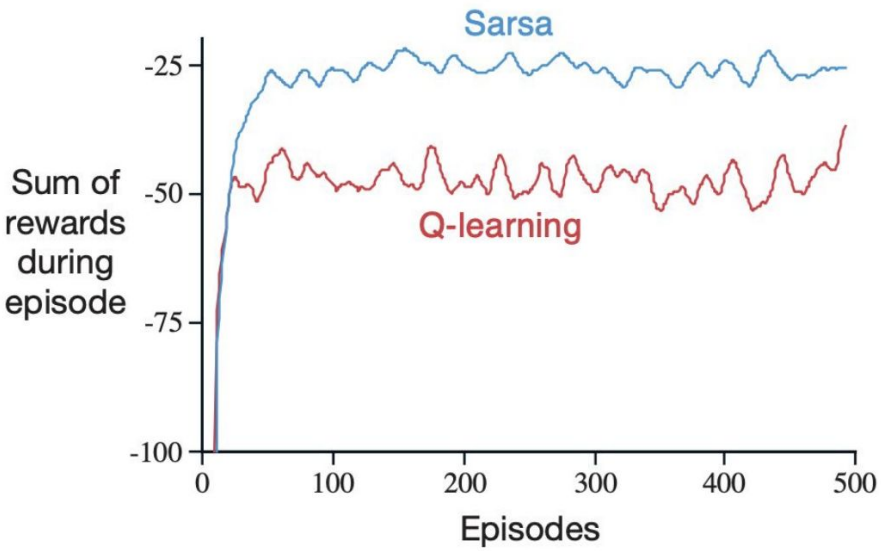


Sutton & Barto. Reinforcement Learning: An Introduction. (Chapter 6)

SARSA vs Q-Learning: The Cliff-walking Example

- **Q-learning** learns the **optimal path** while its online performance is worse than **SARSA**.
- **SARSA** learns the **safer path**.





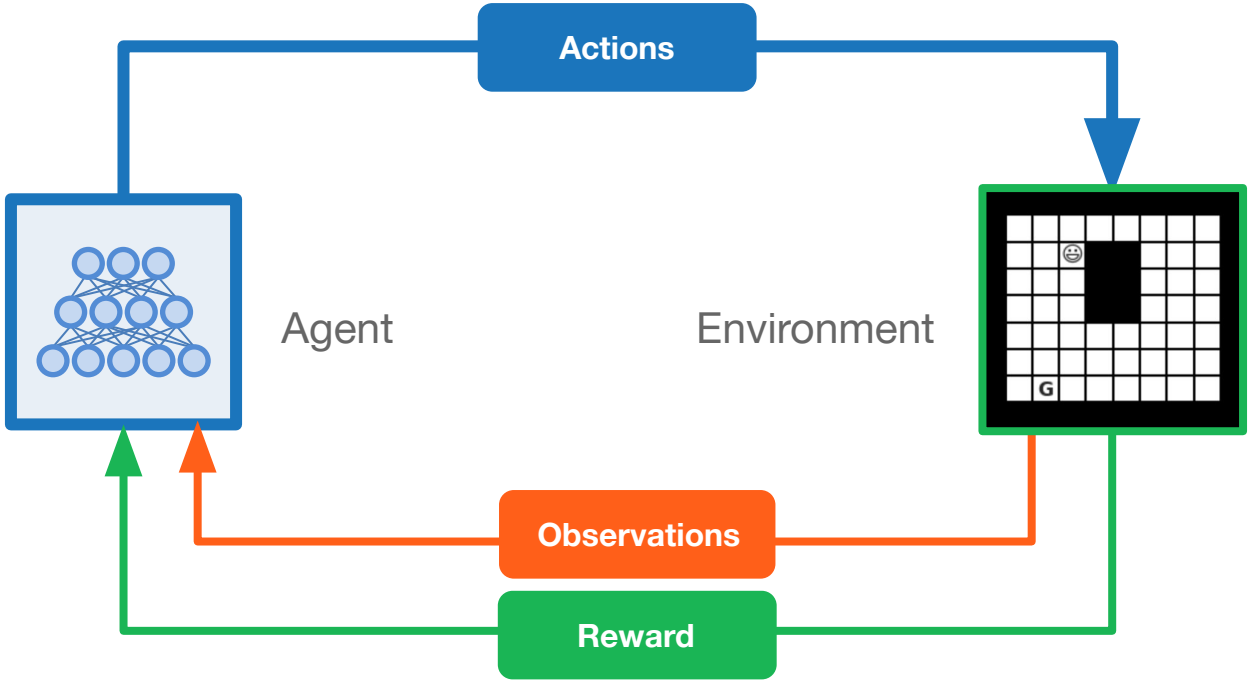
Section 6

Function approximation

Feryal Behbahani

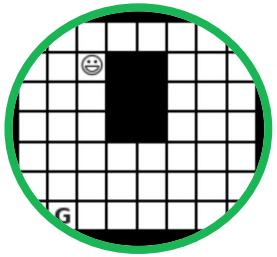
neuromatch academy

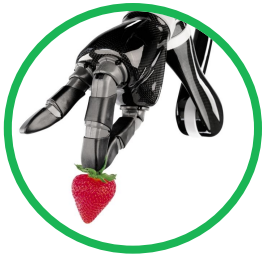
Function approximation



Why function approximation?

