Reinforcement Learning : Introduction

"Learning from interaction is a foundational idea underlying nearly all theories of learning and intelligence".

The slides contain

- Excerpts from the book Reinforcement Learning : An Introduction, 2nd edition, Richard S. Sutton and Andrew G. Barto
- Content acquired using ChatGPT
- Excerpts from Stanford CS234 Course Material available on their website : https://web.stanford.edu/class/cs234/modules.html

What is Reinforcement Learning (RL)?

- Reinforcement learning (RL) is a type of machine learning where an agent learns to make decisions by interacting with an environment.
- The agent receives feedback in the form of rewards or punishments based on its actions, helping it learn optimal strategies over time.
- RL is commonly used in areas like robotics, game playing, and autonomous systems.
- Algorithms such as Q-learning and deep reinforcement learning have advanced the field, allowing agents to learn complex behaviors through trial and error.

Reinforcement Learning

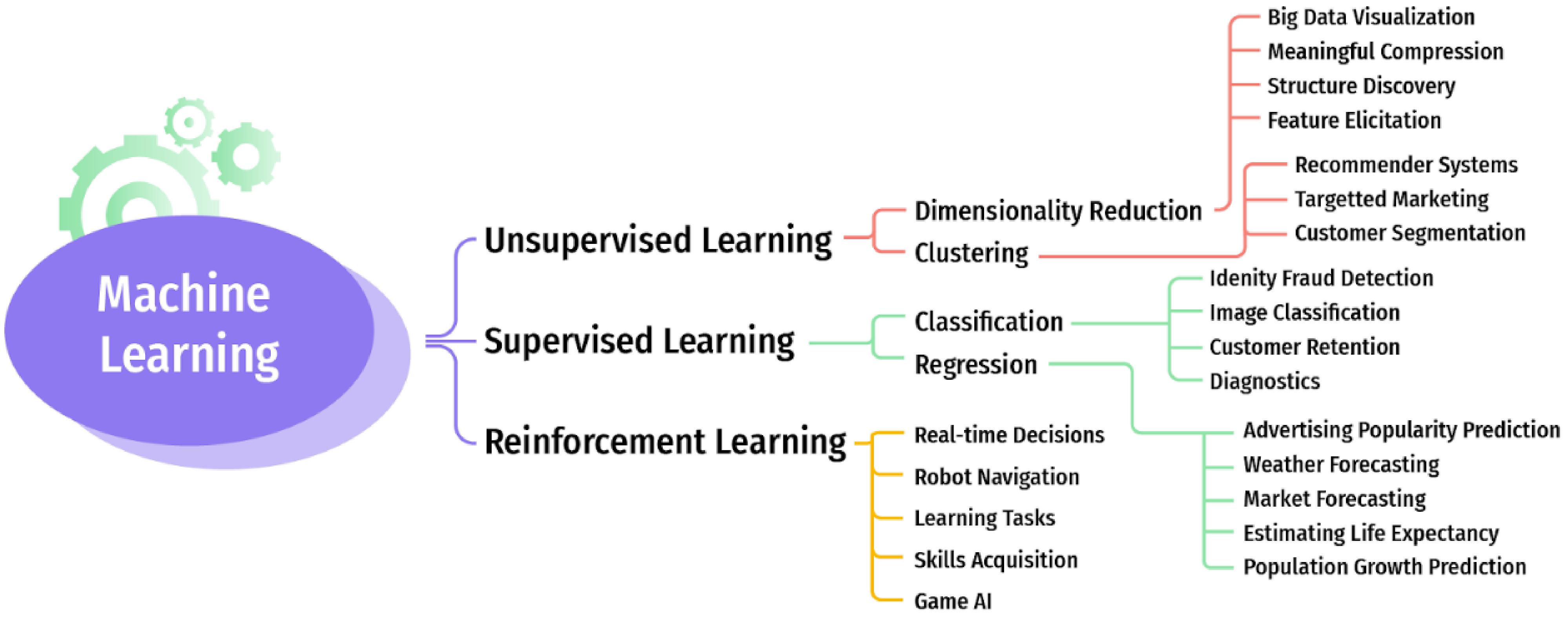
- Reinforcement learning is learning what to do—how to map situations to actions—so as to maximize a numerical reward signal. The learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them.
- In the most interesting and challenging cases, actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards.
- These two characteristics—trial-and-error search and delayed reward—are the two most important distinguishing features of reinforcement learning.

Reinforcement Learning

Reinforcement Learning is simultaneously

- a problem,
- a class of solution methods that work well on the problem, and
- the field that studies this problem and its solution methods.

Types of Machine Learning



Source https://idapgroup.com/blog/types-of-machine-learning-out-there/

Machine Learning (ML) Types

- Supervised Learning:
  - In supervised learning, the algorithm is trained on a labeled dataset, which means the input data is paired with corresponding output labels.
  - The goal is for the algorithm to learn a mapping from inputs to outputs, allowing it to make predictions or decisions on new, unseen data.
  - Algorithms : Linear Regression, Logistic Regression, Decision Trees, Random Forest, Support Vector Machines (SVM), Naive Bayes, K-Nearest Neighbors (KNN), Neural Networks (Deep Learning), Gradient Boosting Algorithms (e.g., XGBoost, LightGBM), Linear Discriminant Analysis (LDA)

Machine Learning (ML) Types

- Unsupervised Learning:
  - Unsupervised learning involves training an algorithm on an unlabeled dataset, where the algorithm needs to find patterns, relationships, or structures in the data without explicit guidance.
  - Clustering and dimensionality reduction are common tasks in unsupervised learning.
  - Algorithms : K-Means Clustering, Hierarchical Clustering, DBSCAN (Density-Based Spatial Clustering of Applications with Noise), Principal Component Analysis (PCA), Independent Component Analysis (ICA), Autoencoders, Generative Adversarial Networks (GANs), t-Distributed Stochastic Neighbor Embedding (t-SNE), Apriori Algorithm, Mean Shift

Machine Learning (ML) Types

Sequential decisions refer to a decision-making process where choices are made one after the other, often in a series or sequence, with each decision influencing or impacting the subsequent ones.An example of sequential decisions is a chess game, where each move is a decision, and the sequence of moves determines the overall strategy and outcome.

- Reinforcement Learning:
  - Reinforcement learning is about training an agent to make sequential decisions by interacting with an environment.
  - The agent receives feedback in the form of rewards or punishments based on its actions, and it learns to optimize its behavior over time.
  - Algorithms : Q-Learning, Deep Reinforcement Learning

RL Involves

- Optimization
- Delayed consequences
- Exploration
- Generalization

RL Involves

- Optimization
  - Optimization in reinforcement learning refers to the process of finding the best policy or strategy that maximizes the cumulative reward over time.
  - Goal is to find an optimal way to make decisions
    - Yielding best outcomes or at least very good outcomes
  - Explicit notion of utility of decisions clearly and specifically understanding and measuring how good or satisfying a decision is.
  - Example: finding minimum distance route between two cities given network of roads

RL Involves

- Delayed Consequences
  - Delayed consequences highlight the challenge in RL where actions may not immediately lead to rewards, requiring the agent to consider long-term effects and plan accordingly.
  - Decisions now can impact things much later...
    - Choosing an elective subject.
  - Introduces two challenges
    - When planning: decisions involve reasoning about not just immediate benefit of a decision but also its longer term ramifications consequence
    - When learning: temporal credit assignment is hard (what caused later high or low rewards?)

figuring out which actions or decisions led to later high or low rewards. It is the difficulty in understanding the cause-and-effect relationship between the actions taken at one point in time and the rewards received at a later time.

For example, in a game, making a move might lead to winning or losing several moves later. Temporal credit assignment difficulty arises when trying to attribute the success or failure to the specific actions taken earlier in the game.

RL Involves

In the context of reinforcement learning, "exploiting" refers to the strategy of choosing actions that are known or believed to yield the highest immediate reward based on the current knowledge or learned policies. When an agent exploits, it is making decisions that leverage its existing understanding to maximize the immediate expected gain.

Exploitation is often contrasted with "exploration." While exploitation focuses on choosing actions that are already known to be good based on past experiences, exploration involves trying out new or uncertain actions in the hope of discovering better strategies or maximizing long-term rewards.

