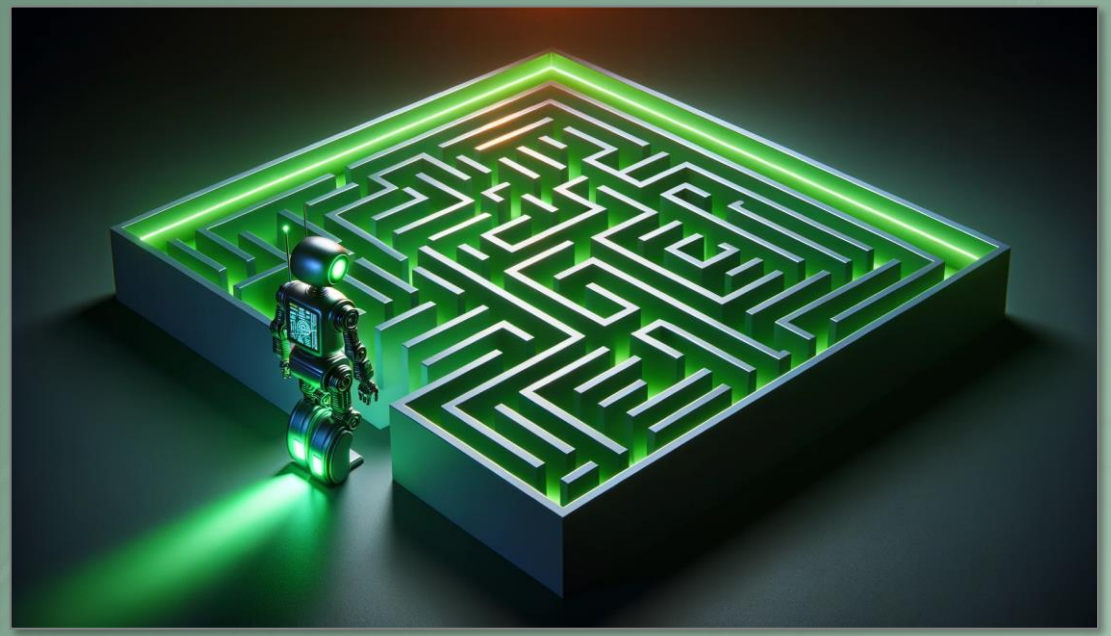
BHT Berliner Hochschule für Technik

# Reinforcement Learning



**Advanced Software-Engineering**

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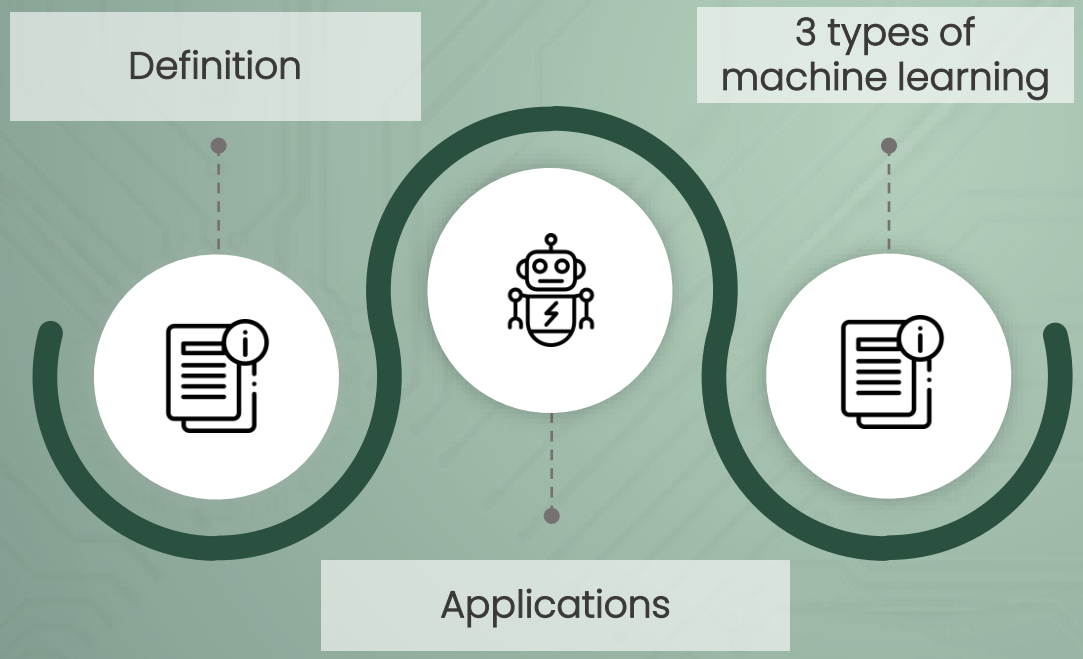
**Dez 2023**

# Agenda

- What is Reinforcement Learning (RL)?
- Basic concepts of RL
- Theoretical foundations of temporal difference learning
- Q-learning
- Code example: Taxi driver with Q-learning

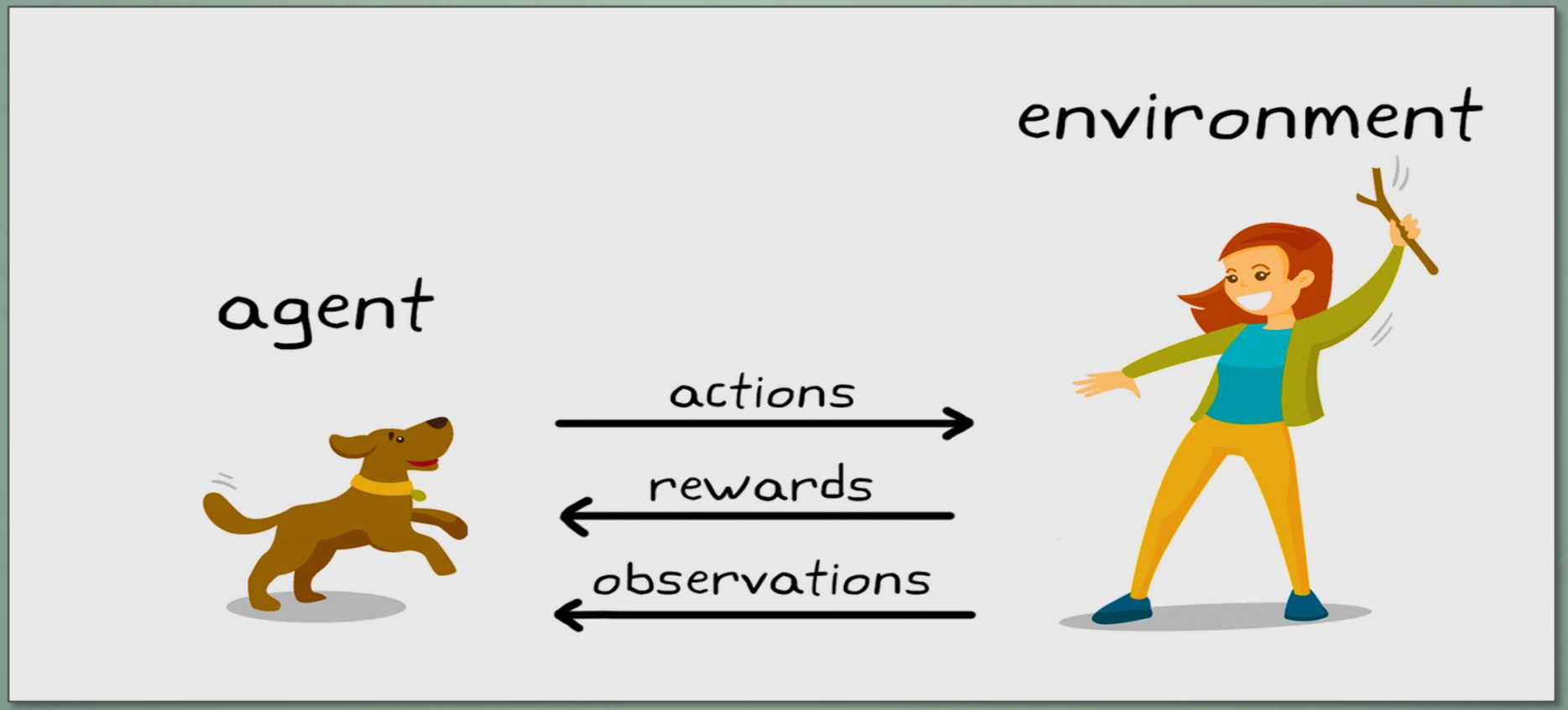
# What is Reinforcement Learning?

... and what is it good for?



# What is Reinforcement Learning?

It is type of machine learning where agents learn how to behave in an environment



# What is Reinforcement Learning?

It is type of machine learning where agents learn how to behave in an environment

**Agent**

- takes actions based on observations
- aiming to achieve best possible outcome

**Goal Setting**

- Primary objective of agent is to maximize cumulative reward over a period
- refining its actions and strategies over time

**Environment Interaction**

- Each action the agent takes impacts its environment
- leading to new situations (states)

**Decision Strategy**

- Through experience, agent develops policy, a guideline on which action to choose in a given situation
- to achieve its long-term reward maximization goal.

**Feedback Mechanism**

- After each action, agent receives feedback in form of rewards/penalties
- indicating the quality of its decision.

**Challenges Faced**

- Ongoing challenge in reinforcement learning is the balance between exploration (trying new actions) exploitation (sticking with known beneficial actions).

# Applications of Reinforcement Learning

Examples are:

- **Game Playing:** Classic games like Tic-Tac-Toe, where the state and action spaces are manageable without deep learning.
- **Multi-Armed Bandit Problems:** Used in areas such as online advertising, clinical trials, and A/B testing to make decisions under uncertainty.
- **Grid World Navigation:** Simple agent navigation tasks in a grid-like environment to reach a goal.
- **Customer Service:** Automated decision-making for handling customer queries or complaints in a predefined and rule-based environment.
- **Dynamic Pricing:** Adjusting prices of products or services in real-time based on demand, competitor prices, or other factors.

