Reinforcement Learning

Notes

Introduction to Reinforcement Learning

Reinforcement learning (RL) is a type of machine learning where an agent learns to make decisions by trial and error, aiming to maximize cumulative rewards.

***Agent**: Learns from interactions with the environment.*

***Environment:** The external system with which the agent interacts.*

***Rewards:** Feedback from the environment indicating how good the agent's actions are.*

***Goal:** Maximize cumulative rewards over time.*

Key Concepts:

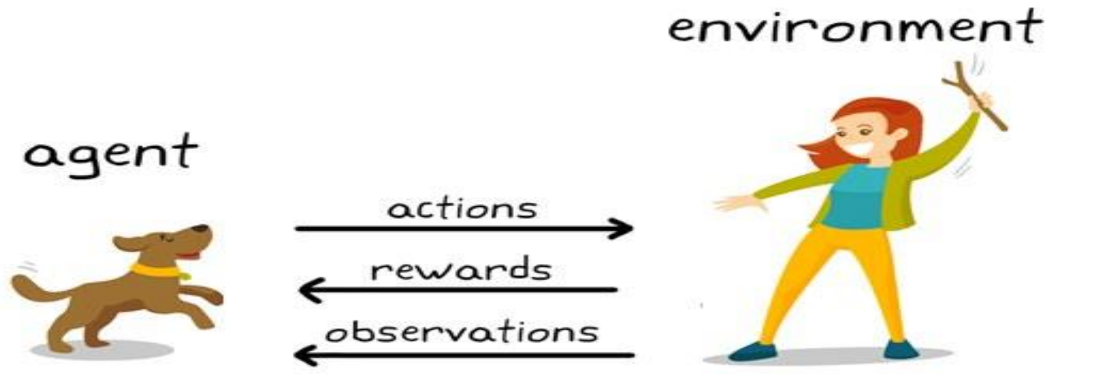
***State:** The current situation of the environment.*

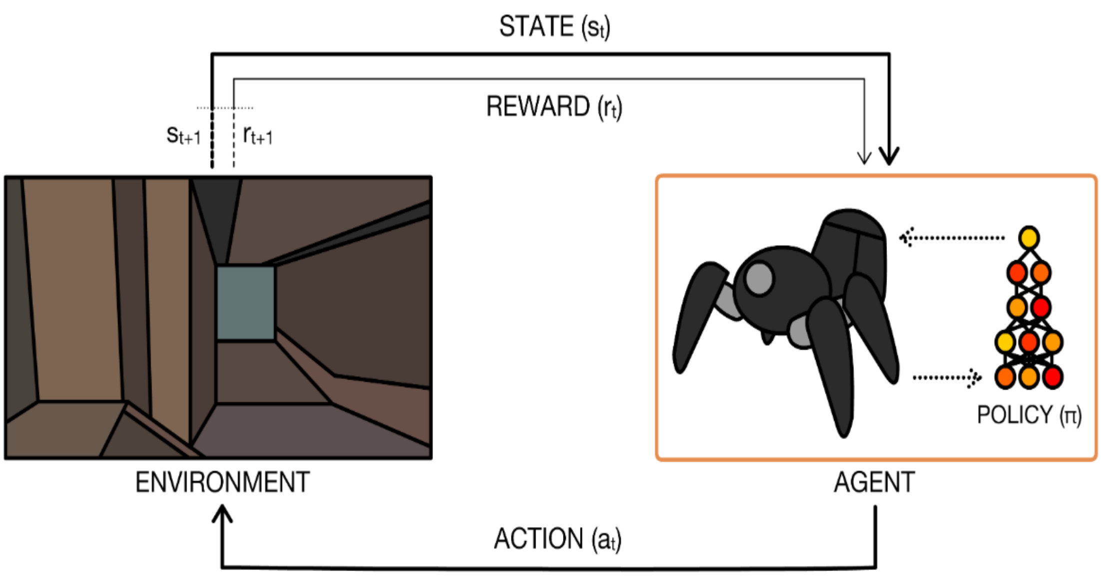
***Action:** Decision made by the agent.*

***Reward:** Feedback from the environment.*

***Policy:** Strategy followed by the agent to select actions.*

***Value**: Expected cumulative reward starting from a particular state.*


environment
agent
actions
rewards
observations


STATE (s_t)
REWARD (r_t)
s_{t+1}
r_{t+1}
POLICY (π)
ENVIRONMENT
AGENT
ACTION (a_t)

MARKOV DECISION PROCESSES (MDPS)

MDPs provide a mathematical framework for modeling decision-making problems.

Components of MDP:

1. ***States (S)****: Set of possible situations.*
2. ***Actions (A)****: Set of possible decisions.*
3. ***Transition Probability (P)****: Probability of transitioning from one state to another given an action.*
4. ***Reward Function (R)****: Immediate reward received after transitioning to a new state.*

Policy in MDPs:

- *A policy is a mapping from states to actions, defining the agent's behaviour.*

Value Functions:

- ***State Value Function (V(s))****: Expected cumulative reward starting from states.*
- ***Action Value Function (Q(s, a))****: Expected cumulative reward starting from states, taking action a, and following a particular policy.*

Q-Learning

Q-learning is a model-free reinforcement learning algorithm that learns the optimal action-value function directly.