Balancing exploitation and exploration is a crucial aspect of reinforcement learning. Too much exploitation may lead to a failure to discover potentially better actions, while too much exploration may result in inefficient decision-making. The challenge lies in finding the right balance to continually improve the agent's understanding of the environment while maximizing short-term rewards.

- Exploration
  - Exploration is the agent's strategy of trying out different actions to discover optimal policies, balancing the need for exploiting known good actions and exploring potentially better ones.
  - Learning about the world by making decisions
  - Agent as scientist
    - Learn to ride a bike by trying (and failing)
  - Censored data
    - Only get a reward for decision made
  - Decisions impact what we learn about
    - If we choose to go to X college instead of Y, we will have different later experiences.

RL Involves

- **Generalization**
  - Generalization involves the ability of a reinforcement learning agent to apply learned knowledge from specific experiences to new, unseen situations, enhancing its adaptability and efficiency.

Reinforcement learning involves generalization, which means the learning agent can take knowledge learned from specific experiences and apply it to new situations. This enhances adaptability, allowing the agent to efficiently make good decisions in scenarios it hasn't encountered before.

The image is a table that compares planning and simulation. The table has two rows, one for planning and one for simulation. The columns in the table are labeled "AI," "SL," "UL," "RL," and "IL." These labels likely refer to different types of artificial intelligence or machine learning algorithms.

The table shows that planning and simulation have different strengths and weaknesses. For example, planning is good at optimization and generalization, but it is not good at learning from experience or dealing with delayed consequences. Simulation, on the other hand, is good at learning from experience and dealing with delayed consequences, but it is not as good at optimization or generalization.

Here is a more detailed breakdown of the table:

Planning: Planning is good at optimization, which means that it can find the best possible solution to a problem. Planning is also good at generalization, which means that it can learn from one problem and apply that knowledge to solve other similar problems. However, planning is not good at learning from experience, which means that it cannot adapt to new situations as they arise. Planning is also not good at dealing with delayed consequences, which means that it cannot take into account the long-term effects of its actions.
Simulation: Simulation is good at learning from experience, which means that it can learn from its mistakes and improve over time. Simulation is also good at dealing with delayed consequences, which means that it can take into account the long-term effects of its actions. However, simulation is not as good at optimization as planning, which means that it may not always find the best possible solution to a problem. Simulation is also not as good at generalization as planning, which means that it may not be able to apply what it has learned from one problem to solve other similar problems.

Comparison

	AI Planning	SL	UL	RL	IL
Optimization				X	X
Learns from Experience		X	X	X	X
Generalization		X	X	X	X
Delayed consequences				X	X
Exploration				X	

Master Chess Player Making a Move:

In RL terms, the chess player is like an agent making decisions.
Exploration: Trying out different moves to understand their effectiveness.
Exploitation: Choosing moves based on their experience of what has worked well in similar situations.
Immediate Rewards: The player gets feedback (rewards or consequences) after each move.
Planning: Anticipating possible responses and counter-responses involves a form of strategic planning.
Informed Decision-Making:

The chess player's choices are a blend of planning (thinking ahead) and immediate, intuitive judgments.
RL involves this combination of strategic thinking (planning) and quick, adaptive decision-making based on the current situation.
In essence, the master chess player's decision-making process aligns with the principles of reinforcement learning, encompassing exploration, exploitation, immediate rewards, and a blend of strategic planning and intuitive judgments.

Examples of RL

- A master chess player makes a move.
  - The choice is informed both by planning (anticipating possible replies and counter replies) and by immediate, intuitive judgments of the desirability of particular positions and moves.
- An adaptive controller adjusts parameters of a petroleum refinery's operation in real time.
  - The controller optimizes the yield/cost/quality trade-off on the basis of specified marginal costs without sticking strictly to the set points originally suggested by engineers.

The adaptive controller in a petroleum refinery adjusts operation parameters in real time to optimize the trade-off between yield, cost, and quality. It uses specified marginal costs for guidance and operates flexibly, not strictly adhering to initial engineer set points.

Examples of RL

- A gazelle calf struggles to its feet minutes after being born.
  - Half an hour later it is running at 20 miles per hour.
- A mobile robot decides whether it should enter a new room in search of more trash to collect or start trying to find its way back to its battery recharging station.
  - It makes its decision based on the current charge level of its battery and how quickly and easily it has been able to find the recharger in the past.
- Phil prepares his breakfast.

Examples of RL : Preparing Breakfast

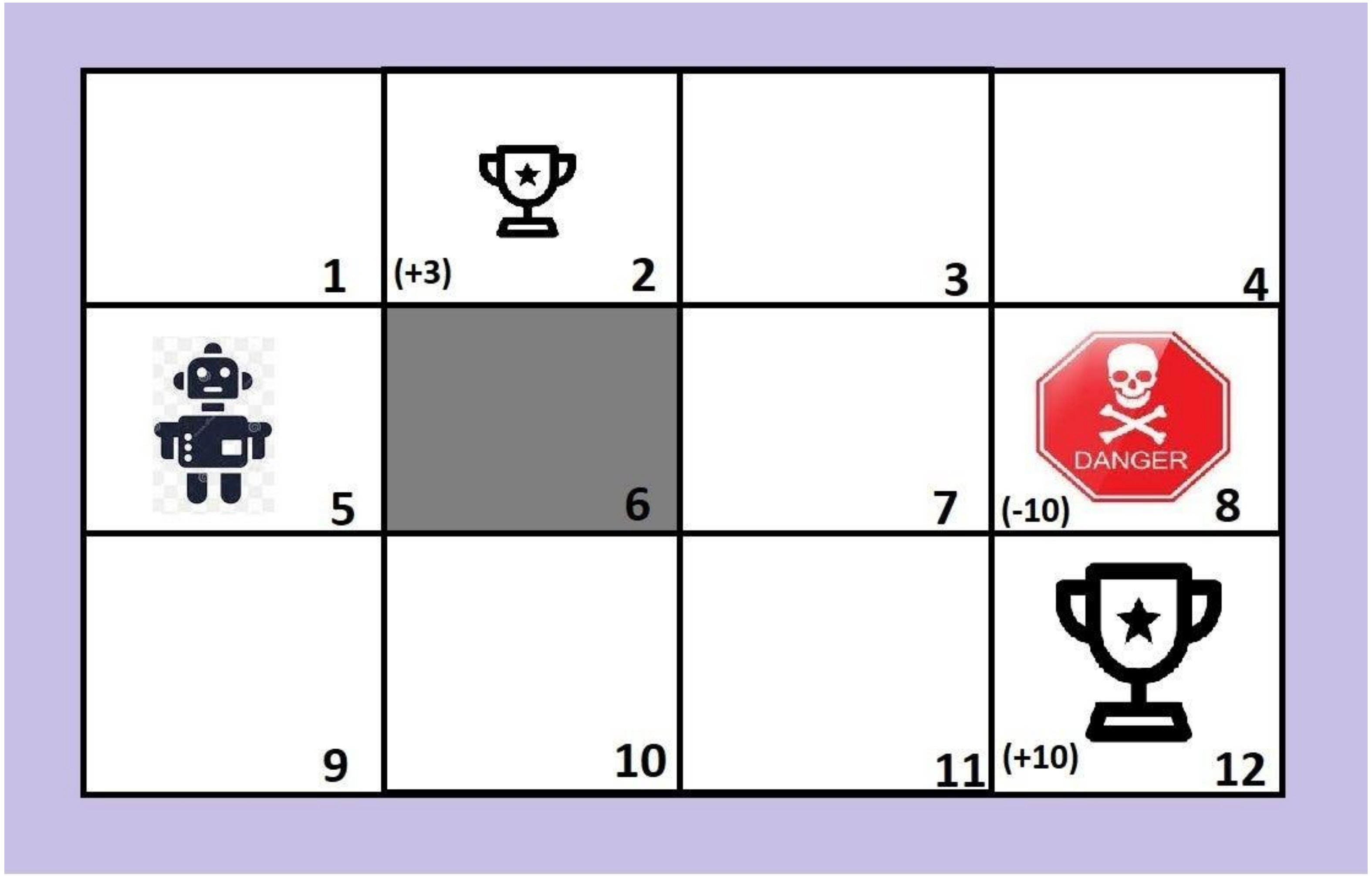
- Closely examined, even this apparently mundane activity reveals a complex web of conditional behavior and interlocking goal–sub goal relationships: walking to the cupboard, opening it, selecting a cereal box, then reaching for, grasping, and retrieving the box.
- Other complex, tuned, interactive sequences of behavior are required to obtain a bowl, spoon, and milk carton.
- Each step involves a series of eye movements to obtain information and to guide reaching and locomotion.