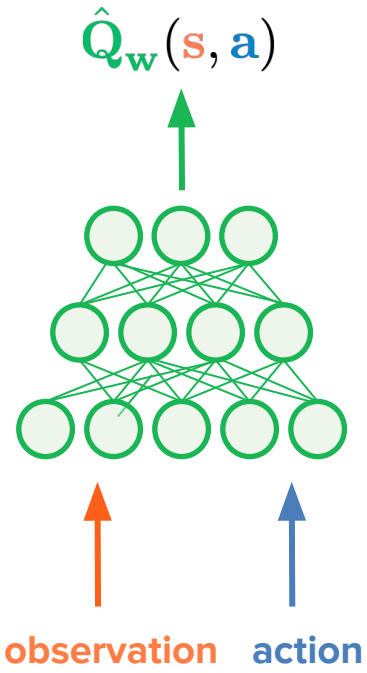
- Up to now we used lookup tables to represent the **value function**, for example each $s \in \mathcal{S}$ and $a \in \mathcal{A}$ has an entry in the **Q-table** $Q(s, a)$
- In **large MDP**s with large **action** and **state** space this becomes infeasible due to **memory requirements** and **inefficiency of learning** the **value** of each **state** in isolation.





How?

- We now have a great machinery to approximate any continuous function efficiently: **neural networks**!
- Given a **state**, use a neural network with parameters $\mathbf{w}$ to predict the **Q-values** of each **action**.
- Allows to **generalize** from **seen states** to **unseen states**.



How?

- We will use the same **TD targets** we saw earlier as a **loss function**.
- Our goal is to find the parameter vector $\mathbf{w}$ minimising the **mean-squared error** between the **approximate value function** $\hat{Q}_{\mathbf{w}}(\mathbf{s}, \mathbf{a})$ and the **true value function.**
- This can be optimized with gradient descent, using automatic differentiation.

The deadly triad

Bad news: there is possibility of **divergence** when we combine these three powerful ingredients:

Off-policy learning

Learning from experiences collected by a different behaviour policy than the target policy we are learning about (e.g. Q-learning).

+ Bootstrapping

Learning value estimates from other value estimates (e.g. in TD and DP)

+ Function approximation

Significantly generalising from experiences

Section 9

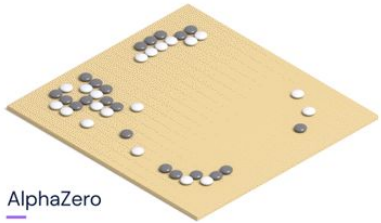
Real-world applications and ethics

Jane Wang

neuromatch academy

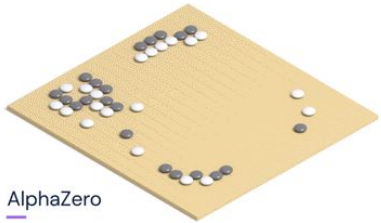
Real-world Reinforcement Learning: **Examples**

Game playing
(more on this tomorrow)



Real-world Reinforcement Learning: **Examples**

Game playing
(more on this tomorrow)

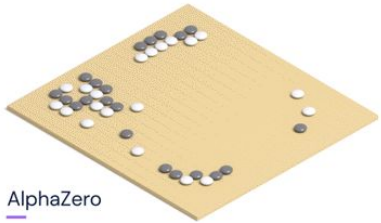


Robotics / Manipulation

Self-driving cars

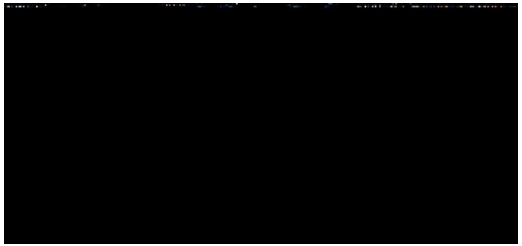
Real-world Reinforcement Learning: **Examples**

Game playing
(more on this tomorrow)