# 3 types of machine learning

## Unsupervised Learning

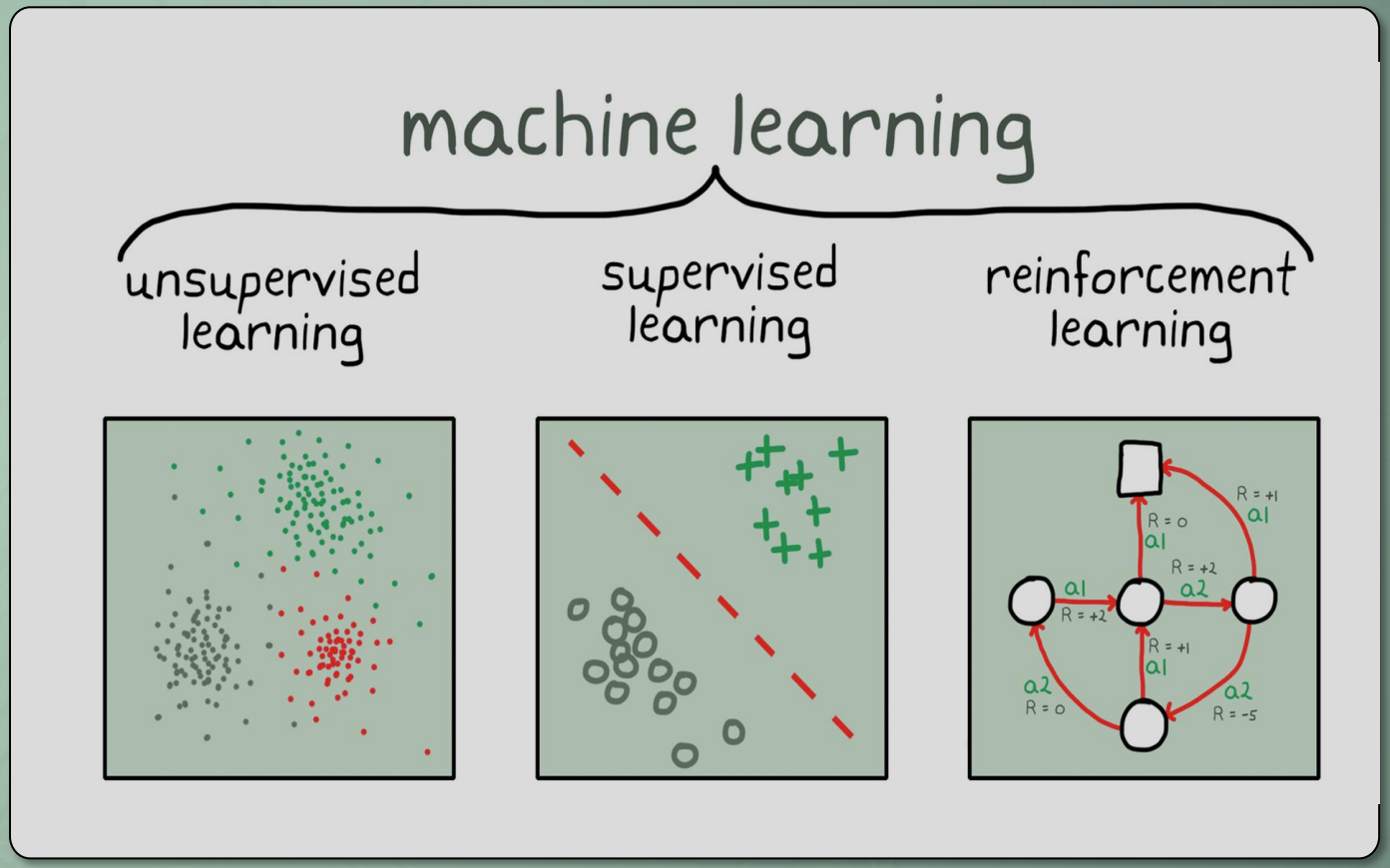
- Type of machine learning that deals with unlabeled data and aims to identify underlying patterns or structures.
- The model learns to represent the data without explicit guidance.

## Supervised Learning

- Machine learning paradigm where a model is trained on labeled data to make predictions or classifications.
- The model learns a function that maps input features to output labels.

## Reinforcement Learning

- Represents the policy or value function, guiding the agent's decisions.
- These methods play a crucial role in capturing semantic meaning and relationships between words and phrases.

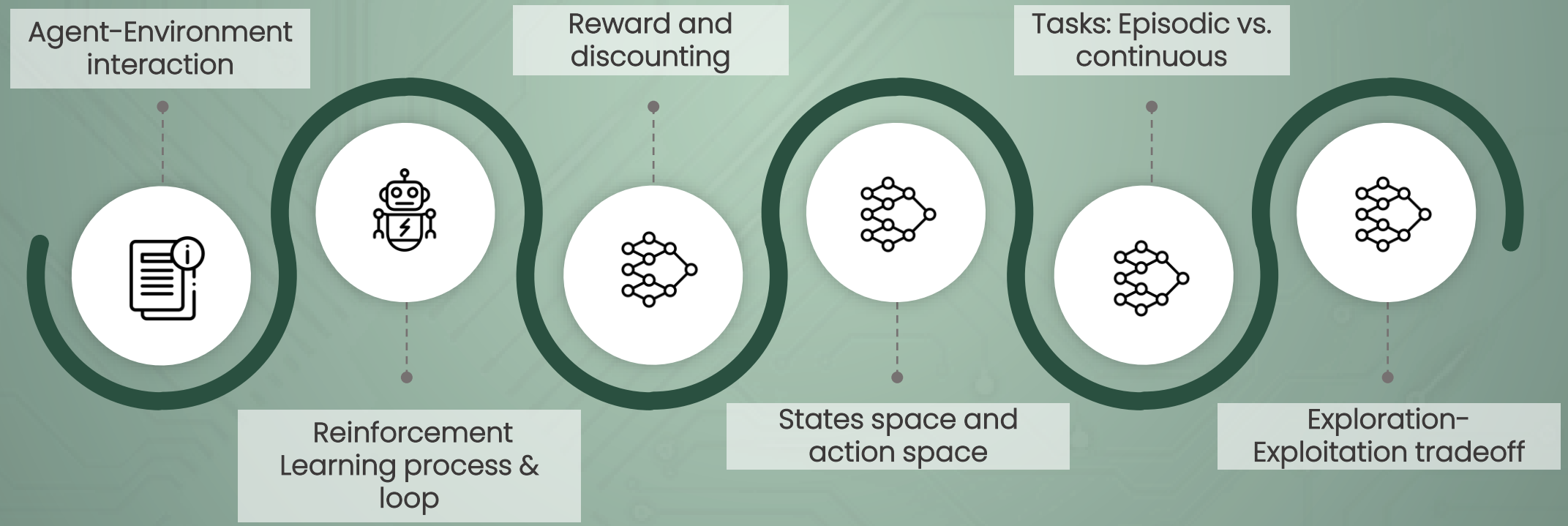


# 3 types of machine learning

Focus

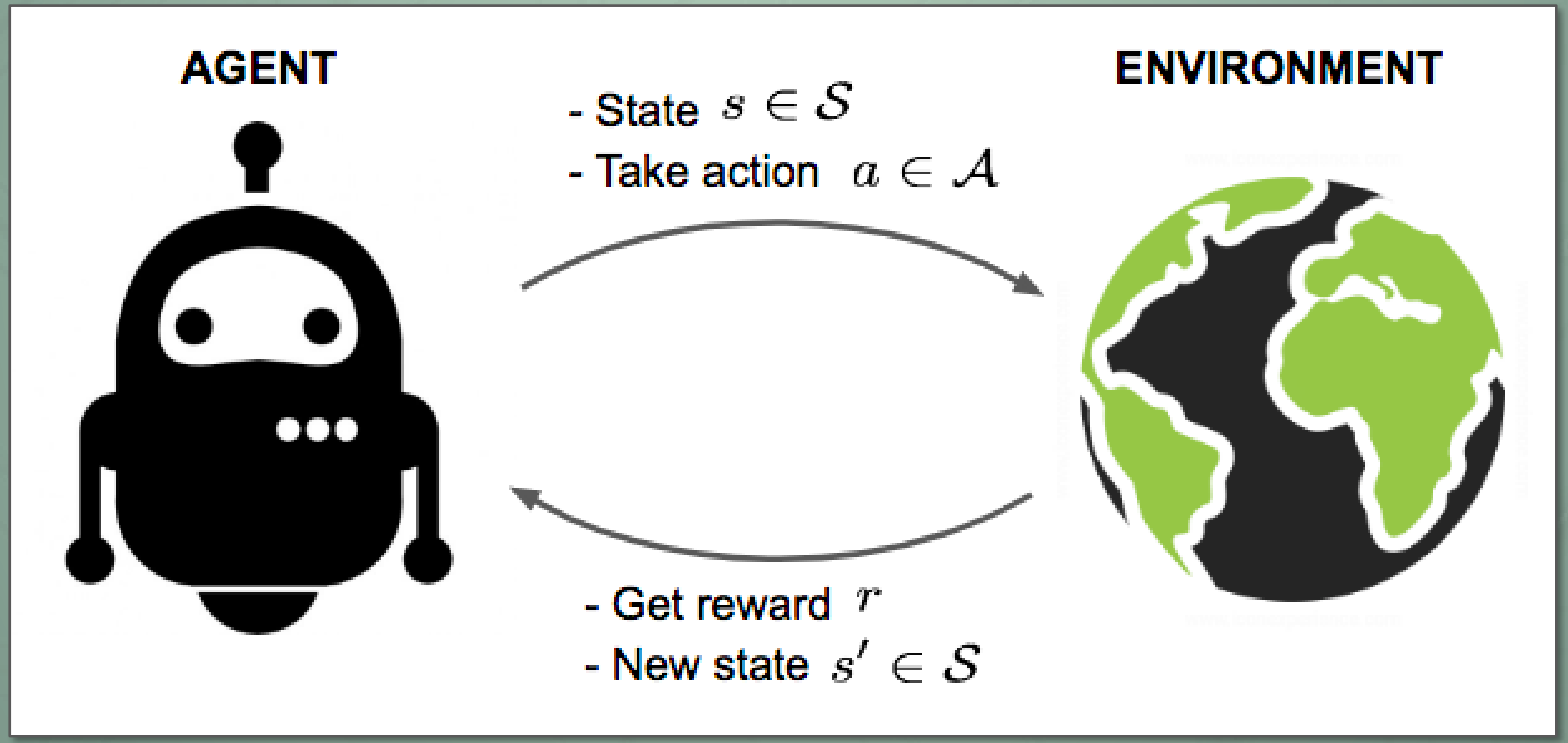
| | 1 Unsupervised Learning | 2 Supervised Learning | 3 Reinforcement Learning |
|---|---|---|---|
| **INPUT DATA** | Unlabeled: no „right answer" specified | Labeled: the „right answer" is included | Data are not part of the input, they are collected through trial and error |
| **GENERAL TASKS** | Discovery of clusters, patterns, relationships | Classification, regression | **Explorative controlling:** Solution of reward-based problems by exploration and exploitation |
| **SOLUTION** | Finds similarities and differences in input data | Maps input to output | Finds which states and actions would maximize the total cumulative reward of the agent |
| **EXAMPLES** | Customer segmentation, product recommendation | Image detection, stock market prediction | Game playing, robotic vacuum cleaners |
| **FEEDBACK** | No | Yes. The correct set of actions is provided. | Yes, through rewards and punishments (positive and negative rewards) |

# Basic concepts of RL



# Agent-environment interaction

... provides a mathematical framework for modeling decision-making in situations where outcomes are partly random and partly under the control of a decision-maker



# Reinforcement Learning process

… is a Markov decision process that provides mathematical framework for modeling decision-making when outcomes are partly random, partly under decision-maker's control

- 5-tuple of $(S, A, T, R, \gamma)$ with
  - $S$ the state space
  - $A$ the action space
  - $T$ the transition function
  - $R$ the reward function
  - $\gamma$ the discount factor

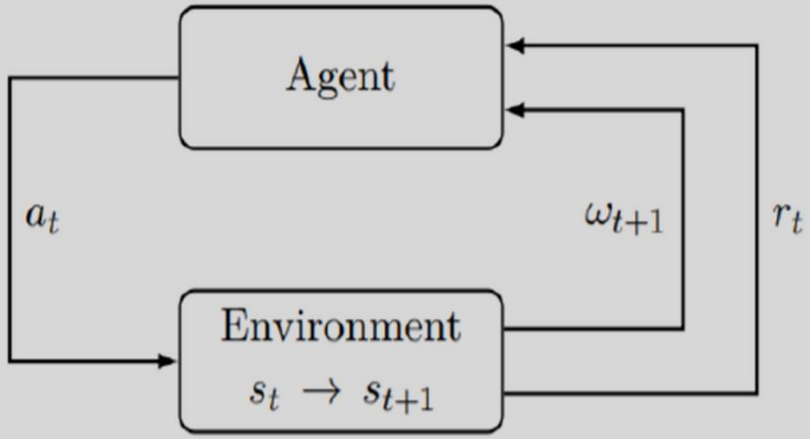



Figure 1: The agent-environment interaction [1]