Examples of RL : Preparing Breakfast

- Rapid judgments are continually made about how to carry the objects or whether it is better to ferry some of them to the dining table before obtaining others.
- Each step is guided by goals, such as grasping a spoon or getting to the refrigerator, and is in service of other goals, such as having the spoon to eat with once the cereal is prepared and ultimately obtaining nourishment.
- Whether he is aware of it or not, Phil is accessing information about the state of his body that determines his nutritional needs, level of hunger, and food preferences.

Exploration and Exploitation

Exploration and Exploitation



Elements of Reinforcement Learning

Elements of Reinforcement Learning

- Policy
- Reward
- Value Function
- Model

Elements of RL : Policy

- A policy defines the learning agent's way of behaving at a given time.
- Roughly speaking, a policy is a mapping from perceived states of the environment to actions to be taken when in those states.

A lookup table is an array of data that maps input values to output values, thereby approximating a mathematical

- In some cases the policy may be a simple function or lookup table, whereas in others it may involve extensive computation such as a search process.
- The policy is the core of a reinforcement learning agent in the sense that it alone is sufficient to determine behavior.

A policy is a set of rules or a strategy that defines how a learning agent behaves at a particular time.
Mapping States to Actions:

Essentially, it is a map from the observed or perceived states of the environment to the actions the agent should take in those states.
Representation of Policy:

Policies can vary in complexity. They can be a simple function, a lookup table, or involve more intricate computations like a search process.
Central Role of the Policy:

The policy is crucial to a reinforcement learning agent; it alone is sufficient to determine the agent's behavior.
In summary, a policy in RL guides the agent's behavior by mapping environmental states to appropriate actions. It can be as simple as a function or more complex involving extensive computations, and it plays a central role in determining how the agent interacts with its environment.

Elements of RL : Reward

A reward signal is a numerical signal that defines the goal of a reinforcement learning problem.

Timing of Rewards: On each time step, the environment provides the reinforcement learning agent with a single number known as the reward.

Objective of the Agent: The agent's primary goal is to maximize the total cumulative reward it receives over the long run.

Defining Good and Bad Events: The reward signal categorizes events for the agent, defining what is considered good or bad in the learning process.

Basis for Policy Alteration: The reward signal is crucial in altering the policy of the agent.
If an action chosen by the current policy results in a low reward, the policy may be adjusted to select a different action in a similar situation in the future.

In summary, the reward signal in RL serves as the guide for the agent's behavior, defining goals and influencing policy changes based on the desirability of outcomes measured by the received rewards.

- A reward signal defines the goal of a reinforcement learning problem.
- On each time step, the environment sends to the reinforcement learning agent a single number called the reward.
- The agent’s sole objective is to maximize the total reward it receives over the long run.
- The reward signal thus defines what are the good and bad events for the agent.
- The reward signal is the primary basis for altering the policy; if an action selected by the policy is followed by low reward, then the policy may be changed to select some other action in that situation in the future.

Defining the goal of a problem means specifying the desired outcome or objectives one aims to achieve, providing a clear direction for decision-making and actions within the problem-solving context. In reinforcement learning, this is often embodied in the reward signal, guiding the learning agent's behavior toward maximizing cumulative rewards.

Rewards (Immediate Desirability): Rewards tell us how good or bad a situation is right now. They provide immediate feedback on the desirability of the current state.
Values (Long-Term Desirability): Values consider the bigger picture. They look ahead and assess how good a state is over the long term, taking into account not only the current rewards but also what might happen in the future and the rewards associated with those future states.
In summary, while rewards focus on the present, values take a more forward-looking approach, evaluating the desirability of a state by considering the future states and rewards that are likely to follow.

Elements of RL : Value function

- Whereas the reward signal indicates what is good in an immediate sense, a value function specifies what is good in the long run.
- Roughly speaking, the value of a state is the total amount of reward an agent can expect to accumulate over the future, starting from that state.
- Whereas rewards determine the immediate, intrinsic desirability of environmental states, values indicate the long-term desirability of states after taking into account the states that are likely to follow and the rewards available in those states.
- For example, a state might always yield a low immediate reward but still have a high value because it is regularly followed by other states that yield high rewards. Or the reverse could be true.
- To make a human analogy, rewards are somewhat like pleasure (if high) and pain (if low), whereas values correspond to a more refined and farsighted judgment of how pleased or displeased we are that our environment is in a particular state.

Juxtaposing Rewards and Value Functions

- Rewards are in a sense primary, whereas values, as predictions of rewards, are secondary. derived from the primary reward
- Without rewards there could be no values, and the only purpose of estimating values is to achieve more reward.
- It is values with which we are most concerned when making and evaluating decisions. Action choices are made based on value judgments.
- We seek actions that bring about states of highest value, not highest reward, because these actions obtain the greatest amount of reward for us over the long run.
- Unfortunately, it is much harder to determine values than it is to determine rewards. Rewards are basically given directly by the environment, but values must be estimated and re-estimated from the sequences of observations an agent makes over its entire lifetime.

Elements of RL : Model

A model in RL is something that imitates or represents the behavior of the environment.
It allows for making predictions or inferences about how the environment will behave.
In simpler terms, a model in RL acts as a simulation or representation of the environment, helping the learning agent understand and predict how the environment will respond to different actions or decisions.

- Model is something that mimics the behavior of the environment, or more generally, that allows inferences to be made about how the environment will behave.
- For example, given a state and action, the model might predict the resultant next state and next reward.
- Models are used for planning, by which we mean any way of deciding on a course of action by considering possible future situations before they are actually experienced. models help the learning agent simulate or predict how the environment might behave in the future, allowing it to plan and make informed decisions before directly interacting with the real-world environment.
- Methods for solving reinforcement learning problems that use models and planning are called model-based methods, as opposed to simpler model-free methods that are explicitly trial-and-error learners—viewed as almost the opposite of planning.
- Modern reinforcement learning spans the spectrum from low-level, trial-and-error learning to high-level, deliberative planning.

The field of modern reinforcement learning covers a wide range, from basic trial-and-error learning at a low level to more advanced, thoughtful planning at a high level.