Robotics / Manipulation

User personalization



Self-driving cars

Managing energy usage

Real-world Reinforcement Learning: **Challenges**

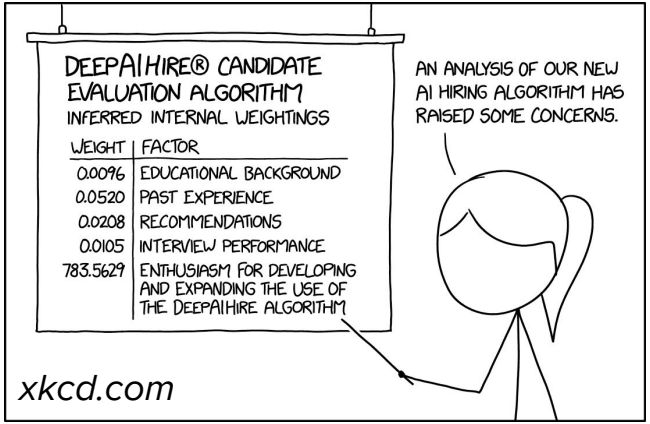
- Learning difficulty:
  - Large action and state spaces
  - Smart / continuing **exploration**
  - Requirements for **fast inference** / Generalization

Real-world Reinforcement Learning: **Challenges**

- Learning difficulty:
  - Large action and state spaces
  - Smart / continuing **exploration**
  - Requirements for **fast inference** / Generalization
- Safety concerns
  - Usually interaction with the environment is **expensive** e.g. robotics
  - Large and unknown delays in actuators, sensors and rewards
  - Reward function is **unspecified**, **risk sensitive** or **multi-objective**

To find out more

- **Safety:** Victoria Krakovna's list of resources (vkrakovna.wordpress.com/)



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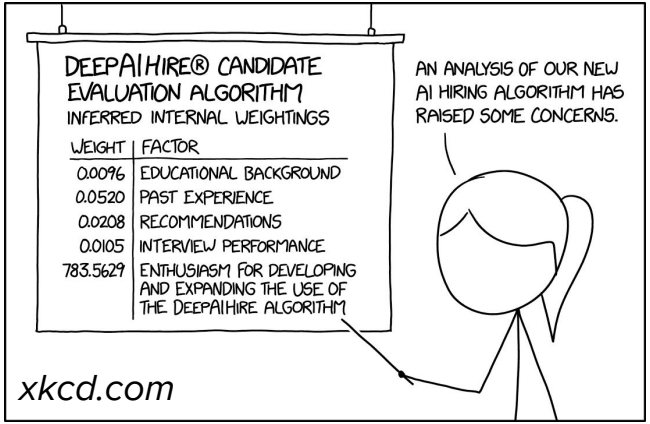
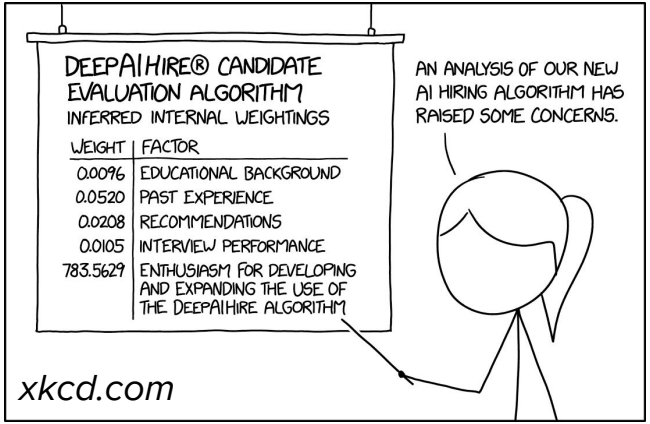
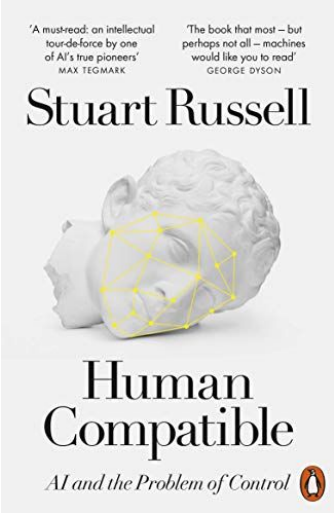
- **Fairness, ethics:** Timnit Gebru, Joy Buolamwini (Gender Shades)



To find out more

- **Safety:** Victoria Krakovna's list of resources (vkrakovna.wordpress.com/)
- **Fairness, ethics:** Timnit Gebru, Joy Buolamwini (Gender Shades)
- **Beneficial AI:** Stuart Russell (Human Compatible)





Ethics - discuss with a group partner or partners (3 min each):

- **Safety:** What are some safety issues that arise in RL that don't arise with e.g. supervised learning?
- **Generalization:** How should we deal with situations where our agents "go out of distribution"?
- How important do you think **interpretability** is in the ethical and safe deployment of RL agents in the real world?

Section 10

How to learn more?