Algorithm:

1. *Initialize Q(s, a) arbitrarily.*
2. *Repeat until convergence:*
    - *Choose an action a and observe the reward r and next states*
    - *Update Q(s, a) using the Bellman equation:* $Q(s,a) \leftarrow Q(s,a) + \alpha\left(r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right)$ *where:*
        - *α is the learning rate.*
        - *γ is the discount factor.*

Exploration vs. Exploitation:

Balancing exploration (trying new actions) and exploitation (using known actions) is crucial for learning.

Negative Reinforcement

1. Apply steady, light pressure
2. Increase amount & frequency of pressure
3. Wait for horse to respond
4. Immediately release

Positive Reinforcement

1. Use clicker or verbal instructions
2. Reward with treats or scratching of withers or forehead

Deep Q-Networks (DQN)

Deep Q-Networks combine Q-learning with deep neural networks to handle large state spaces.

Key Components:

1. ***Experience Replay**: Store agent's experiences (state, action, reward, next state) and sample mini-batches for training.*
2. ***Target Network**: Separate network to stabilize training by fixing target values.*

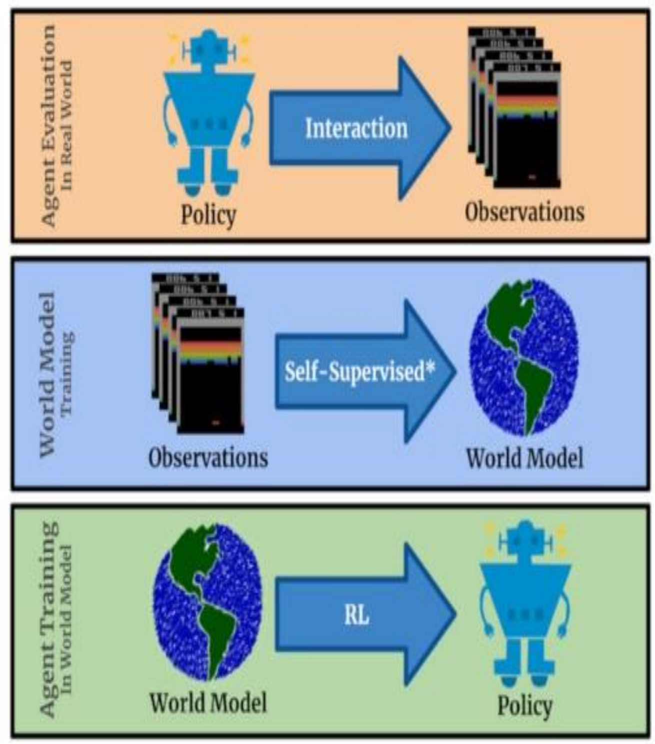
Algorithm:

1. *Initialize Q-network with random weights.*
2. *Repeat until convergence:*
    - *Select action using ϵ-greedy policy.*
    - *Execute action, observe reward and next state.*
    - *Store experience in replay memory.*
    - *Sample mini-batch from replay memory.*
    - *Update Q-network parameters using mini-batch.*

Extensions:

- *Double DQN, Dueling DQN, Rainbow DQN, etc., improve upon the basic DQN architecture for better performance.*


World Model
Training
Observations
World Model
Agent Evaluation
In Real World
Agent Training
In World Model
Policy


Agent Evaluation
In Real World
Interaction
Policy
Observations
World Model
Training
Self-Supervised*
Observations
World Model
Agent Training
In World Model
RL
World Model
Policy

Advanced Topics

Multi-armed Bandits

Multi-armed bandits refer to a class of problems where an agent must decide which actions to take in order to maximize cumulative reward, balancing exploration (trying out new actions) with exploitation (leveraging known actions). This concept finds applications in various fields such as clinical trials, online advertising, and resource allocation.

Monte Carlo Methods

Monte Carlo methods involve using random sampling to solve problems. In reinforcement learning, Monte Carlo methods are utilized for estimating value functions and improving policies through simulation and statistical analysis. They offer a powerful framework for learning from experience without requiring a model of the environment.

Function Approximation Techniques

Function approximation techniques enable the representation of value functions and policies in large state and action spaces. Methods like deep learning facilitate the approximation of complex functions, allowing reinforcement learning algorithms to scale to high-dimensional problems such as image-based inputs in robotics and autonomous vehicles.