Types of RL

Reinforcement Learning : Types

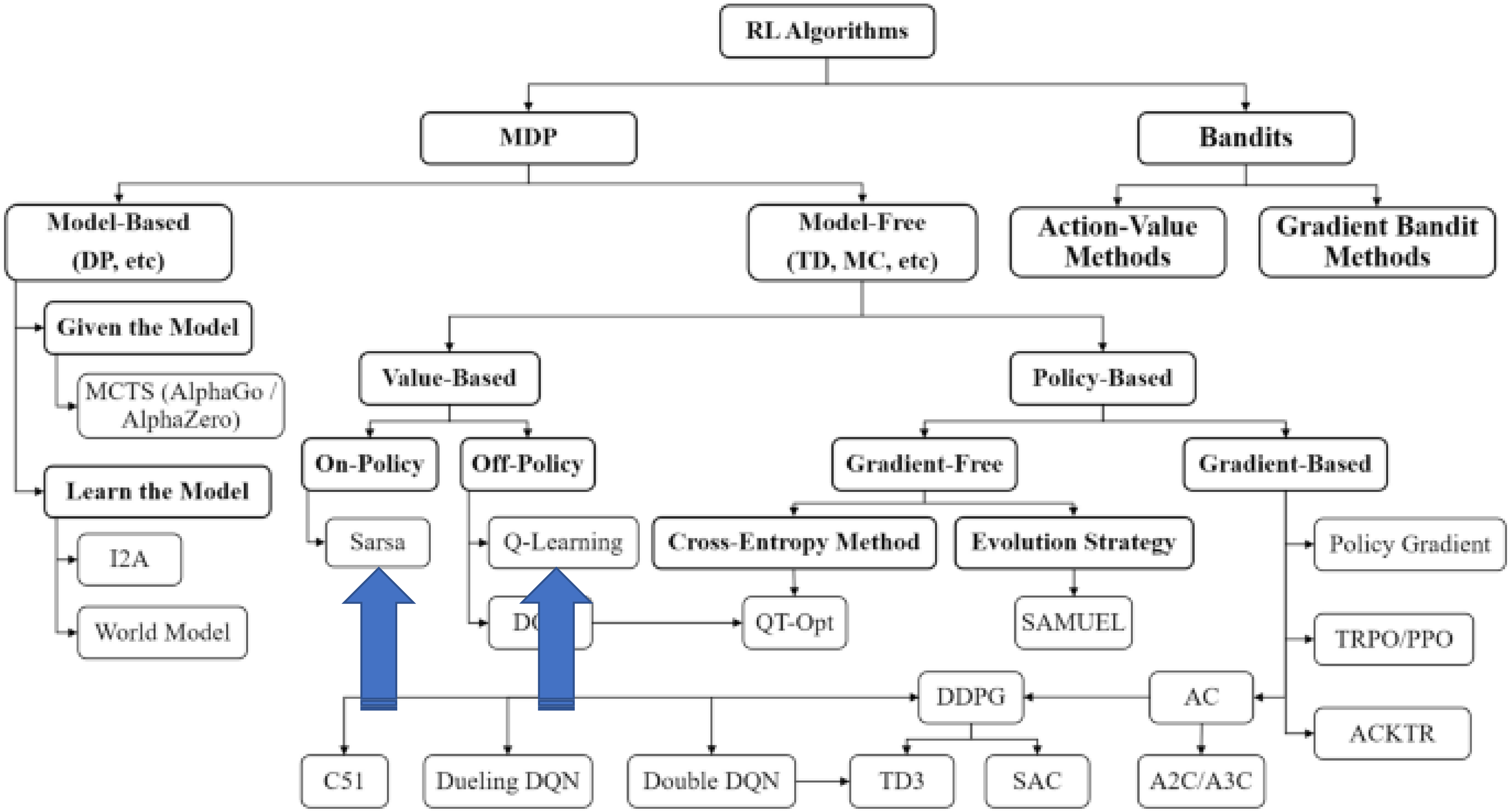
- Model-based methods:
  - These methods use a model of the environment to predict the next state and reward.
  - Examples include Markov decision processes (MDPs) and dynamic programming.
- Model-free methods:
  - These methods do not use a model of the environment and instead learn from experience.
  - Examples include Q-learning and State Action Reward State action (SARSA).

Reinforcement Learning : Types

- Value-based methods:
  - These methods learn to estimate the value of each state or state-action pair.
  - Examples include Q-learning and deep Q-networks (DQNs).
- Policy-based methods:
  - These methods learn a policy that maps states to actions.
  - Examples include policy gradient methods and actor-critic methods.

RL Algorithms

Reinforcement Learning : Algorithms



Source : https://link.springer.com/chapter/10.1007/978-981-15-4095-0_3

Markov Decision Process Introduction

Markov Decision Process (MDP)

- MDP is a mathematical framework used to model decision-making problems where an agent interacts with an environment over a sequence of discrete time steps.
- It provides a mathematical framework for modeling decision making in situations where outcomes are partly random and partly under the control of a decision maker.
- The MDP framework is widely used in the field of reinforcement learning to formalize problems and algorithms.

Markov Decision Process (MDP)

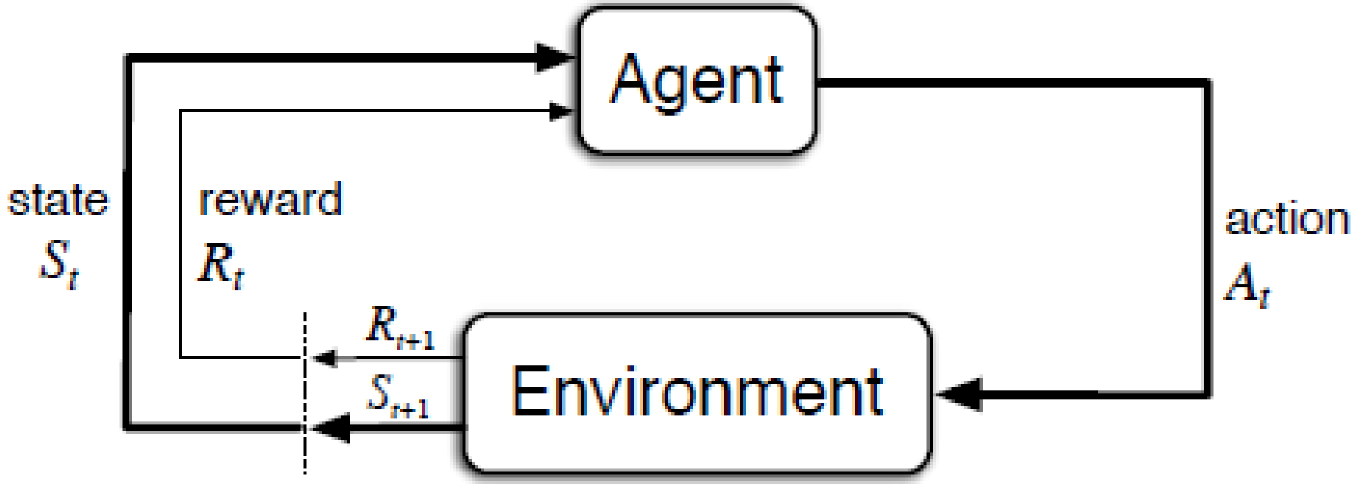


Figure : The agent–environment interaction in a Markov decision process.

Markov Decision Process (MDP)

- Key components of an MDP include:
  - **States (S):** A finite set of possible situations or configurations the system can be in. At each time step, the system is in a specific state.
  - **Actions (A):** A finite set of possible actions the agent can take. The available actions may depend on the current state.
  - **Transition Probabilities (P):** The probabilities of moving from one state to another based on the chosen action. It defines the dynamics of the system.
  - **Rewards (R):** Immediate numerical values that the agent receives as a consequence of taking a specific action in a particular state. The goal is to maximize the cumulative reward over time.
  - **Policy (π):** A strategy or mapping from states to actions that guides the agent's decision-making. It represents the agent's behavior in the environment.
  - **Discount Factor (γ):** A parameter that influences the agent's preference for immediate rewards over future rewards. It determines the importance of future rewards in the decision-making process.
  - **Value Function (V or Q):** The expected cumulative reward an agent can achieve starting from a particular state (V) or state-action pair (Q) following a given policy.

the discount factor helps the learning agent decide how much weight to give to immediate rewards compared to rewards that are expected in the future. A higher discount factor means the agent prioritizes immediate rewards more, while a lower discount factor values future rewards more.

Markov Decision Process (MDP), which is a mathematical model used to represent decision-making processes under uncertainty.

Markov Property in MDP

This property states that the future state of the system depends only on the current state and action, not on the entire history of states and actions leading up to the present.

- The dynamics of an MDP satisfy the Markov property, meaning the future state depends only on the current state and action, and not on the sequence of states and actions that preceded it.
  - making the decision-making process memoryless.

The current state and action provide all the information needed to determine the future, making the sequence of past states and actions unnecessary for predicting what comes next.