Feryal Behbahani

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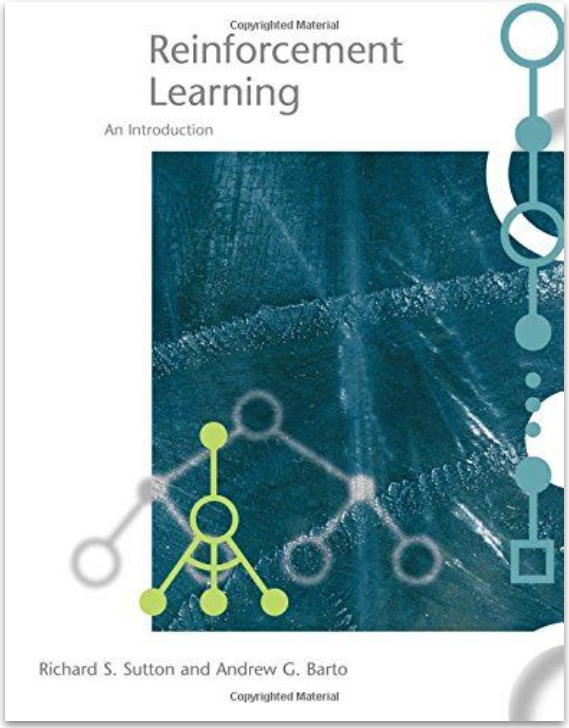
Reinforcement Learning: An Introduction



Want to learn more?

Books

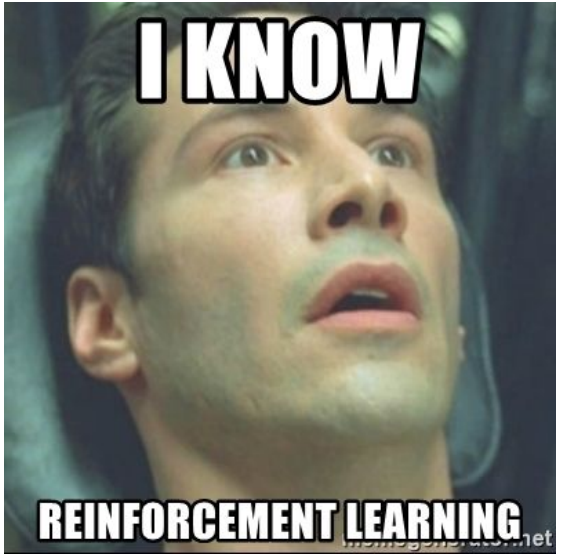
- Reinforcement Learning: an Introduction by Sutton & Barto
- Algorithms for Reinforcement Learning by Csaba Szepesvari

Lectures and course

- RL Course by David Silver
- Reinforcement Learning Course | UCL & DeepMind
- Emma Brunskill Stanford RL Course
- RL Course on Coursera by Martha White & Adam White

More practical

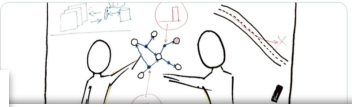
- Spinning Up in Deep RL by Josh Achiam
- Acme white paper & Colab tutorial



David Abel @dabelcs · Jun 22
Replying to @FeryalMP
I wrote a simple python library during my time at Brown that I've used in courses before, this could be helpful? Here's the GitHub:

david-abel/
simple_rl

Arjun Chandra 🇮🇳
@boelger
Replying to @boelger and @FeryalMP
I do also run a reading group, in case this can be of some use for someone:



Xavier Giró
@DocXavi
Replying to @FeryalMP
Our course on Deep & Reinforcement Learning at @UPCTelecos Barcelona:

telecombcn-dl.github.io/drl-2020/

Robin Ranjit Singh Chauhan @robinc · Jun 22
Replying to @FeryalMP

TalkRL: The Reinforcement Learning Podcast on Apple Podcasts
Technology · 2021
podcasts.apple.com

Johan S. Obando 👍
@JS_Obando
Replying to @FeryalMP
I highly recommend the Revisiting Rainbow 🌈 paper and its implementation. 📚🤩
📜Paper: arxiv.org/abs/2011.14826
🐙Code:

JohanSamir/
revisiting_rainbow
Revisiting Rainbow

2 Contributors · 0 Issues · 45 Stars · 1 Fork

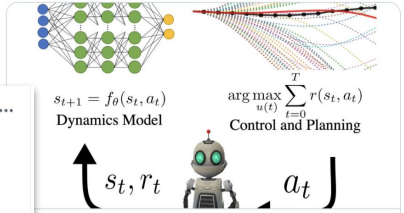
Feryal
@FeryalMP

If you have used or made any tutorials/videos/blog posts/open-source projects/libraries that helps with learning about 🧀 Reinforcement Learning 🐁 can you please share the links here?

10:40 AM · Jun 22, 2021 · Twitter for Android

61 Retweets **4** Quote Tweets **275** Likes

Nathan Lambert @natolambert · Jun 22
Replying to @FeryalMP
Some work on model-based RL:
- debugging / details tutorial: natolambert.com/writing/debugg...
- high level motivation robotic.substack.com/p/mbrl
- Hyperparameter sensitivity



Importance of Hyperparameter Optimization for Model-based ...
BAIR Blog

Ifty Mohammad Rezwan @imr165 · Jun 22
Replying to @FeryalMP
Lillian weng's p

Rohini Das @rohini__das · Jun 23
Replying to @FeryalMP
Here's the course website for Csaba's RL theory course at the UofA:
rltheory.github.io
Has all the lectures videos for the Winter 2021 term.