Applications of Reinforcement Learning

- ***Robotics***

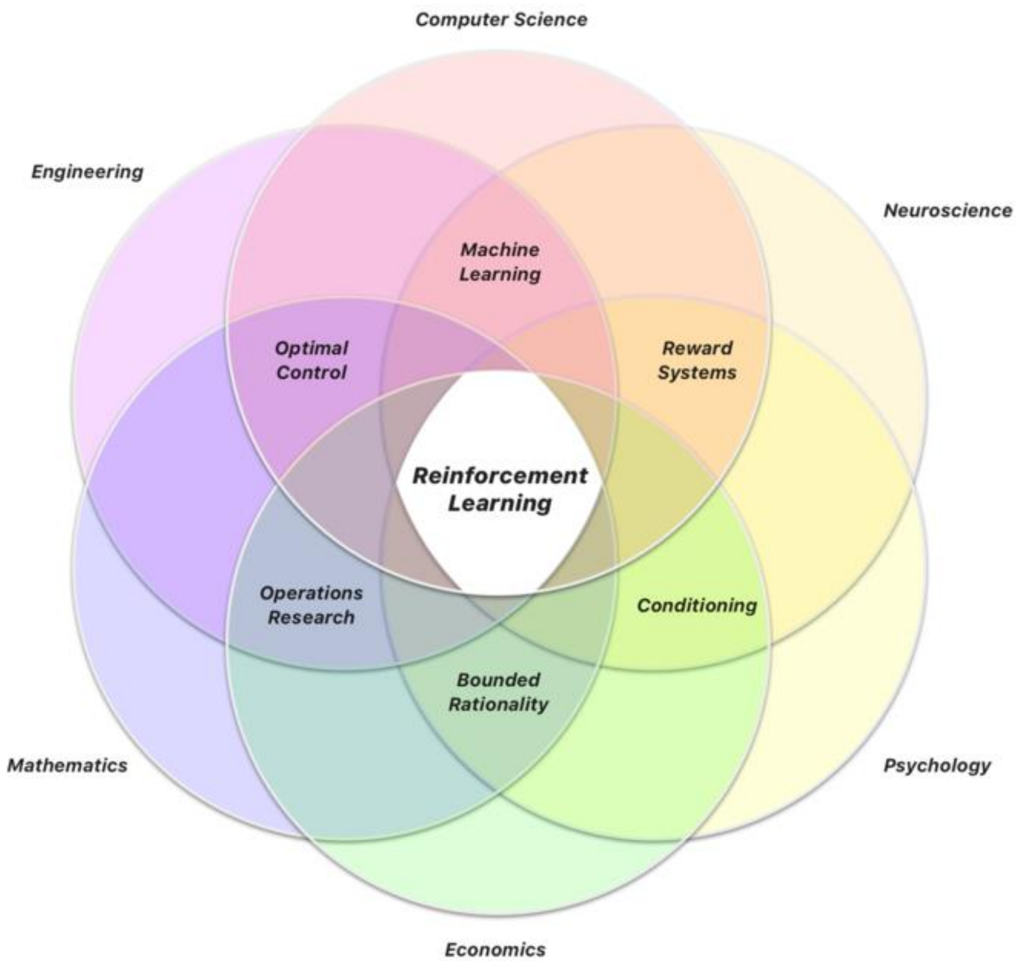
Reinforcement learning plays a crucial role in robotics by enabling robots to learn from experience and adapt to changing environments. Applications range from robot manipulation and locomotion to tasks like object recognition and path planning.

- ***Game Playing (e.g., AlphaGo)***

Reinforcement learning has demonstrated remarkable success in game playing, as seen with AlphaGo, which defeated world champions in the ancient game of Go. By learning optimal strategies through self-play and deep reinforcement learning techniques, AI agents have achieved superhuman performance in complex board games.

- ***Autonomous Vehicles***

Autonomous vehicles rely on reinforcement learning for decision-making in dynamic and uncertain environments. RL algorithms enable vehicles to navigate safely, make driving decisions, and optimize energy efficiency, contributing to the advancement of self-driving technology.


Computer Science
Engineering
Neuroscience
Machine Learning
Optimal Control
Reward Systems
Reinforcement Learning
Operations Research
Conditioning
Bounded Rationality
Mathematics
Psychology
Economics

Challenges and Future Directions

- ***Sample Efficiency***

Improving sample efficiency remains a significant challenge in reinforcement learning. Methods that can learn effectively from limited data are essential for real-world applications where data collection may be costly or time-consuming.

- ***Generalization to New Environments***

Generalizing learned policies to unseen environments is crucial for deploying reinforcement learning systems in the real world. Research efforts focus on developing algorithms capable of adapting to diverse conditions and transfer learning techniques for leveraging knowledge from related tasks.

- ***Ethical Considerations***

As reinforcement learning technologies advance, ethical considerations regarding safety, fairness, and accountability become increasingly important. Addressing issues such as algorithmic bias, unintended consequences, and societal impact is essential for responsible AI development.

Conclusion

Reinforcement learning encompasses a diverse set of concepts and algorithms, including multi-armed bandits, Monte Carlo methods, and function approximation techniques. Its applications span robotics, game playing, and autonomous vehicles, driving innovation across various domains. Despite challenges such as sample efficiency and ethical considerations, reinforcement learning continues to play a pivotal role in advancing artificial intelligence, offering powerful tools for learning and decision-making in complex environments.

References

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