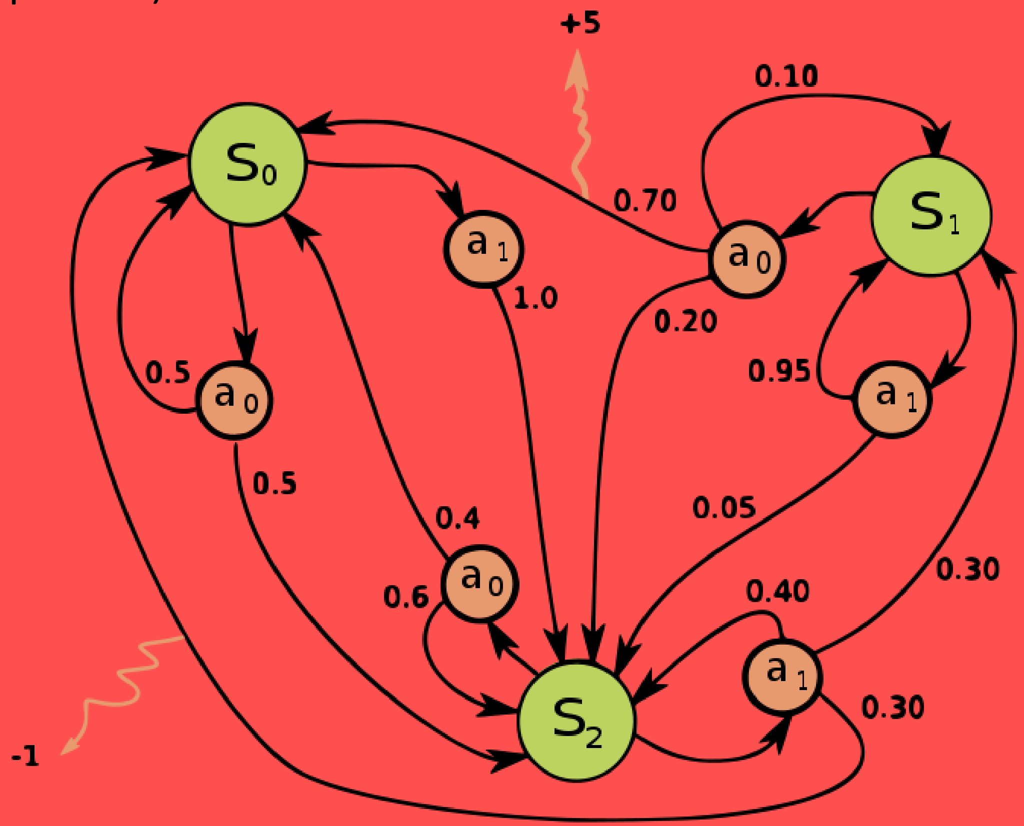
in an MDP with the Markov property, the current state and action are sufficient for predicting the future state, eliminating the need to consider the entire history of states and actions. This property simplifies the decision-making process, making it more manageable and efficient.

MDP (from Wikipedia)

A Markov decision process is a 4-tuple (S, A, P_a, R_a), where:

- S is a set of states called the *state space*,
- A is a set of actions called the *action space* (alternatively, A_s is the set of actions available from state s),
- $P_a(s, s') = \Pr(s_{t+1} = s' \mid s_t = s, a_t = a)$ is the probability that action a in state s at time t will lead to state s' at time $t+1$,
- $R_a(s, s')$ is the immediate reward (or expected immediate reward) received after transitioning from state s to state s', due to action a

MDP (from Wikipedia)



Example of a simple MDP with three states (green circles) and two actions (orange circles), with two rewards (orange arrows).

Reinforcement Learning : Algorithms

- Q-Learning
- State Action Reward State action (SARSA)

Q-Learning

$Q(s_t,a_t) \leftarrow (1-\alpha) \cdot Q(s_t,a_t) + \alpha \cdot (r_{t+1} + \gamma \cdot \max_a Q(s_{t+1},a))$

Q-Learning Algorithm

- Create a table Q(s, a) to represent the Q-values for each state-action pair. Initialize the Q-values arbitrarily, often with zeros.
- For each time step t, observe the current state s_t.
- Select an action a_t using the exploration-exploitation strategy.
  - Common strategies include ε-greedy, where with probability ε, a random action is selected, and with probability 1-ε, the action with the highest Q-value is chosen.
- Execute the selected action and observe the immediate reward r_{t+1} and the new state s_{t+1}.
- Update the Q-value of the current state-action pair using the equation:

$$Q(s_t, a_t) \leftarrow (1-\alpha) \cdot Q(s_t, a_t) + \alpha \cdot (r_{t+1} + \gamma \cdot max_a Q(s_{t+1}, a))$$

Q-Learning : Learning Rate (α)

- **Role:** The learning rate (α) determines the extent to which the Q-values are updated in each iteration. It controls the weight given to new information compared to the existing knowledge in the Q-table.
- **Range:** $0 < \alpha \leq 1$.
- **Effect:** A higher learning rate gives more weight to recent experiences, potentially leading to faster convergence but also making the algorithm more sensitive to noise. A lower learning rate makes the algorithm more stable but slower to adapt to changes in the environment.

Q-Learning : Discount Factor (γ)

- **Role:** The discount factor (γ) determines the importance of future rewards in the Q-value update. It reflects the agent's preference for immediate rewards over delayed rewards.
- **Range:** $0 \leq \gamma \leq 1$.
- **Effect:** A higher discount factor values future rewards more, encouraging the agent to consider long-term consequences. A lower discount factor makes the agent focus more on immediate rewards.

Q-Learning

- $Q(s_t,a_t) \leftarrow (1-\alpha) \cdot Q(s_t,a_t) + \alpha \cdot (r_{t+1} + \gamma \cdot max_a Q(s_{t+1},a))$

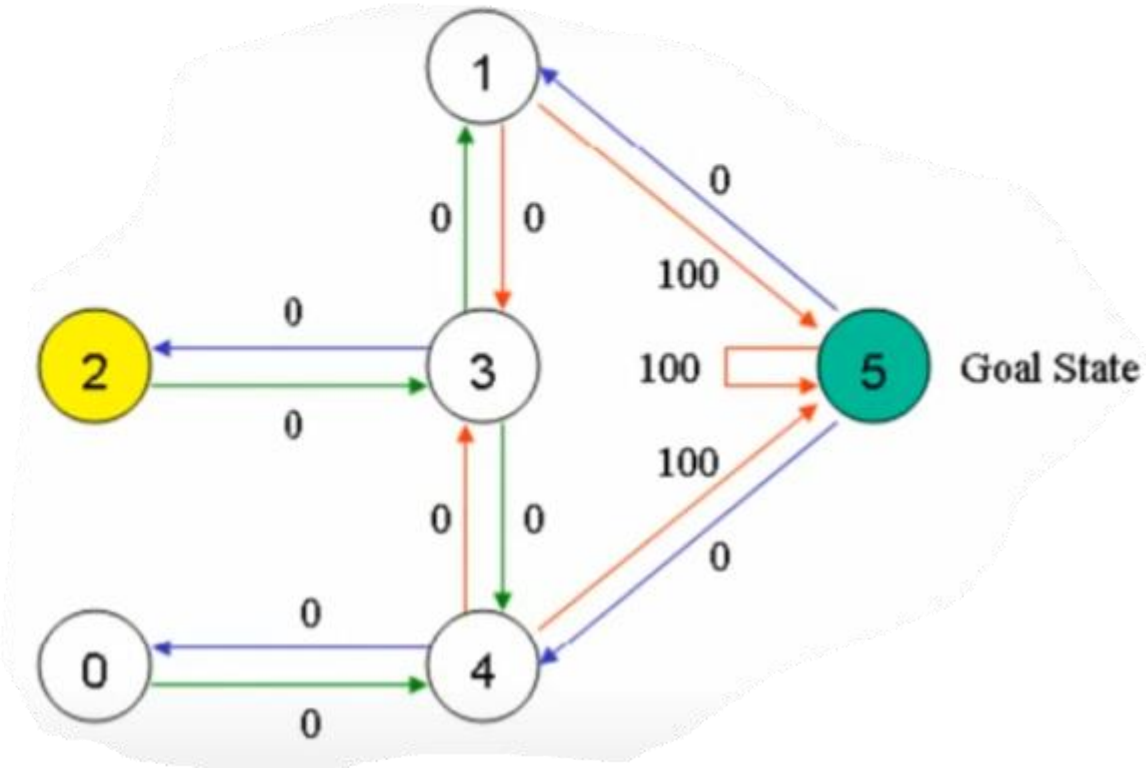
- Assume $\alpha = 1$
  - What does it signify?
  - $Q(s_t,a_t) \leftarrow r_{t+1} + \gamma \cdot max_a Q(s_{t+1},a)$