Home
Homepage of the course CMPUT 653: Theoretical Foundations of Reinforcement ...
rltheory.github.io

Pablo Samuel Castro
@pcastr
Replying to @FeryalMP
I wrote an intro to RL with colab and video:
psc-g.github.io/posts/mentorin...

There's a version of the video in Spanish as well (linked from the same site) 🙂

References

- Mnih et al., 2013 Playing Atari with Deep Reinforcement Learning
- Bellemare, Dabney, Munos, 2017 A Distributional Perspective on Reinforcement Learning
- van Hasselt et al., 2018 Deep Reinforcement Learning and the Deadly Triad
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- Sutton et al., 2000 Policy Gradient Methods for Reinforcement Learning with Function Approximation
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- OpenAI et al., 2019 Solving Rubik's Cube with a Robot Hand
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- Schulman et al., 2017 Proximal Policy Optimization Algorithms
- Espeholt et al., 2018 IMPALA: Scalable Distributed Deep-RL with Importance Weighted Actor-Learner Architectures
- Abdolmaleki et al., 2018 Maximum a Posteriori Policy Optimisation
- Wang et al., 2016 Sample Efficient Actor-Critic with Experience Replay
- Silver et al., 2017 A general reinforcement learning algorithm that masters chess, shogi and Go through self-play
- Fu et al., 2020 D4RL: Datasets for Deep Data-Driven Reinforcement Learning
- Gulcehre et al., 2020 RL Unplugged: Benchmarks for Offline Reinforcement Learning

Thank you

Special thanks to

Kelson Shilling-Scrivo, Konrad Kording, Anis Zahedifard

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academy

Section 7

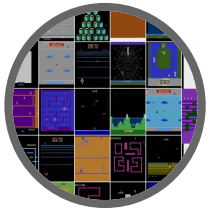
Deep Q-Networks (DQN)

Feryal Behbahani

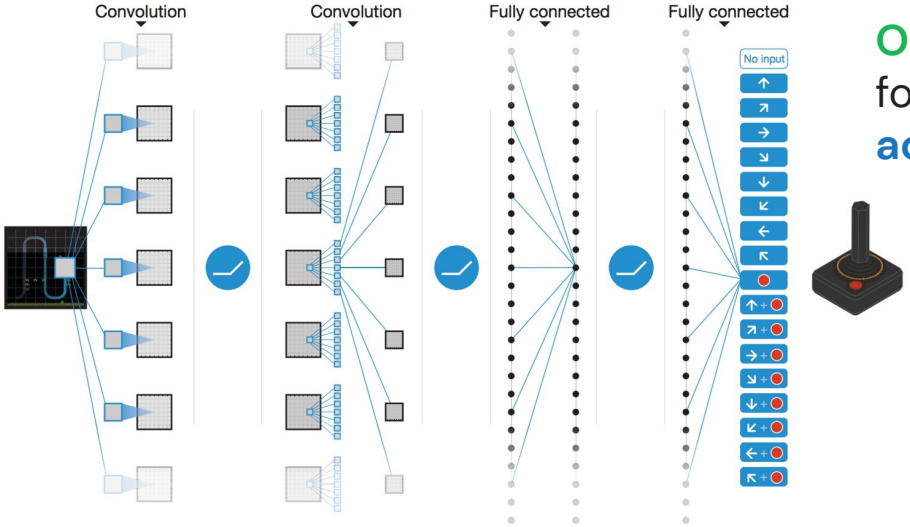
neuromatch academy

Deep Q-Networks (DQN)

End-to-end learning of the **value function** $Q(s, a)$ from **pixels**.



Input is the stack of raw pixels from the last 4 frames.



Output is the **Q-function** for the 18 possible joystick **actions**.

(Mnih et al., 2013)

Deep Q-Networks (DQN)

End-to-end learning of the **value function** $\mathbf{Q}(\mathbf{s}, \mathbf{a})$ from **pixels**.