→ Theoretical Framework of Reinforcement Learning

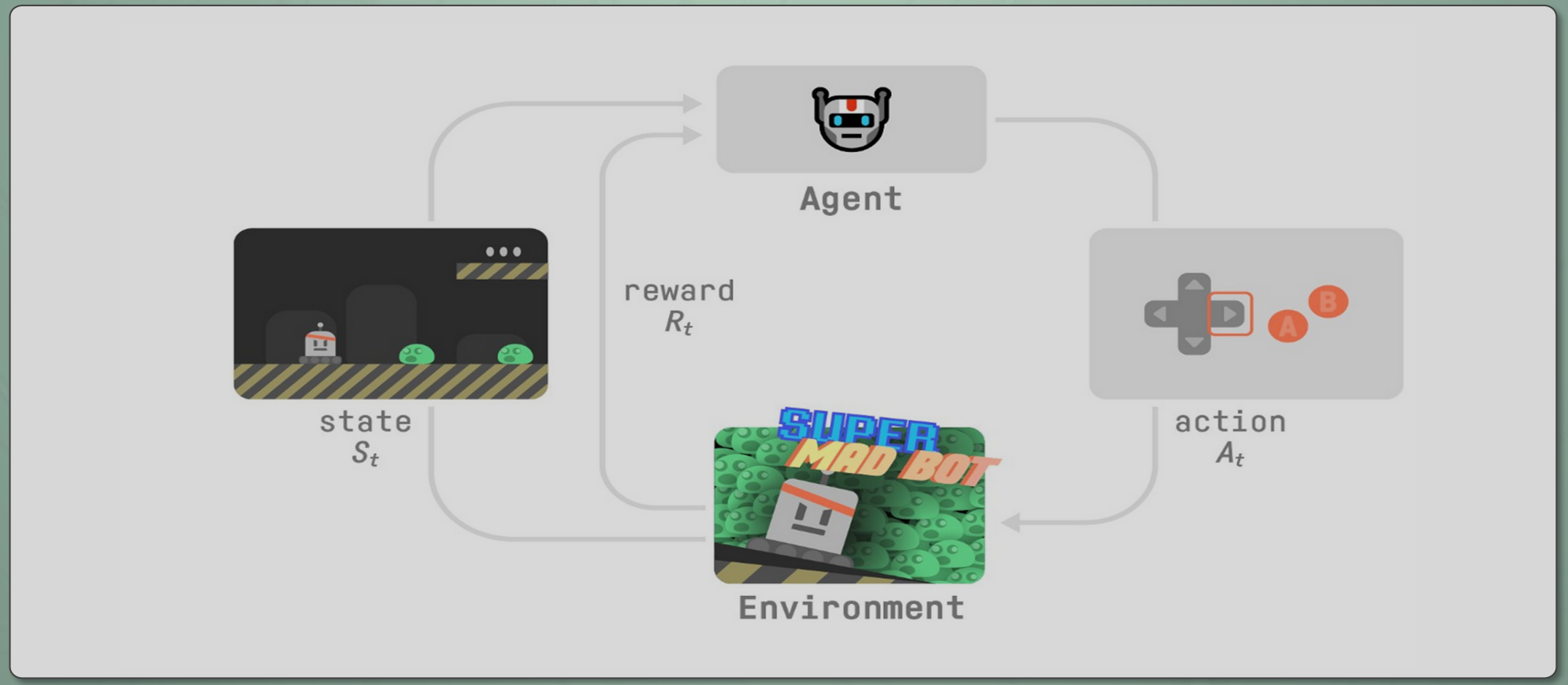
→ The agent wants to maximize his rewards

**Markov Property:**

implies that our agent needs only current state to decide what action to take without the history of all states and actions they took before.

# Example: Video game

... for Markov Decision Process in RL context



# Reinforcement Learning loop

... outputs a sequence of state, action, reward and next state.


**The agent's goal:**

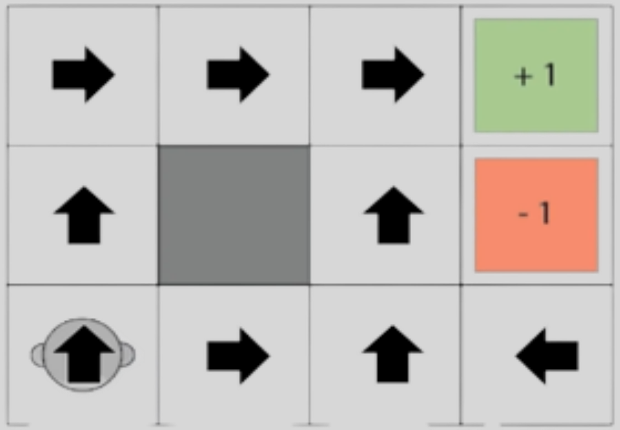
... to maximize its cumulative reward called the expected return.

# The reward hypothesis

... is that all goals can be described as the maximization of the expected return (expected cumulative reward)

## Sum of Future Rewards

- Discount factor $\gamma = 0.9$
- Return at state = (0, 2) is 1
- Return at state = (0, 1) is 0.9
- Return at state = (0, 0) is 0.81

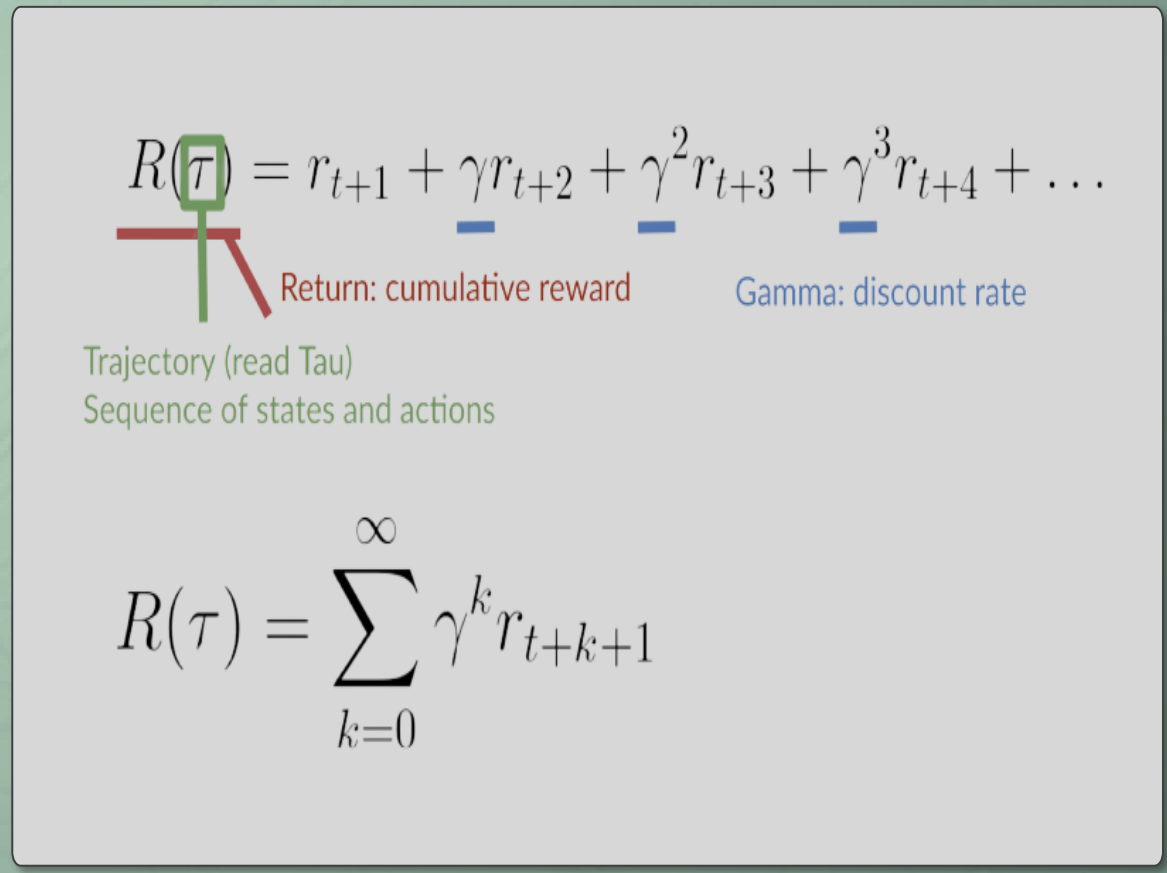


# Rewards and discounting

Reward is fundamental in RL because it's the only feedback for the agent. Thanks to it, our agent knows if the action taken was good or not

**To discount the rewards, we proceed like this:**

- Discount rate gamma between 0 and 1 is defined
- Most of the time between 0.95 and 0.99.
  (The larger the gamma, the smaller the discount. This means our agent cares more about the long-term reward)
- Each reward will be discounted by gamma to the exponent of the time step.
- As time step increases, agent approaches final round, if task is episodic. Then sum of discounts vanishes.



# Observations/States Space

... are the information our agent gets from the environment

- **Board game (complete information):**
  position of game pieces
- **Card game (incomplete information):**
  visible cards
- **Video game (incomplete information):**
  frame / screenshot
- **Trading agent (incomplete information):**
  value of certain stock, news, etc.

State (complete information): complete description of the state of the world

Observation (incomplete information): Partial description of the state of the world

# Action Space

... is the set of all possible actions in an environment

- **Board game, card game:**
  possibilities to move game pieces, play cards
- **video game:**
  left, right, accelerate, break, don't push any button
- **trading agent:**
  buy, sell, don't change portfolio

**Discrete:**
Finite number of possible actions


**Continuous:**
Infinite number of possible actions

# Task

… is an instance of a Reinforcement Learning problem. Two types: episodic and continuing

### Episodic task

- There is starting point and ending point (a terminal state).
- This creates an episode: list of States, Actions, Rewards, and new States.

### Continuous task

- Agent must learn how to choose the best actions
- and simultaneously interact with the environment.