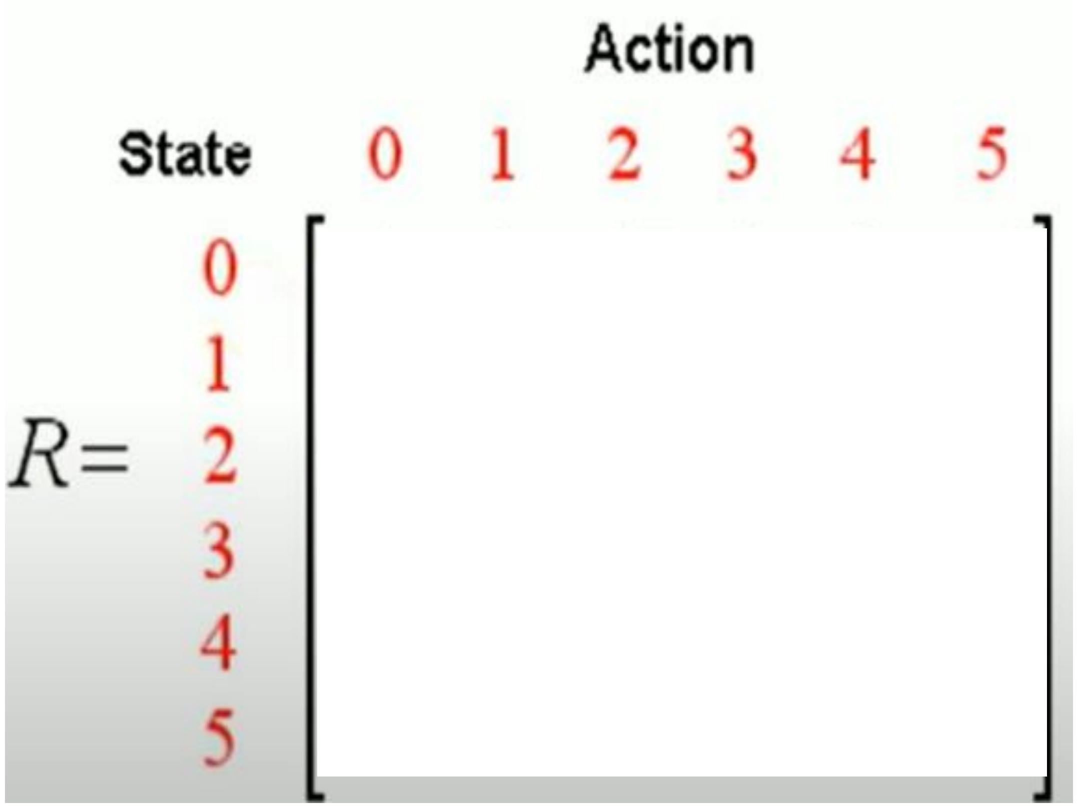
https://youtu.be/_O9a5xbBe-s?si=i8rgxVpxyoouuUQe

Q-Learning : Example

Consider Rewards as

- -1 for ‘No Connection’
- 0 for ‘Non Goal State’
- 100 for ‘Goal State’





Q-Learning

- Initialize Q matrix to Zero

$$
R = \begin{array}{c c}
 & \text{Action} \\
\text{State} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} -1 & -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 & -1 & 100 \\ -1 & -1 & -1 & 0 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 100 \\ -1 & 0 & -1 & -1 & 0 & 100 \end{bmatrix}
\end{array}
\qquad
Q = \begin{array}{c c}
 & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}
\end{array}
$$

Q-Learning

- Consider discount factor (γ) = 0.8
- Initial State as 1
- We can go to ??
  - 3 or 5
- How to select one of it?

https://youtu.be/J3qX50yyiU0?si=SECGXkG9hLMPj1BB

$$
\begin{array}{cc}
 & \text{Action} \\
\text{State} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
R = \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} -1 & -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 & -1 & 100 \\ -1 & -1 & -1 & 0 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 100 \\ -1 & 0 & -1 & -1 & 0 & 100 \end{bmatrix}
\end{array}
$$

Q-Learning

- Assume 5 is Selected
  - Calculate Q (1,5)
  - Which actions from 5 ??
  - 1, 4 or 5
- Calculations
  - $Q(s_t,a_t) \leftarrow r_{t+1} + \gamma \cdot max_a Q(s_{t+1},a)$
  - Q (1,5) = 100 + 0.8 Max [Q(5,1), Q(5,4), Q(5,5)]
  - Q (1,5) = 100 + 0.8 Max [0 , 0, 0]
  - Q (1,5) = 100 + 0.8 * 0
  - Q (1,5) = 100

$$
\begin{array}{c}
\text{Action} \\
\begin{array}{cc}
\text{State} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
R = \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} -1 & -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 & -1 & 100 \\ -1 & -1 & -1 & 0 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 100 \\ -1 & 0 & -1 & -1 & 0 & 100 \end{bmatrix}
\end{array}
\end{array}
$$

$$
\begin{array}{cc}
 & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
Q = \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}
\end{array}
$$

Q-Learning

$$
R = \begin{array}{c} \\ \text{State} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array}
\begin{array}{c} \text{Action} \\ \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{bmatrix} -1 & -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 & -1 & 100 \\ -1 & -1 & -1 & 0 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 100 \\ -1 & 0 & -1 & -1 & 0 & 100 \end{bmatrix} \end{array}
$$

- Q(1,5) is calculated as 100
- Next state selected is 5.
- We can't go anywhere from 5, since it is goal state.
- One episode is over.
- For next episode, randomly choose the starting stage.
  - Let us say 3
  - From 3 we can go to ??
    - 1, 2 or 4
    - Assume 1 is selected, Calculate Q (3,1)

Q-Learning

- Q (3,1)

  = R(3,1) + 0.8 * Max [Q(1,3), Q(1,5)]

  = 0 + 0.8 * Max [0, 100]

  = 0.8 * 100

  = 80

Action

$$
R = \begin{array}{c} \text{State} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array}
\begin{array}{c}
\begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{bmatrix}
-1 & -1 & -1 & -1 & 0 & -1 \\
-1 & -1 & -1 & 0 & -1 & 100 \\
-1 & -1 & -1 & 0 & -1 & -1 \\
-1 & 0 & 0 & -1 & 0 & -1 \\
0 & -1 & -1 & 0 & -1 & 100 \\
-1 & 0 & -1 & -1 & 0 & 100
\end{bmatrix}
\end{array}
$$

$$
Q = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array}
\begin{array}{c}
\begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 100 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\end{array}
$$

$$
Q = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array}
\begin{array}{c}
\begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 100 \\
0 & 80 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\end{array}
$$

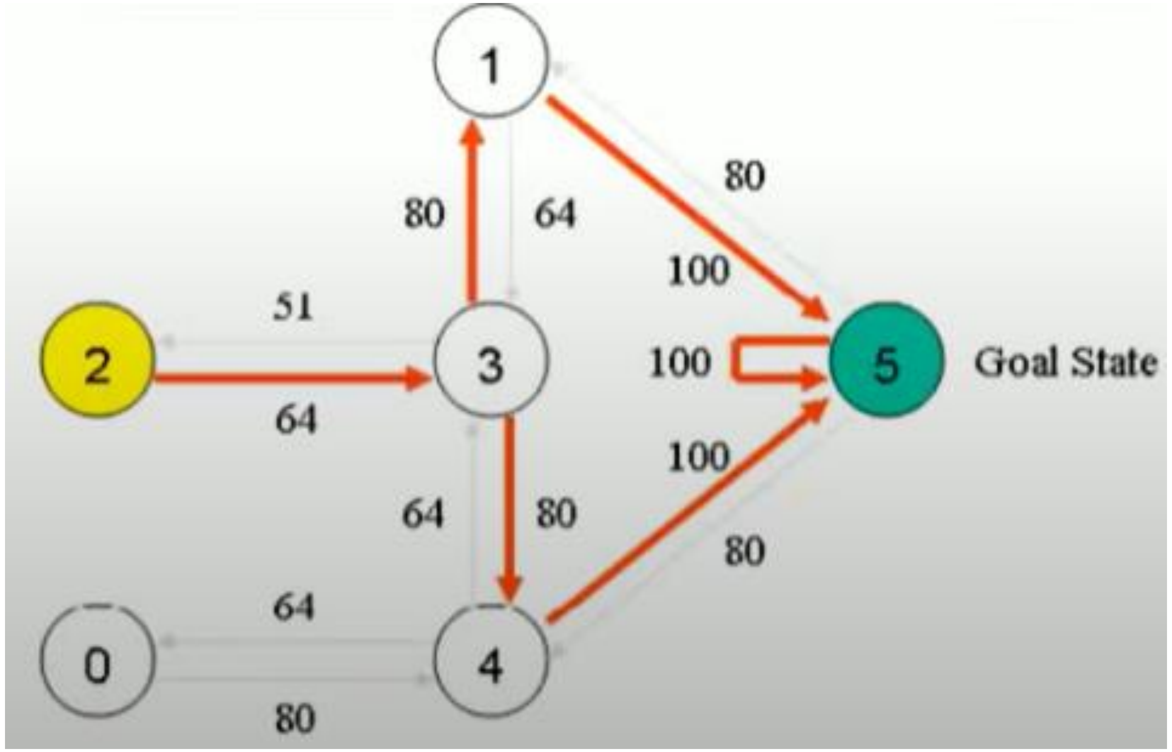
Q-Learning

- The agent learns more through further episodes.
- It will finally reach to convergence values in Matrix Q as