DQN addressed main challenges with **value function** approximation

- Non-stationary targets
- Correlation between samples

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- Non-stationary targets → **Target Network**
- Correlation between samples → **Experience Replay**

The DQN Loss

We minimize the loss between

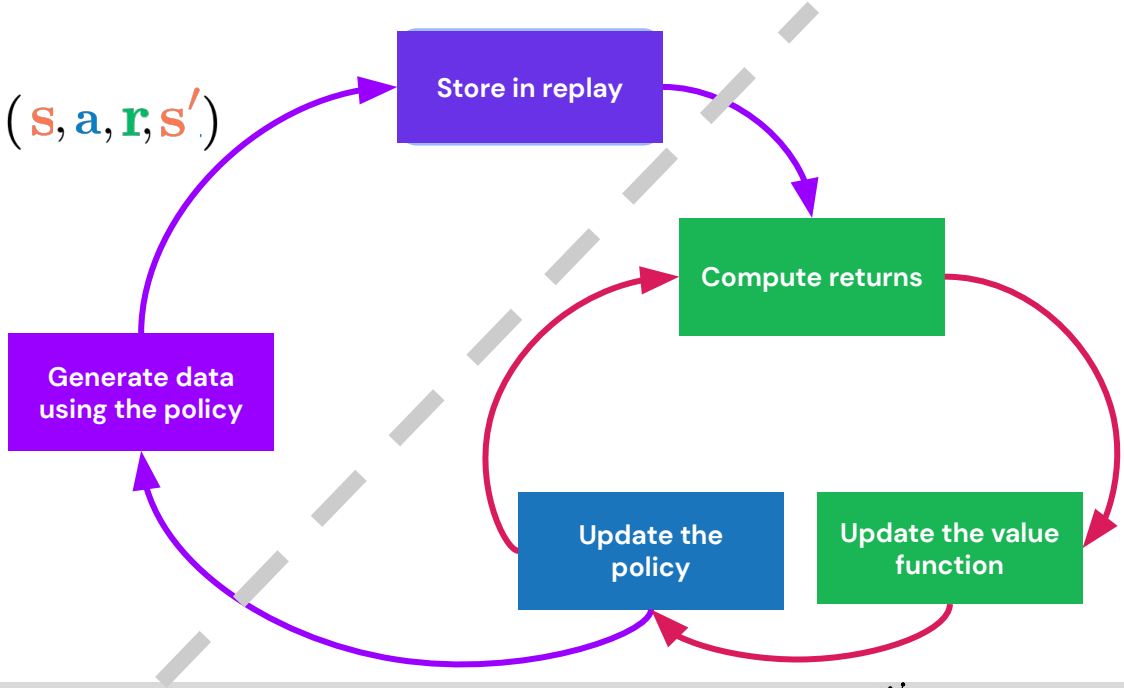
- the **TD Target**
- the **current value**

$$L(\mathbf{W}) = \mathbb{E}_{\mathbf{s},\mathbf{a},\mathbf{s}'}\left[\left(\mathbf{R}(\mathbf{s},\mathbf{a},\mathbf{s}') + \overbrace{\gamma \max_{\mathbf{a}'} \mathbf{Q}_{\mathbf{W}_{\text{old}}}(\mathbf{s}',\mathbf{a}')}^{\text{old/target value function}} - \underbrace{\mathbf{Q}_{\mathbf{W}}(\mathbf{s},\mathbf{a})}_{\text{optimized value function}}\right)^2\right]$$

Target network $\mathbf{W}_{\text{old}}$ uses a different/older set of weights than the weights being updated