**Episodic:**

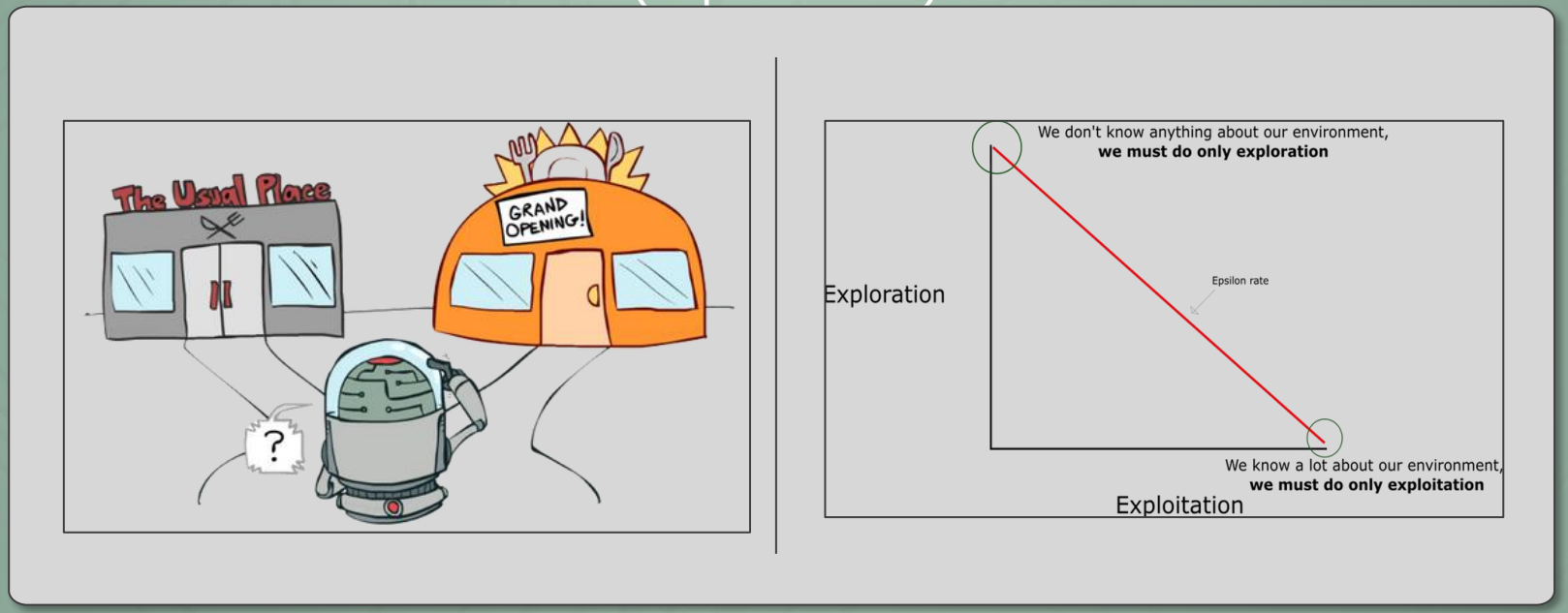
Starting point and an ending point (a terminal state)


**Continuing:**

Task that continue forever (no terminal state)

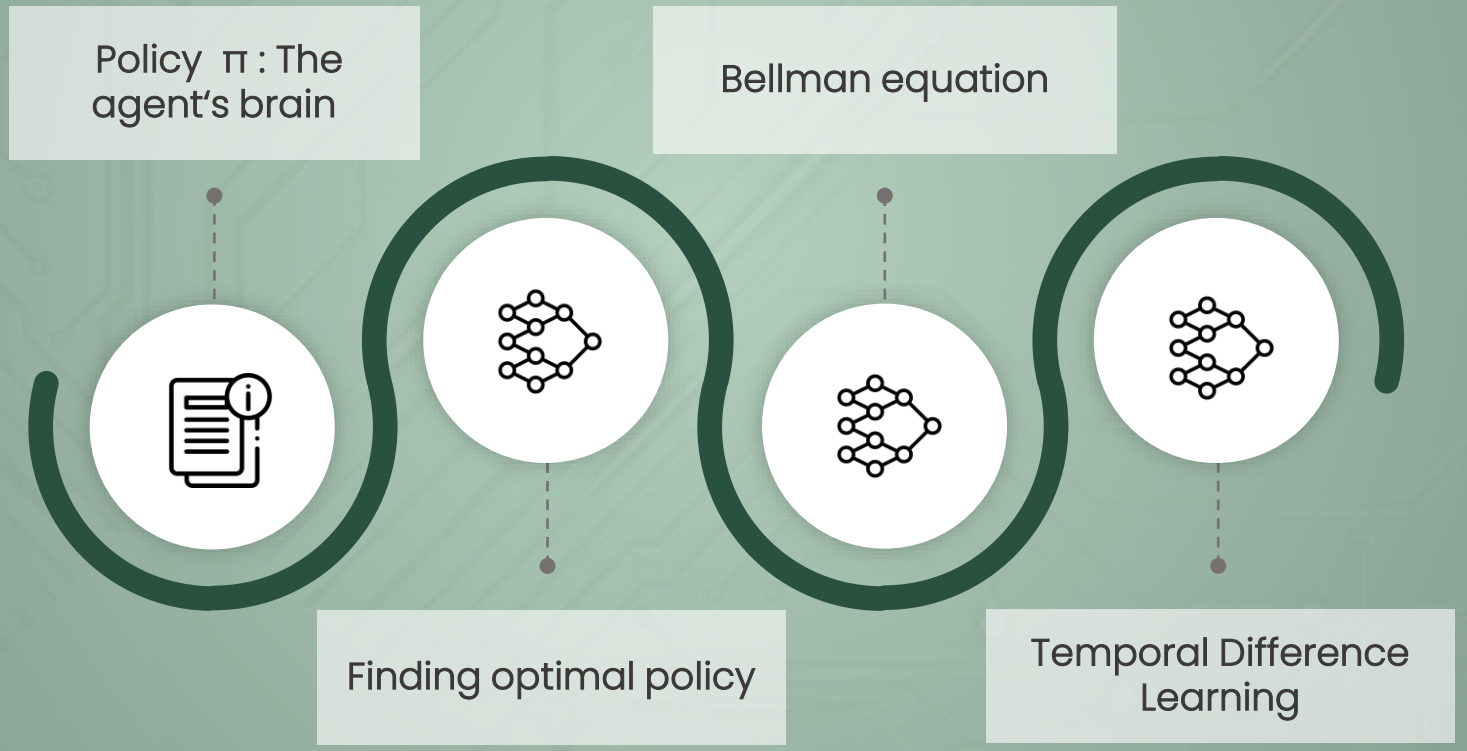
# Exploration vs Exploitation

... is the dilemma where an agent must decide between trying new actions (exploration) or sticking with known beneficial actions (exploitation).




| | |
|---|---|
| **Exploration:** | Trying new actions to discover their outcomes. |
| **Exploitation:** | Choosing actions known to yield good rewards. |
| **Dilemma:** | Gaining knowledge (exploration) ⇔ maximizing rewards with current knowledge (exploitation). |
| **Importance:** | Essential for an agent to adapt to changing environments and avoid local optima. |
| **Strategies:** | Techniques like ε-greedy help manage this trade-off. |

# Theoretical foundations of Temporal Difference Learning



# Policy π: the agent's brain

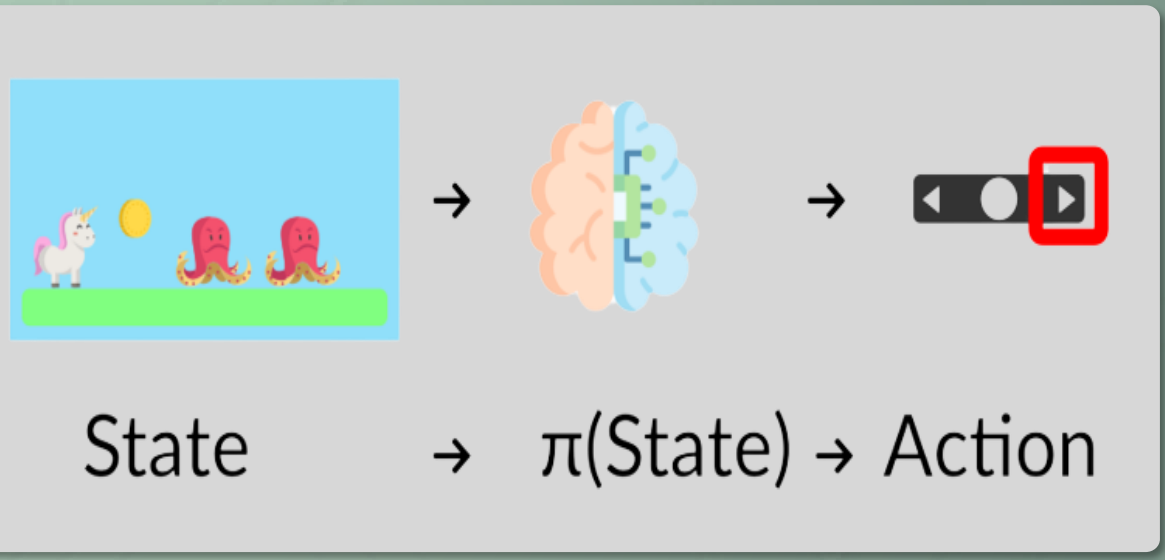
Policy is a strategy used by agent to decide which action to take in a given state.
Represented as $\pi(a|s)$, which denotes the probability of taking action a given state s.

**Role of the Policy:**

- Acts as the "brain" of the agent, guiding its actions as it interacts with the environment.
- Aims to maximize the cumulative reward over time.

**Types of Policies:**

- Deterministic Policy: A policy that always outputs the same action for a given state.
- Stochastic Policy: A policy that outputs a probability distribution over actions, allowing for exploration.



# Finding optimal policy

… by iterating between policy and value

**Policy Iteration:**

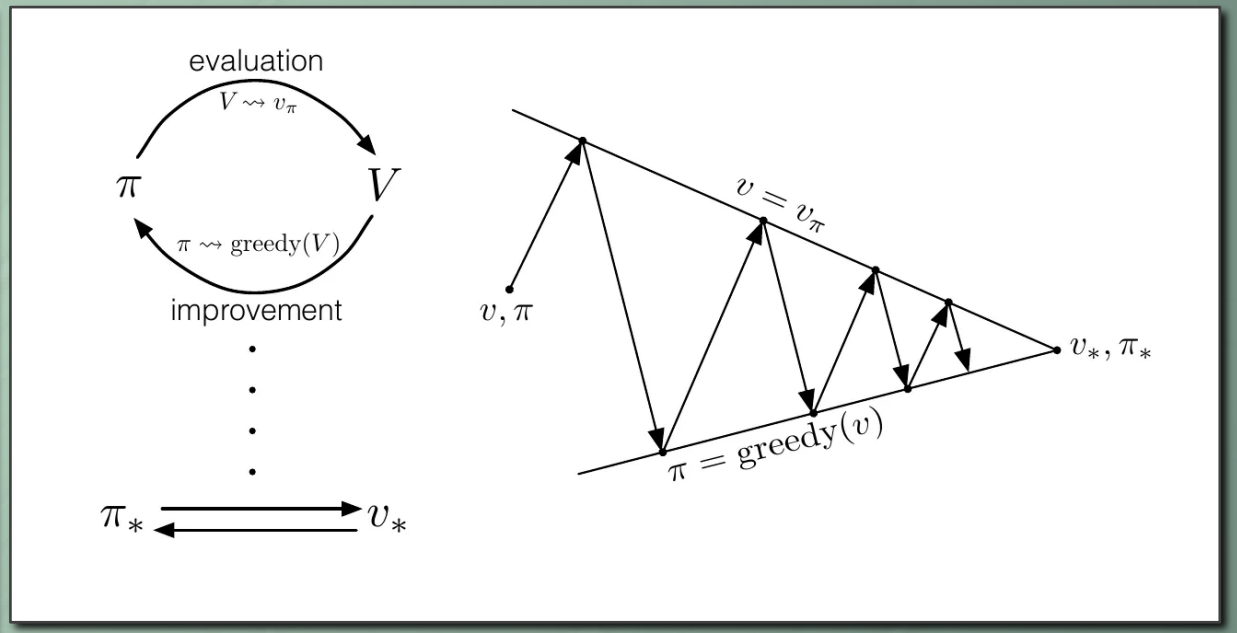
- Evaluation: Circle showing $V \approx \pi$ (value function approximates policy).
- Improvement: Policy is refined using $\pi \approx greedy(V)$

**Convergence:**

- Zig-zag arrows: Iterative steps from initial $(v, \pi)$ to optimal $(v^*, \pi^*)$

**Optimal Policy and Value:**

- Process concludes when reaching optimal policy $\pi^*$ and corresponding value function $\pi^*$, represented at far right of image.