$$Q = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 80 & 0 \\ 0 & 0 & 0 & 64 & 0 & 100 \\ 0 & 0 & 0 & 64 & 0 & 0 \\ 0 & 80 & 51 & 0 & 80 & 0 \\ 64 & 0 & 0 & 64 & 0 & 100 \\ 0 & 80 & 0 & 0 & 80 & 100 \end{bmatrix} \end{array}$$

Q-Learning

- Once fully learnt (convergence happened) the agent may simply follow the action with highest reward at given state to reach the Goal State



SARSA

State-Action-Reward-State-Action

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha \cdot (r_{t+1} + \gamma \cdot Q(s_{t+1},a_{t+1}) - Q(s_t,a_t))$$

SARSA

- SARSA (State-Action-Reward-State-Action) is another reinforcement learning algorithm, similar to Q-learning, used for learning optimal policies in Markov Decision Processes (MDPs).

enable agents to make optimal decisions through interactions with their environments

- Like Q-learning, SARSA is a model-free algorithm, meaning it does not require knowledge of the underlying dynamics of the environment.

SARSA Overview

1. **Initialize Q-values**:
   - Start by initializing the Q-values for all state-action pairs.
   - This is typically done by creating a Q-table and initializing its entries with arbitrary values.
2. **Exploration-Exploitation Tradeoff**:
   - Define an exploration-exploitation strategy, similar to Q-learning, to balance exploration of new actions and exploitation of learned knowledge.
   - Common strategies include ε-greedy, where with probability ε, a random action is selected, and with probability 1-ε, the action with the highest Q-value is chosen.

the -greedy strategy helps the learning agent balance between trying out new actions (exploration) and sticking to actions it believes are currently the best (exploitation). The parameter E determines the degree of randomness in decision-making, influencing the agent's overall learning and performance.

SARSA Overview

3. **Learning Process:**
   - For each time step *t*, observe the current state s_t.
   - Select an action a_t using the exploration-exploitation strategy.
   - Execute the selected action and observe the immediate reward r_{t+1} and the new state s_{t+1}.
   - Select a new action a_{t+1} using the same exploration-exploitation strategy.
   - Update the Q-value of the current state-action pair using the SARSA update rule:
   - $$Q(s_t,a_t) \leftarrow Q(s_t,a_t)+\alpha\cdot(r_{t+1}+\gamma\cdot Q(s_{t+1},a_{t+1})-Q(s_t,a_t))$$
     - α is the learning rate ($0 < \alpha \le 1$), determining the extent to which new information replaces old information.
     - γ is the discount factor ($0 \le \gamma \le 1$), which discounts the importance of future rewards.
4. **Repeat:**
   - Continue the learning process for multiple episodes or until convergence.

a policy outlines what action the agent should take when it finds itself in a particular state

SARSA Overview

On-policy means that SARSA learns and updates the policy that it follows during training.

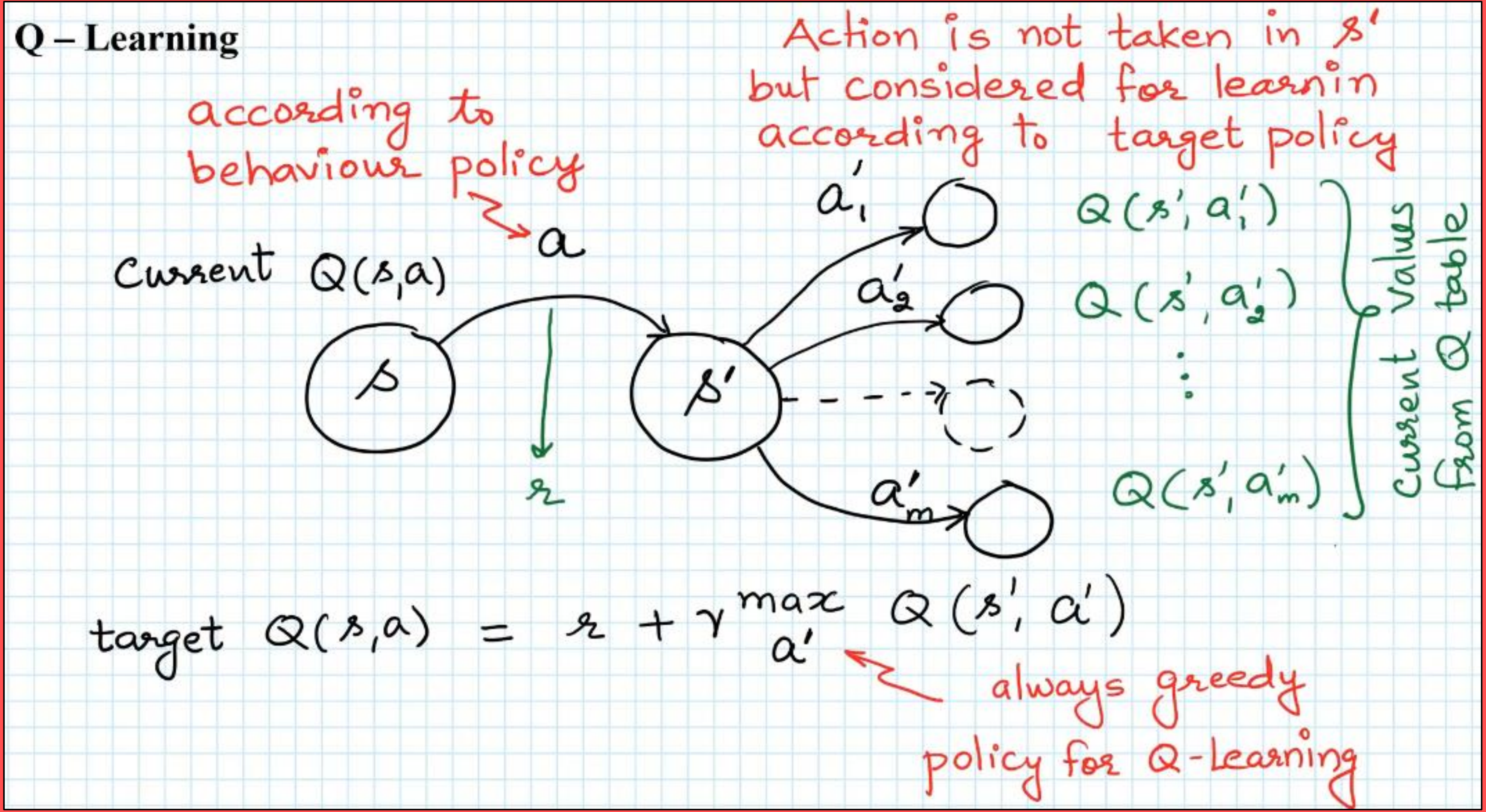
- SARSA is an on-policy algorithm, meaning it learns the policy that it follows during training.
- It is suitable for scenarios where the policy needs to be continuously updated based on the agent's actions.

Temporal Difference represents the difference between the predicted value of a state or state-action pair and the actual observed value. In other words, it measures how much the agent's prediction deviates from the true outcome at a given time step.
The agent uses this temporal difference error to update its Q-values (expected cumulative rewards) and improve its understanding of the environment.
The update rules for Q-learning and SARSA involve adjusting the Q-values based on this error, allowing the agent to learn and make better decisions over time.