Experience Replay

Remove temporal correlations by storing transitions in a **replay**



In some sense there are **two loops:**

- **Data Generation**

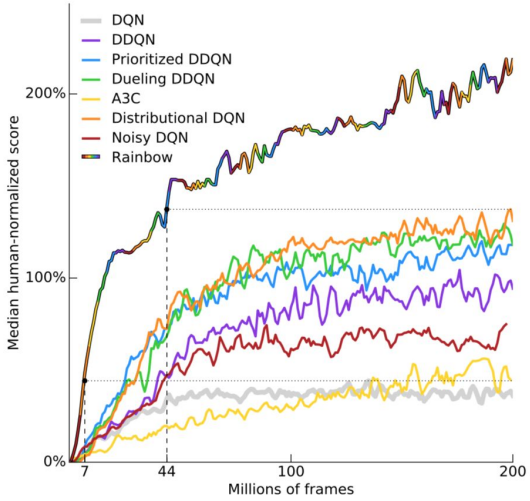
  and

- **Parameter optimization**

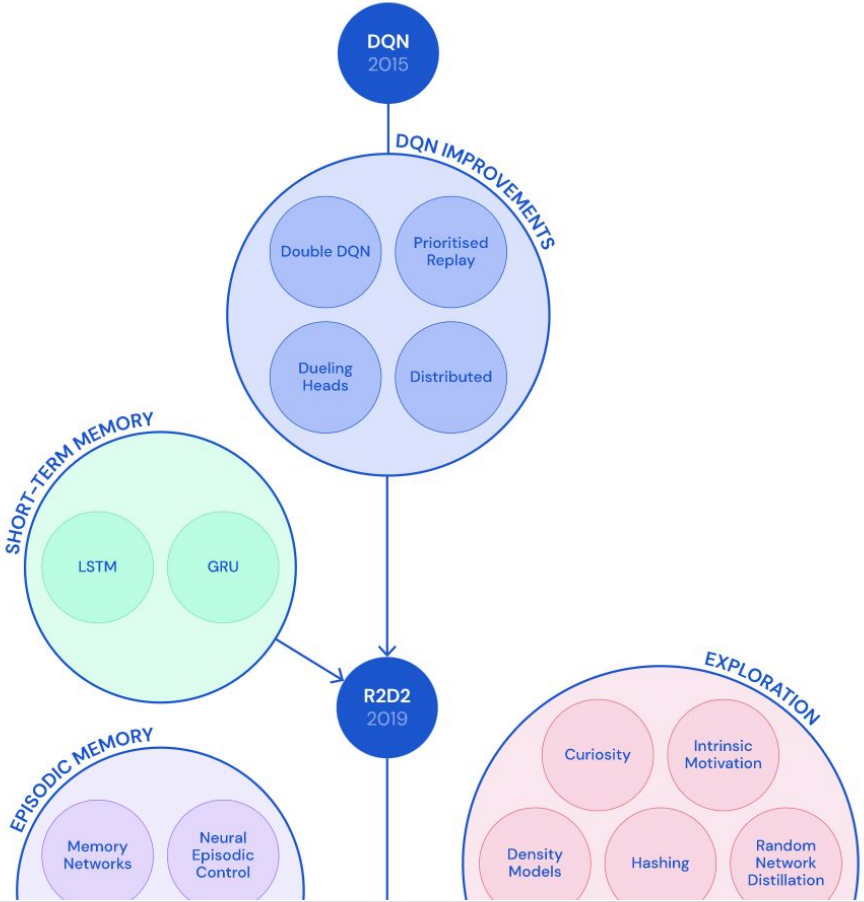
Can we decouple these?

Rainbow

Combines a collection of algorithmic improvements and large-scale training.



(Hessel et al., 2018)

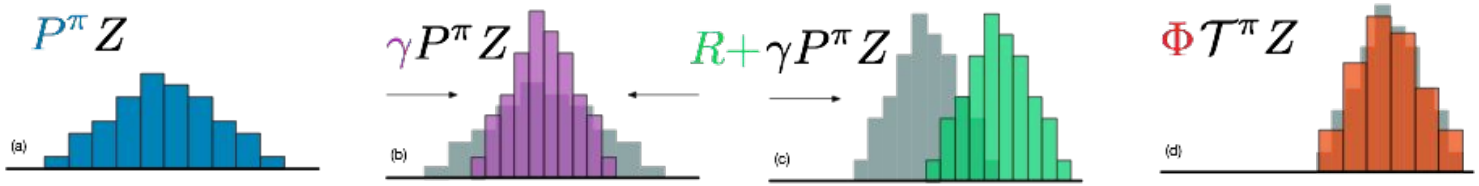


Distributional RL

Distributional RL goes further and learns a **distribution** over **returns**!

$$\mathbf{Q_w}(\mathbf{s}, \mathbf{a}) = \mathbb{E}\underbrace{\mathbf{Z_w}(\mathbf{s}, \mathbf{a})}_{\text{distribution over value}}$$

The **Bellman update** and **loss** now involve these distributions



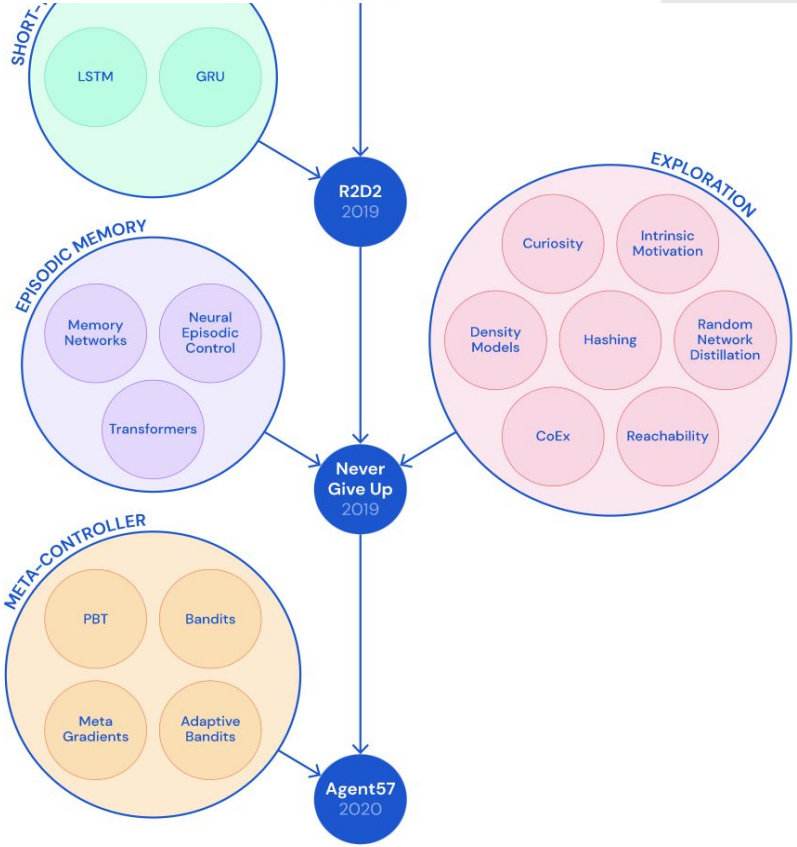
(Bellemare et al., 2017)

Agent-57

- Leverages an efficient exploration strategy which is novelty seeking

- Bandit meta-controller that adapts the long-term vs short-term behaviour of the agent.