# Bellman equation

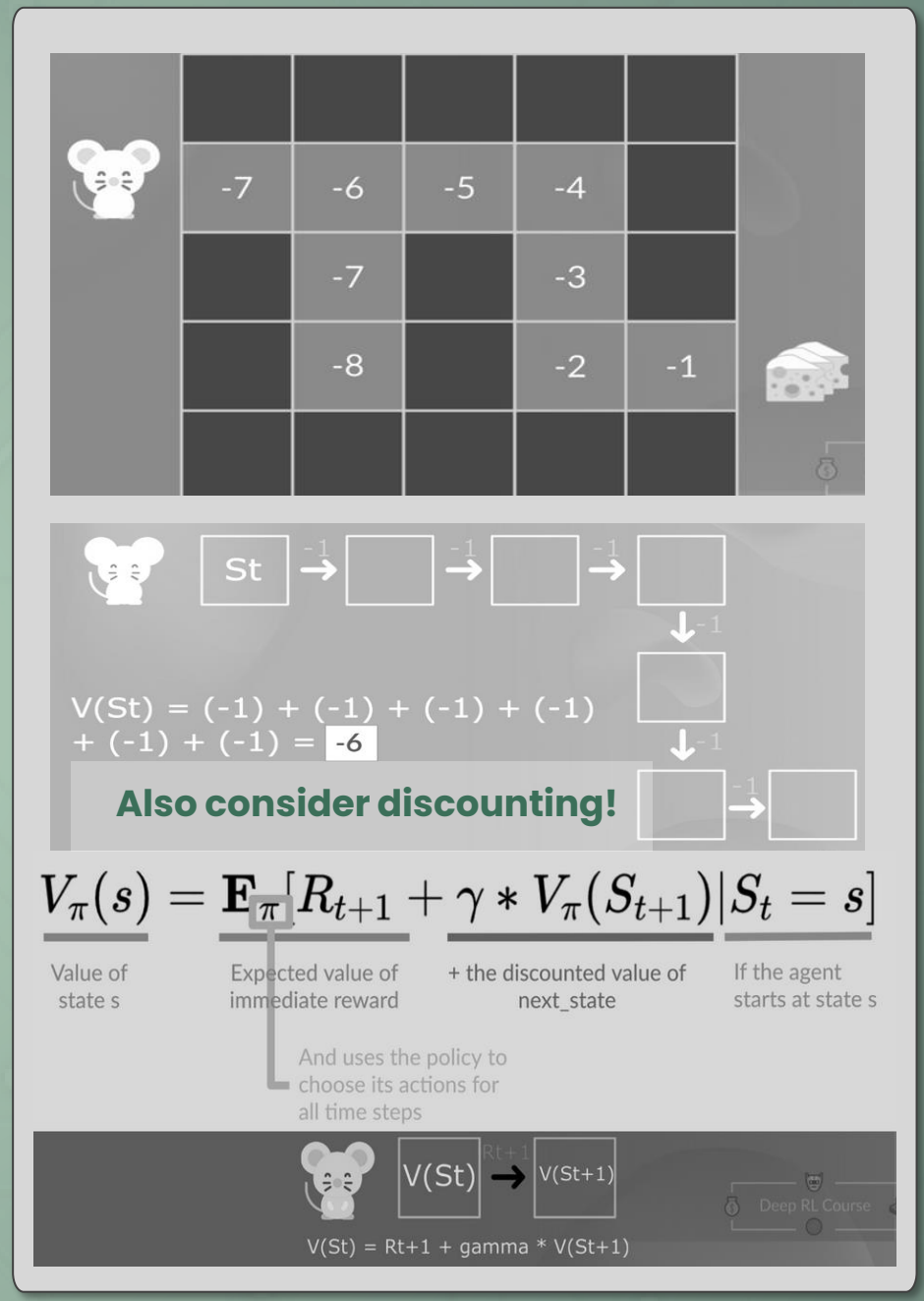
… is under the hood of any reinforcement learning approach.

**The idea:**

- instead of calculating each value as the sum of the expected return, which is a long process
- we calculate the value as the sum of immediate reward + the discounted value of the state that follows.

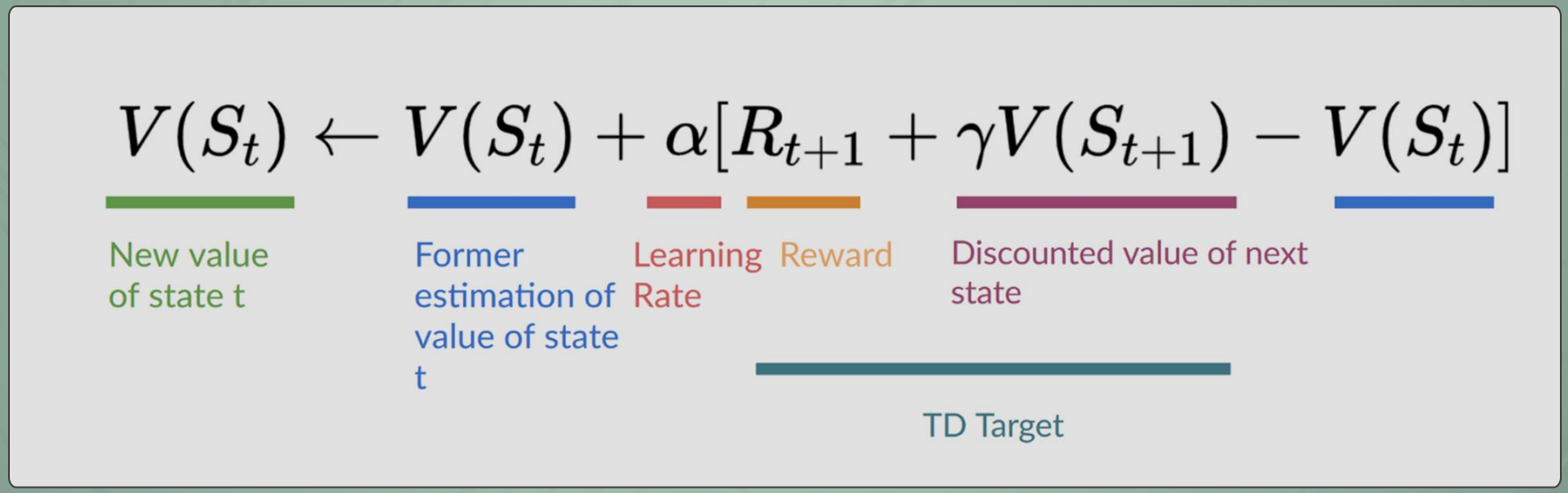
**Role in Value-Based Methods:**

- Bellman Equation is used to update the value functions.
- Leads to optimal policy that maximizes cumulative reward.



# Temporal Difference approach

... Updates value estimates based on a sample of the subsequent state, i.e. at each step instead of at the end of the episode

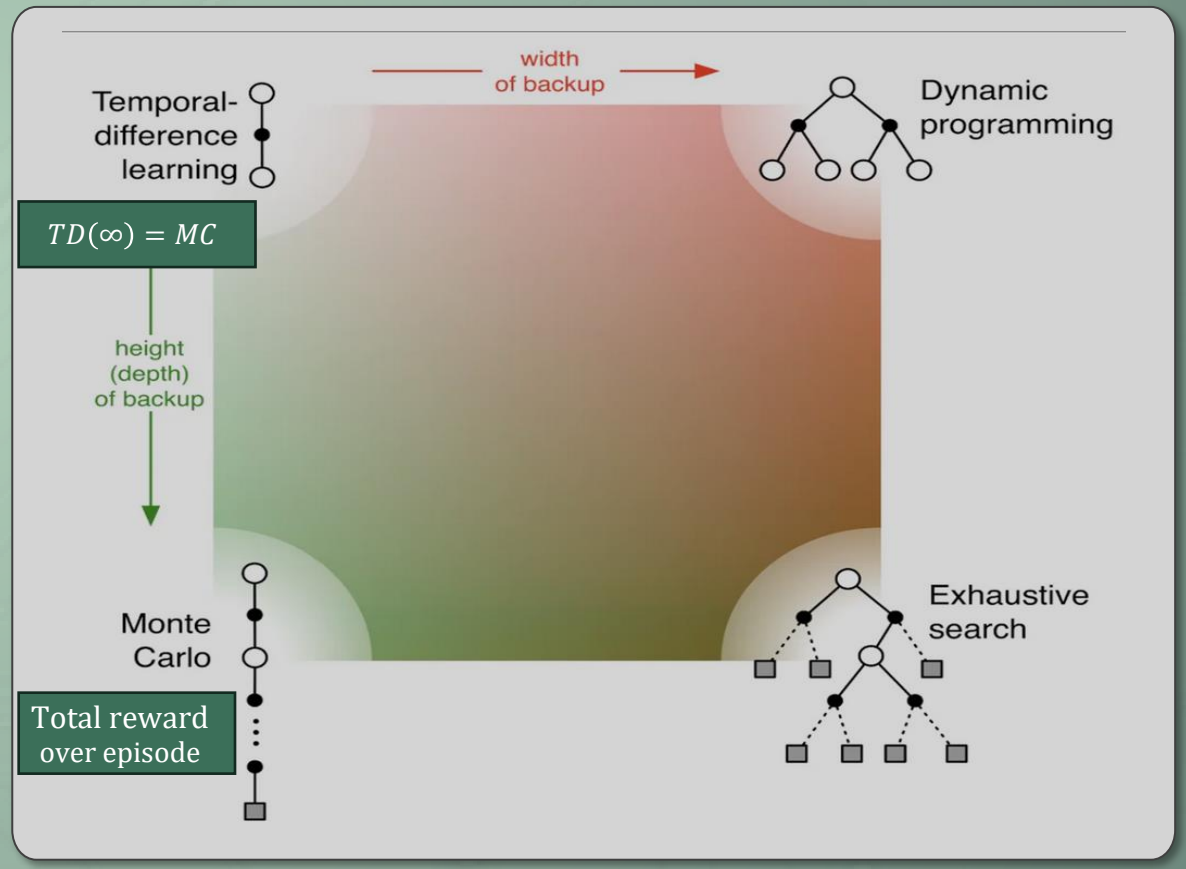


# Temporal Difference learning TD(0)

… learns directly from episodes of experience without a model of the environment. Updates value estimates based on a sample of the subsequent state.