SARSA vs Q-Learning

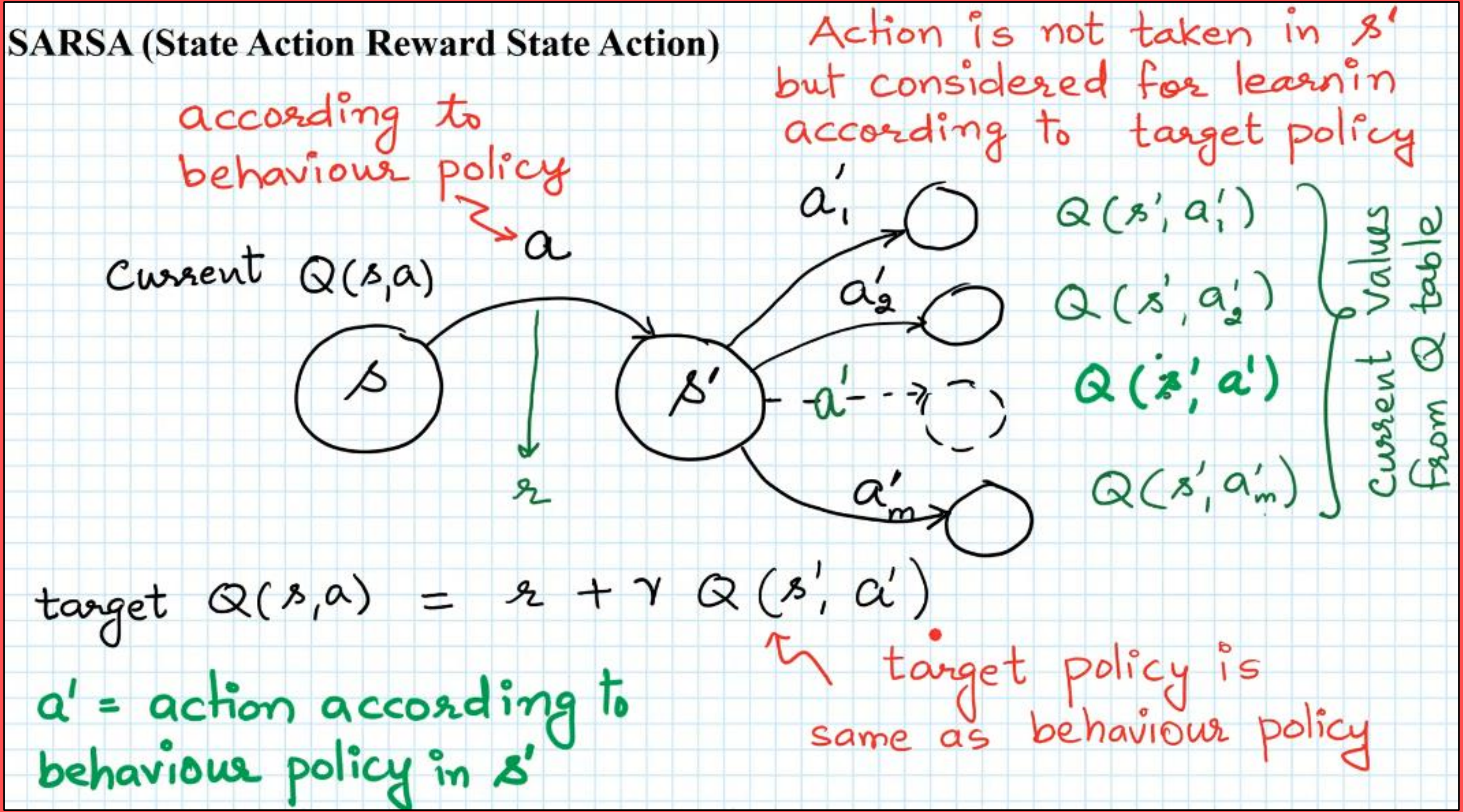
- *Q-Learning :* $Q(s_t,a_t) \leftarrow (1-\alpha) \cdot Q(s_t,a_t) + \alpha \cdot (r_{t+1} + \gamma \cdot \max_a Q(s_{t+1},a))$
- SARSA : $Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha \cdot (r_{t+1} + \gamma \cdot Q(s_{t+1},a_{t+1}) - Q(s_t,a_t))$
- The $(1-\alpha)$ term is not explicitly present in the SARSA update because it's implicitly accounted for in the form of α itself. The SARSA update rule directly multiplies the learning rate (α) with the temporal difference error $(r_{t+1} + \gamma \cdot Q(s_{t+1},a_{t+1}) - Q(s_t,a_t))$.
- In Q-learning, you often see the $(1-\alpha)$ term explicitly because the Q-value update involves both the current Q-value and the maximum Q-value of the next state (which is part of the temporal difference error), and $(1-\alpha)$ scales the current estimate down, leaving room for the updated estimate.
- In summary, the absence of $(1-\alpha)$ in the SARSA update is due to how the learning rate α is incorporated directly into the update rule.

SARSA vs Q-Learning



Credit : Dr. Pankaj Kumar Porwal   Source : https://www.youtube.com/watch?v=FhSaHuC0u2M

SARSA vs Q-Learning



Credit : Dr. Pankaj Kumar Porwal Source : https://www.youtube.com/watch?v=FhSaHuC0u2M

SARSA vs Q-Learning

Q – Learning (Off policy)

$$\overbrace{Q(s,a)}^{\text{Updated Q Value}} = \overbrace{Q(s,a)}^{\text{Current Q Value}} + \alpha \left[\overbrace{r + \underbrace{\max_{a'} \gamma Q(s',a')}_{\textbf{Target policy is always Greedy Policy}}}^{\text{Target Q Value}} - \overbrace{Q(s,a)}^{\text{Current Q Value}} \right]$$

α = Learning Rate

SARSA (State Action Reward State Action) Algorithm (On policy)

$$\overbrace{Q(s,a)}^{\text{Updated Q Value}} = \overbrace{Q(s,a)}^{\text{Current Q Value}} + \alpha \left[\overbrace{r + \underbrace{\gamma Q(s',a')}_{\textbf{Target Policy is always same as Behaviour Policy}}}^{\text{Target Q Value}} - \overbrace{Q(s,a)}^{\text{Current Q Value}} \right]$$

α = Learning Rate

Credit : Dr. Pankaj Kumar Porwal Source : https://www.youtube.com/watch?v=FhSaHuC0u2M

SARSA vs Q-Learning

- On-Policy vs Off-Policy:
  - **Q-learning**: Off-policy. Q-learning learns the optimal Q-values regardless of the policy followed to generate the data. It estimates the maximum expected future rewards for each state-action pair.
  - **SARSA**: On-policy. SARSA learns the Q-values for the policy it is currently following. It updates Q-values based on the actual actions taken and the subsequent state-action pairs.

SARSA vs Q-Learning

- **Update Rule:**
  - **Q-learning:** The update rule is based on the maximum Q-value of the next state, irrespective of the action taken. The Q-value for a state-action pair is updated using the maximum Q-value of the next state.

    $$Q(s_t,a_t) \leftarrow (1-\alpha)\cdot Q(s_t,a_t)+\alpha\cdot(r_{t+1}+\gamma\cdot max_a Q(s_{t+1},a))$$

  - **SARSA:** The update rule considers the Q-value of the next state-action pair based on the policy being followed. It takes into account the action actually taken in the next state.

    $$Q(s_t,a_t) \leftarrow Q(s_t,a_t)+\alpha\cdot(r_{t+1}+\gamma\cdot Q(s_{t+1},a_{t+1})-Q(s_t,a_t))$$

SARSA vs Q-Learning

- Policy Used for Exploration:
  - **Q-learning**: Typically uses an epsilon-greedy strategy for exploration. It exploits the current best action with high probability and explores randomly with a small probability.
  - **SARSA**: Also often uses epsilon-greedy, but it explores and updates its policy simultaneously, as it's an on-policy algorithm.
- Usage:
  - **Q-learning**: Can be more effective in situations where exploration is crucial, and the learned policy may deviate significantly from the behavior policy.
  - **SARSA**: Tends to be more stable in environments where the agent should follow a specific policy closely, such as in applications where safety is a primary concern.

End