(Puigdomènech Badia, et al., 2020)



Section 8

Other deep RL methods

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Challenges for value-based learning methods

- **Continuous** action space (value-based methods don't naturally handle this)
- Large action spaces - **hard to explore**
- Optimal policy is a **stochastic** one - epsilon greedy not optimal

Observations $\longrightarrow$ $Q(s, a)$ $\longrightarrow$ **Policy**

Why policy optimization?

- Learning the **policy** **directly** can sometimes be simpler than learning the **value function**
- Particularly better suited in **continuous control** and **large action spaces**.
- In **some** problems the optimal policy is **stochastic**
- But stochasticity can make **exploration** easier

What is policy optimization?

We explicitly represent the **policy** with its own parameters independent of any **value function**

$$\mathbf{a_t} \sim \boldsymbol{\pi_\theta}(\mathbf{a_t}|\mathbf{s_t}) \quad \text{vs} \quad \mathbf{a_t} = \arg\max_{\mathbf{a}} \mathbf{Q}(\mathbf{s_t}, \mathbf{a}) = \boldsymbol{\pi}(\mathbf{s})$$

We update the **policy parameters** using **gradient ascent** to **maximise expected future reward**.

Directly parameterizing the policy

We'll now turn to **parameterized policies** given by $\boldsymbol{\theta}$

$$\mathbf{a_t} \sim \pi_{\boldsymbol{\theta}}(\mathbf{a_t} | \mathbf{s_t})$$

Future rewards exactly as seen previously!

and we will write the **expected return** as a function of these parameters

$$\mathbf{J}(\boldsymbol{\theta}) = \mathbb{E}_{\mathbf{s_{0:T+1}}, \mathbf{a_{0:T}}} \left[\sum_{t=0}^{T} \gamma^t \, \mathbf{R}(\mathbf{s_t}, \mathbf{a_t}, \mathbf{s_{t+1}}) \right]$$

$$= \sum_{\mathbf{s_{0:T+1}}, \mathbf{a_{0:T}}} \left[\sum_{t=0}^{T} \gamma^t \, \mathbf{R}(\mathbf{s_t}, \mathbf{a_t}, \mathbf{s_{t+1}}) \right] \Pr(\mathbf{s_{0:T+1}}, \mathbf{a_{0:T}})$$

Summing over all possible trajectories

Multiplied by their probability

High level intuition

- **Gradient of performance is in same direction as gradient of policy**
- Key takeaway:
  - Starting with some random initial policy for acting
  - Sample some actions to interact with environment
  - In proportion to the return (or estimated future value), adjust the weights to increase probability of taking those same actions

$$\nabla_{\boldsymbol{\theta}} \mathbf{J}(\boldsymbol{\theta}) \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=0}^{T} \mathbf{G}_{\mathbf{t}}^{(\mathbf{i})} \nabla \log \boldsymbol{\pi}_{\boldsymbol{\theta}}(\mathbf{a}_{\mathbf{t}}^{(\mathbf{i})} | \mathbf{s}_{\mathbf{t}}^{(\mathbf{i})})$$

Advantage Actor Critic (A2C) and Baselines

The **policy gradient** can have *high variance*. **Can we reduce it?**

Baseline! Expectation zero because independent of $\mathbf{a}$

$$\nabla_\theta \mathbf{J}(\theta) = \mathbb{E}_{d^\pi(\mathbf{s})\pi(\mathbf{a}|\mathbf{s})}\left[\underbrace{\left(\mathbf{Q}^{\pi_\theta}(\mathbf{s},\mathbf{a}) - \mathbf{V}^{\pi_\theta}(\mathbf{s})\right)}_{\mathbf{A}^{\pi_\theta}(\mathbf{s},\mathbf{a})} \nabla \log \pi_\theta(\mathbf{a}|\mathbf{s})\right]$$

The **advantage** measures how much **better** $\mathbf{a}$ is than following the policy $\pi_\theta(\mathbf{s})$

A2C:

- Estimate **Q** using returns $\mathbf{G}_\mathbf{t}^{(\mathbf{i})}$
- Estimate **V** with a neural network

(Mnih, et al., 2015)

Plethora of RL methods

Value-based

vs

policy-based

Model-based

vs

Model-free

on-policy

vs

off-policy

Offline

vs

Online

Episodic

vs

Lifelong

...