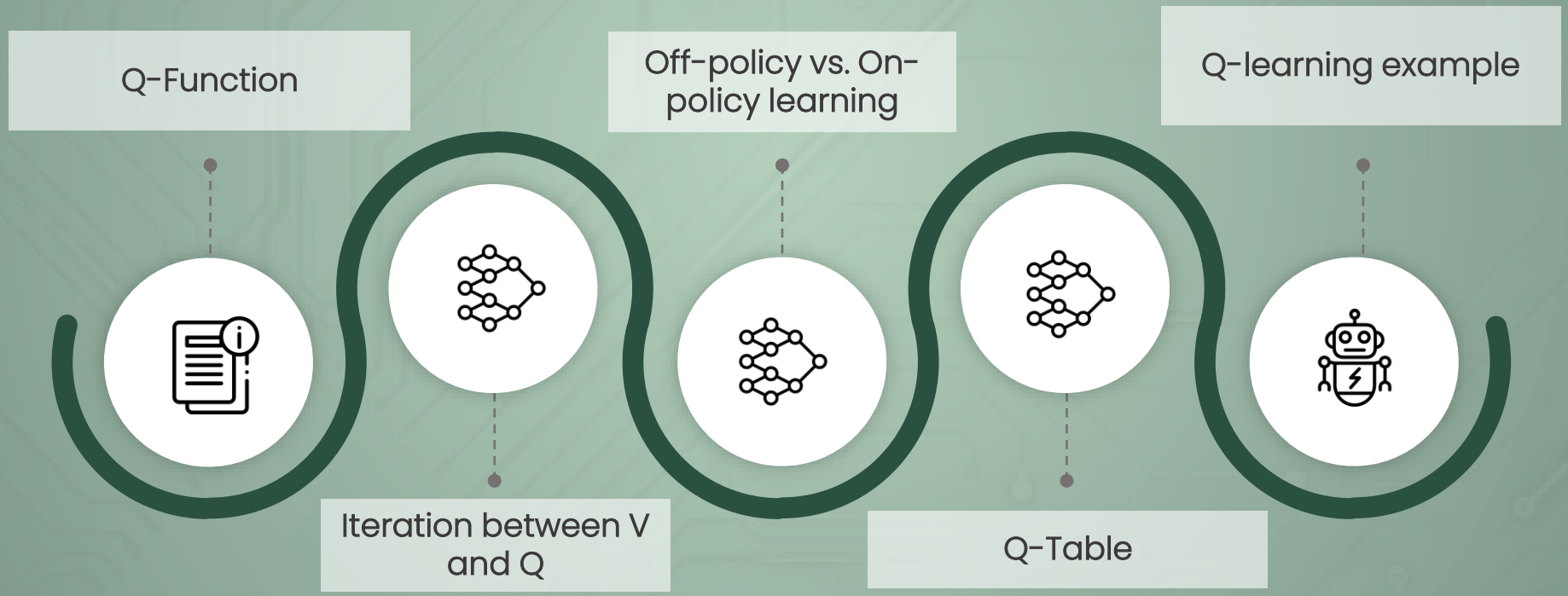
**Comparison to other controlling approaches:**

- Exhaustive search:
  - evaluates all possible paths and strategies, which can be computationally expensive or infeasible.
  - TD Learning incrementally adjusts value estimates and does not require exploring all possibilities.
- Dynamic Programming:
  - requires a complete and accurate model of the environment.
  - TD Learning does not require a model and learns from incomplete and imperfect episodes by learning online after every step
- Monte Carlo:
  - updates only occur after an entire episode has completed.
  - TD Learning updates values after each time step, leading to faster learning.
  - TD is more suitable for continuing (non-episodic) tasks.



# Q-Learning

... is an off-policy value-based method that uses a TD approach to train its action-value function



# Q-Function

... represents the expected return of taking action a in state s. Captures both immediate rewards and potential future gains. Q-Values are updated iteratively based on the agent's experiences in order to derive optimal policy

$$\text{New } Q(s,a) = Q(s,a) + \alpha\,[R(s,a) + \gamma\, \mathbf{argmax}_{a'} \boldsymbol{Q}(s',a') - Q(s,a)]$$

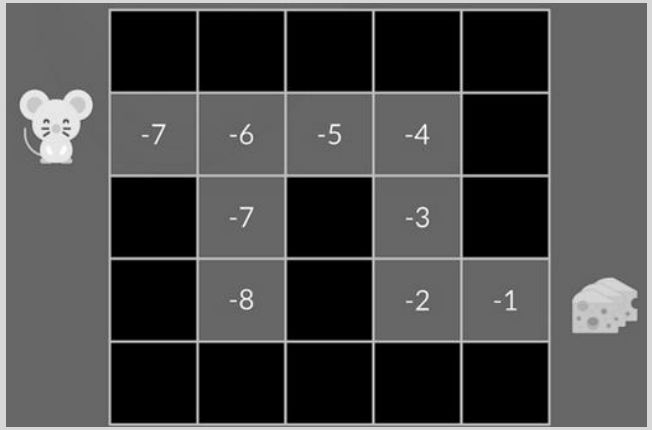
- New Q Value for that state and the action
- Learning Rate
- Reward for taking that action at that state
- Current Q Values
- Maximum expected future reward given the new state (s') and all possible actions at that new state choosing the best available action regardless of policy function
- Discount Rate

# Iteration between V and Q

... i.e. between value of state and value of state-action

**State-Value-Function**

Calculate the value of state




$$V_\pi(s) = \mathbf{E}_\pi[G_t | S_t = s]$$

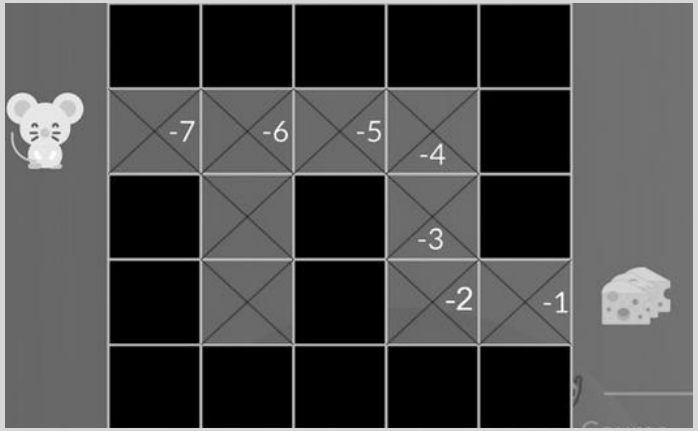
Value of state s

Expected return

If the agent starts at state s

And uses the policy to choose its actions for all time steps

For each state,
the state-value function outputs
the expected return
if the agent starts in that state
and then follows the policy forever after.




$$Q_\pi(s,a) = \mathbf{E}_\pi[G_t | S_t = s, A_t = a]$$

Value of state-action pair s,a

Expected return

If the agent starts at state s

and chooses action a

And then uses the policy to choose its actions for all time steps

For each state and action,
the action-value function outputs
the expected return
if the agent starts in that state
and takes the action
and then follows the
policy forever after.

**Action-Value-Function**

Calculate the value of state action pair

# Off-policy vs. On-policy learning

**On-Policy:** Algorithm learns, evaluates policy that it follows to make decisions → SARSA

**Off-Policy:** Algorithm learns optimal policy independently of policy it follows → Q-Learning.

**Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$**

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$

Loop for each episode:
  Initialize $S$
  Loop for each step of episode:
    Choose $A$ from $S$ using policy derived from $Q$ (e.g., $\varepsilon$-greedy)
    Take action $A$, observe $R$, $S'$
    $Q(S, A) \leftarrow Q(S, A) + \alpha\left[R + \gamma \max_a Q(S', a) - Q(S, A)\right]$
    $S \leftarrow S'$
  until $S$ is terminal

**Off policy**

- Using a different policy for acting and for updating
- "Playing the best move regarding short-term incentive and updating policy, if improvement took place"
- More explorative, less stable

**Focus on**

**Q-Learning**

**On policy**

- Using a same policy for acting and for updating
- "Playing the best available move from existing policy"
- Less explorative, more stable

**Sarsa (on-policy TD control) for estimating $Q \approx q_*$**

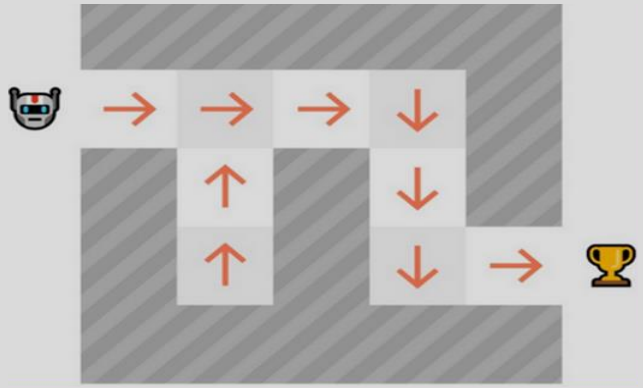
Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$

Loop for each episode:
  Initialize $S$
  Choose $A$ from $S$ using policy derived from $Q$ (e.g., $\varepsilon$-greedy)
  Loop for each step of episode:
    Take action $A$, observe $R$, $S'$
    Choose $A'$ from $S'$ using policy derived from $Q$ (e.g., $\varepsilon$-greedy)
    $Q(S, A) \leftarrow Q(S, A) + \alpha\left[R + \gamma Q(S', A') - Q(S, A)\right]$
    $S \leftarrow S'$; $A \leftarrow A'$;
  until $S$ is terminal

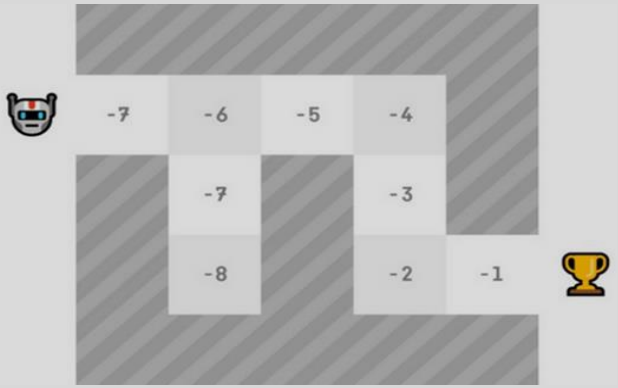
# Off-policy vs. On-policy learning

Policy vs. value based methods

Policy Based Method: Train the agent to learn which action to take given a state



Value-Based Methods : Train the agent to learn which state is more valuable and take the action that leads to it.




**Focus on Q-Learning**

**Difference:**

- In policy-based training, the optimal policy (denoted π*) is found by training the policy directly.
- In value-based training, finding an optimal value function (denoted Q* or V*, we'll study the difference below) leads to having an optimal policy.

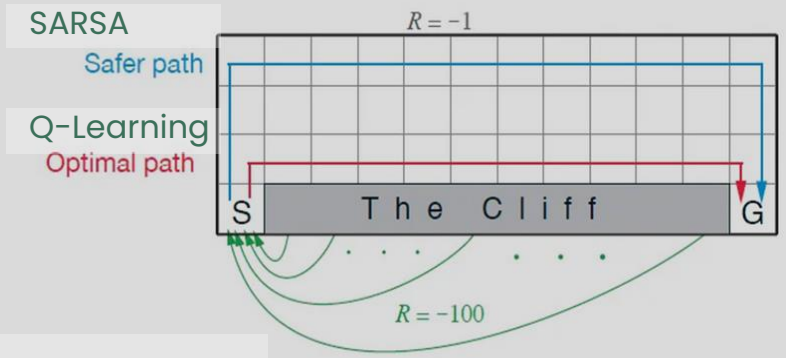
# Cliff Walking Example

… is a standard gridworld environment used to illustrate the difference between on-policy and off-policy methods like SARSA and Q-learning

- Agent can take actions to move in one of four directions: up, down, left, right.
- Moving into "Cliff" state incurs large negative reward (e.g., -100), sends agent back to "Start" state.
- Each other move typically has small negative reward (e.g., -1), incentivizing agent to reach goal quickly

**Comparing SARSA and Q-Learning:**

- SARSA:
  - agent tends to take longer but safer route
  - avoiding edge adjacent to cliff, because it considers future action which might be exploratory and lead it into the cliff.
- Q-Learning:
  - agent usually learns optimal policy to skirt dangerously close to cliff for shortest path to goal
  - but it may occasionally fall into cliff during exploration due to greedy nature of its learning


**Focus on**

**Q-Learning**

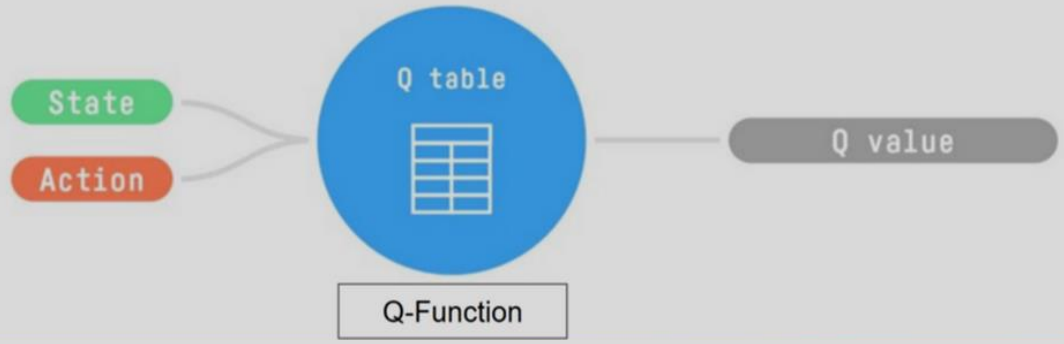
# Implementing Q-Function with Q-Table

## Implementing the Q-Function:

- The Q-Table essentially implements the Q-Function.
- The agent consults the Q-Table to decide which action to take in a given state, usually choosing the action with the highest Q-Value.
- Over time, with enough exploration and consistent updates, the Q-Table converges to the optimal Q-Function, Q*(s, a).

## Be aware of exploration-exploitation dilemma:

- Ensure adequate exploration of the state-action space to find the optimal policy
- i.e. do not always use Q-Table for determining next step, but to it randomly in small share of cases $\varepsilon$



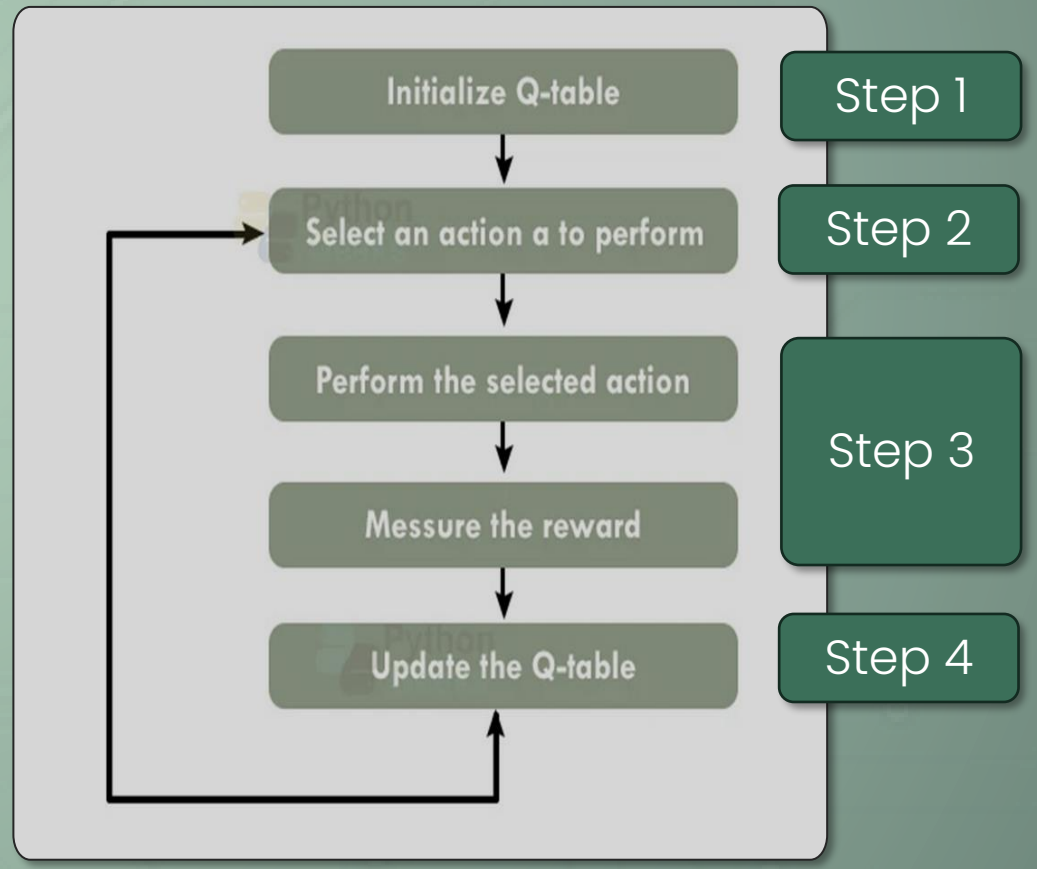

To train the Q-function, that given a state and action as input, output the value we use Q-learning algorithm.

Given a state and action, our Q Function outputs a state-action value (also called Q-value)

# Q-Table loop

... or how the Q-Table is trained

- **Initialize Q-table:**
  The process begins with initializing the Q-table.
- **Select an action "a" to perform:**
  After initialization, agent selects an action based on current state and Q-table. Exception: With small prob ε random action is selected
- **Perform the selected action:**
  Agent then performs chosen action in environment.
- **Measure the reward:**
  After performing action, agent receives and measures reward based on outcome.
- **Update the Q-table:**
  Using obtained reward and new state, Q-table is updated to better estimate action values.
- **Loop Structure:**
  Process from selecting action to updating Q-table is depicted as loop, indicating repetition until termination condition
  (not shown in the image).



# Q-learning example

... is a  tabular form for storing Q-Values corresponding to state-action pairs.

How can the mouse reach both cheese fields without running into the poison field?

Step 1

Actions

States

| | ← | → | ↑ | ↓ |
|---|---|---|---|---|
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |

**Structure of Q-Table:**

- Rows represent all possible states.
- Columns represent all possible actions.
- Entries in the table store the Q-Values, Q(s, a).

**Learning with Q-Table:**

- Agents select actions based on Q-Values in table, typically choosing action with highest Q-Value in current state.
- After taking an action and observing the reward and next state, the Q-Value is updated

# Q-learning example

… or how the Q-Table is trained

Step 2

**Choose action using ε-greedy policy, i.e. choose action $A_t$ using policy derived from $Q$:**

ε-greedy

- Exploitation: selects optimal ("greedy") action
- Exploitation: selects random action

Step 3

**Take action $A_t$ and observe:**

- reward $R_t$
- State $S_t$

Step 4

**Update $Q(S_t, A_t)$:**

$$V(S_t) \leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)]$$

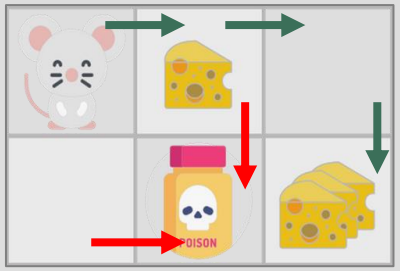
New value of state t | Former estimation of value of state t | Learning Rate | Reward | Discounted value of next state | TD Target

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma max_a Q(S_{t+1}, a) - Q(S_t, A_t)]$$

New Q-value estimation | Former Q-value estimation | Learning Rate | Immediate Reward | Discounted Estimate optimal Q-value of next state | Former Q-value estimation | TD Target | TD Error

# Q-learning example

The trained Q-Table tells the mouse where to go and where not to go.



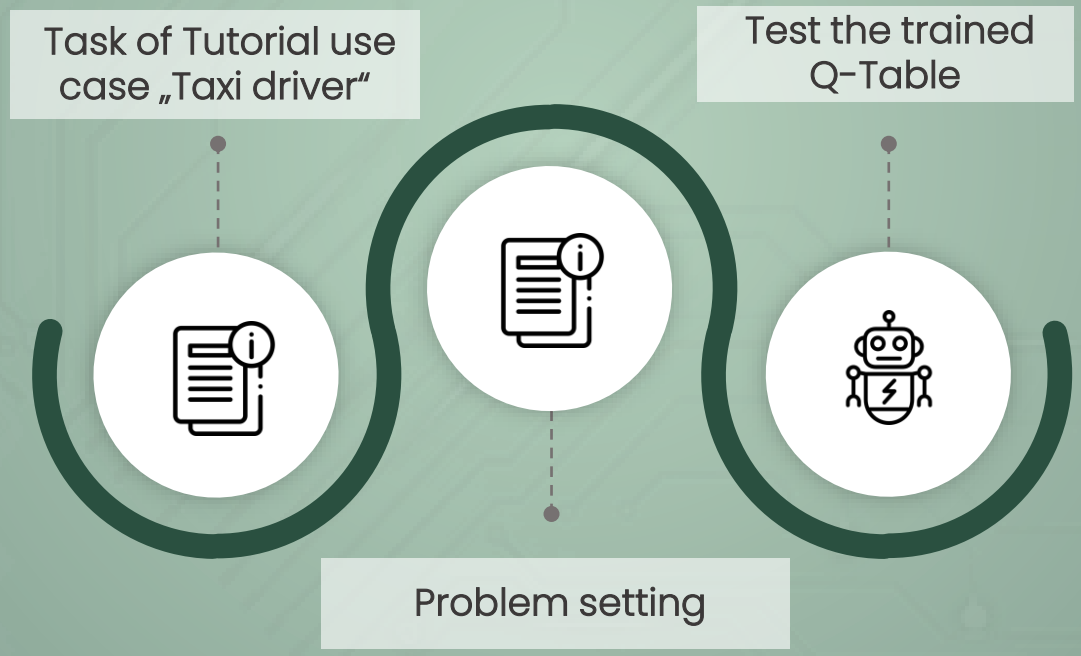

| | ← | → | ↑ | ↓ |
|---|---|---|---|---|
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |

Training

| | ← | → | ↑ | ↓ |
|---|---|---|---|---|
| | 0 | 10.8 | 0 | 0 |
| | 0 | 9.9 | 0 | -10 |
| | 0 | 0 | 0 | 10 |
| | 0 | -10 | 0 | 0 |
| | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 |

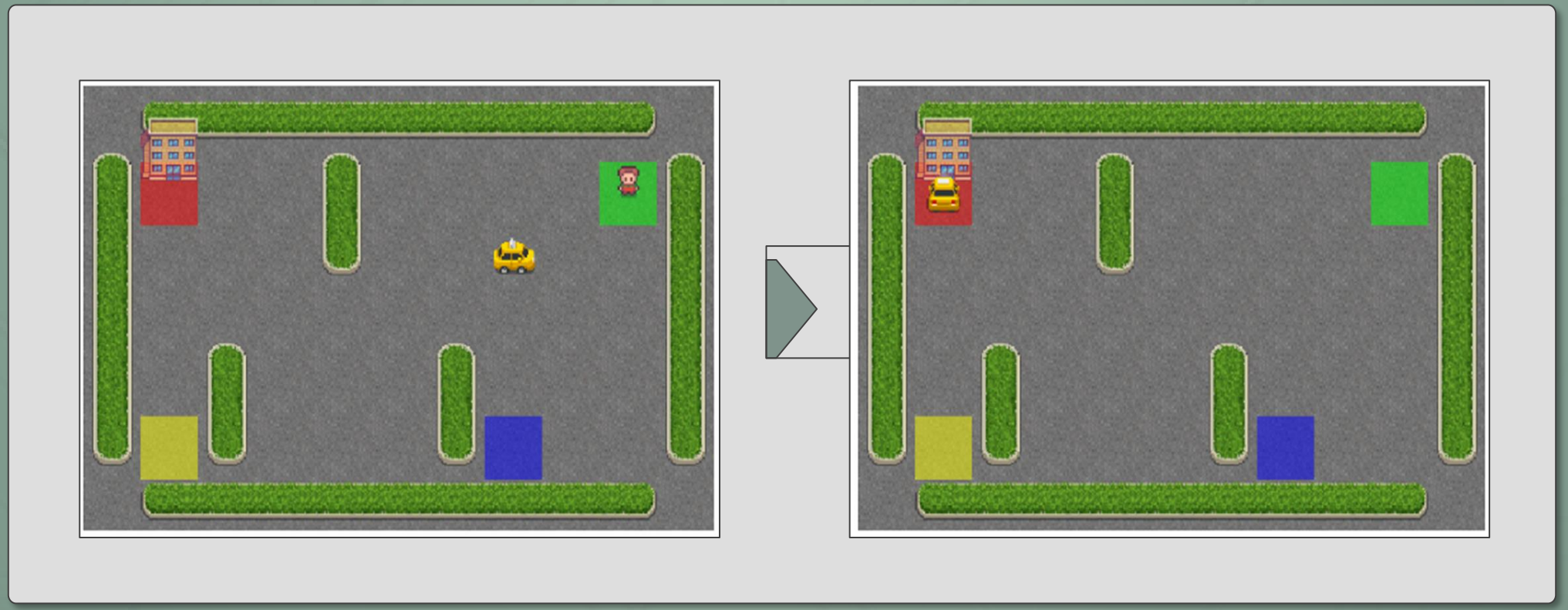
# Use Case: Taxi driver

...a taxi should pick up passengers and drop them at their destination on a parking lot



# Task of Tutorial use case „Taxi driver“

...a taxi should pick up passengers and drop them at their destination on a parking lot



# Problem setting

**State space:**

- Grid, number of fields: 25 (5*5)
- Pickup positions: 5 (Y, R, G, B or in the taxi)
- Possible destinations: 4

Number of states: 500

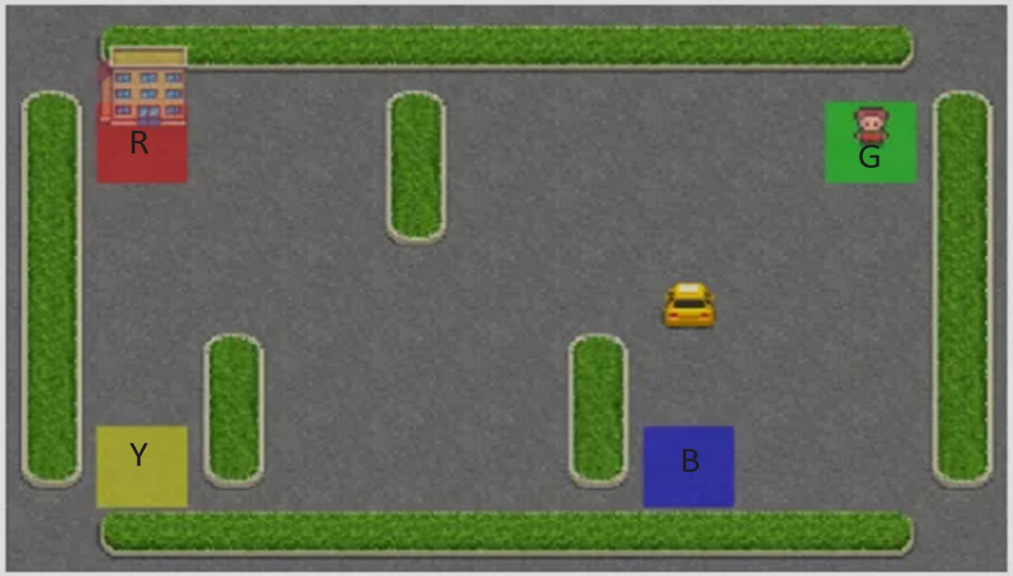
**Action space:**

- Down, Up, Left, Right
- Drop, Pick up passenger

**Reward function:**

- Move: -1
- Failed drop-off: -10
- Successful drop-off: 10

```
State space: Discrete(500)
Action space: Discrete(6)
State: 364
Action: 1
Action mask: [1 1 1 0 0 0]
Reward: -1
```



# Test the trained Q-Table

# Links

i.e. sources for self-learning

| | Title | Link |
|---|---|---|
| Overview | Sutton, Barto: Reinforcement Learning: An Introduction | http://incompleteideas.net/book/bookdraft2017nov5.pdf |
| | Artificial Intelligence: Reinforcement Learning in Python | https://www.udemy.com/course/artificial-intelligence-reinforcement-learning-in-python/ |
| | Fundamentals of Reinforcement Learning | https://levelup.gitconnected.com/fundamental-of-reinforcement-learning-markov-decision-process-8ba98fa66060 |
| | Reinforcement Learning Series: Overview of Methods | https://www.youtube.com/watch?app=desktop&v=i7q8bISGwMQ |
| | Reinforcement Learning in Machine Learning | https://pythongeeks.org/reinforcement-learning-in-machine-learning/ |
| | Easy Introduction to Reinforcement Learning | https://www.scribbr.com/ai-tools/reinforcement-learning/ |
| | A (Long) Peek into Reinforcement Learning | https://lilianweng.github.io/posts/2018-02-19-rl-overview/ |

| | Title | Link |
|---|---|---|
| Basic concepts of RL | The Exploration/Exploitation trade-off | https://huggingface.co/learn/deep-rl-course/unit1/exp-exp-tradeoff |
| | Dynamic Programming RL | https://shirsho-12.github.io/blog/rl_dp/ |
| | Elucidating Policy Iteration in Reinforcement Learning — Jack's Car Rental Problem | https://towardsdatascience.com/elucidating-policy-iteration-in-reinforcement-learning-jacks-car-rental-problem-d41b34c8aec7 |

# Links

i.e. sources for self-learning

| | Title | Link |
|---|---|---|
| Q-Learning | Temporal-Difference (TD) Learning | https://towardsdatascience.com/introduction-to-reinforcement-learning-rl-part-6-temporal-difference-td-learning-2a12f0aba9f9 |
| | Reinforcement Learning 6. Temporal Difference Learning | https://www.slideshare.net/SeungJaeLee17/reinforcement-learning-an-introduction-chapter-6 |
| | Diving deeper into Reinforcement Learning with Q-Learning | https://medium.com/free-code-camp/diving-deeper-into-reinforcement-learning-with-q-learning-c18d0db58efe |
| | Fundamentals of Reinforcement Learning: Navigating Cliffworld with SARSA and Q-learning | https://medium.com/gradientcrescent/fundamentals-of-reinforcement-learning-navigating-cliffworld-with-sarsa-and-q-learning-cc3c36eb5830 |
| | Reinforcement Learning: SARSA and Q-Learning | https://arshren.medium.com/reinforcement-learning-sarsa-and-q-learning-e11ebe87dca9 |
| | An introduction to Q-Learning: reinforcement learning | https://www.freecodecamp.org/news/an-introduction-to-q-learning-reinforcement-learning-14ac0b4493cc/ |
| | Walking Off The Cliff With Off-Policy Reinforcement Learning | https://towardsdatascience.com/walking-off-the-cliff-with-off-policy-reinforcement-learning-7fdbcdfe31ff |
| | A Beginners Guide to Q-Learning | https://towardsdatascience.com/a-beginners-guide-to-q-learning-c3e2a30a653c |
| | Q-Learning: Model Free Reinforcement Learning and Temporal Difference Learning | https://www.youtube.com/watch?v=0iqz4tcKN58 |

# Links

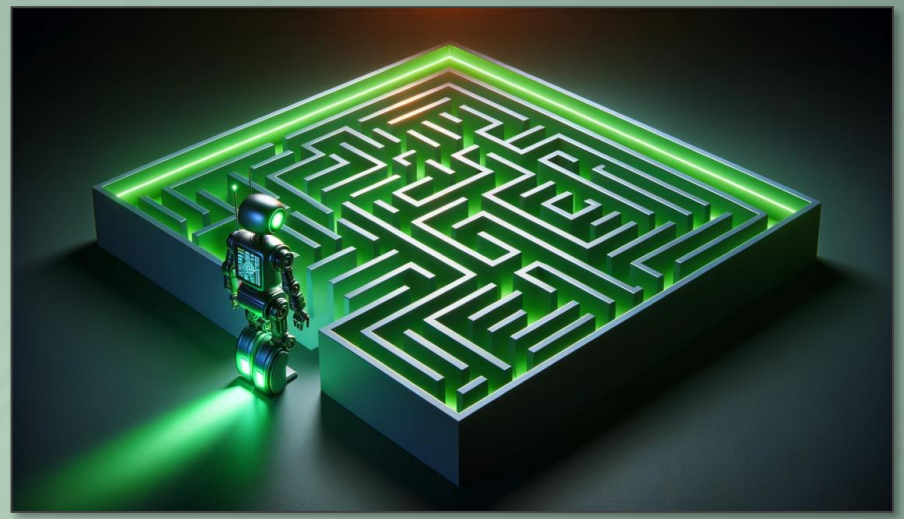
i.e. sources for self-learning

| | Title | Link |
|---|---|---|
| Tutorial Applications | Solving The Taxi Environment With Q-Learning — A Tutorial | https://towardsdatascience.com/solving-the-taxi-environment-with-q-learning-a-tutorial-c76c22fc5d8f |
| | Text-Flappy Bird | https://aspram.medium.com/learning-flappy-bird-agents-with-reinforcement-learning-d07f31609333 |
| | Practical Reinforcement Learning using Python - 8 AI Agents | https://www.udemy.com/course/practical-reinforcement-learning/ |

| | Title | Link |
|---|---|---|
| Real world Applications | 9 awesome real world applications of Reinforcement Learning | https://medium.com/@mlblogging.k/9-awesome-applications-of-reinforcement-learning-e1306ed25c09 |
| | Reinforcement Learning and its Real-Life Applications | https://blogs.skillovilla.com/reinforcement-learning-and-its-real-life-applications/ |
| | Mastering the game of Go with deep neural networks and tree search | https://www.nature.com/articles/nature16961.pdf |

# ChatGPT/Dall-E3 Prompts

High-quality render depicting a maze with a gradient backdrop, starting with a rich green hue and fading to a refined gray. A robot, designed with cutting-edge sensors, stands ready at the maze's start. As it commences its navigation, the illumination it emits changes from green to gray, symbolizing its ongoing journey.



High-resolution render of a maze reflecting the complexity of city streets, set on a gradient background moving from a lush green hue to a calm gray tone. An avant-garde autonomous taxi waits at the beginning of the maze, its emitted light transitioning from green at the outset to gray as it confidently finds its path.

# ChatGPT/Dall-E3 Prompts

Create an illustration that visually represents various machine learning concepts using a green to gray gradient color scheme. On the left side of the image, depict a 'Multi-Armed Bandit Problem' with several slot machines, each with a different arm pulled down, symbolizing the exploration and exploitation strategy. In the middle of the image, illustrate 'Grid World Navigation' with a simple grid layout, and a small character navigating through it. On the right side, show 'Customer Service' with a headset icon and a speech bubble. Below these, depict 'Dynamic Pricing' with fluctuating price tags, and at the bottom, illustrate 'Game Playing' with abstract game pieces. Ensure that the entire image follows a green to gray gradient color scheme, creating a cohesive and thematic visual representation of these machine learning concepts.

# About me

**Dr. Harald Stein**

- Data Scientist ~ 7 years experience
- Algotrader ~ 4 years experience
- Ph.D. in Economics, Game Theory

- LinkedIn: https://www.linkedin.com/in/harald-stein-phd-1648b51a
- ResearchGate: https://www.researchgate.net/profile/Harald-Stein