Reinforcement Learning: Principles and Applications

Reinforcement learning is an area of machine learning concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward. Reinforcement learning differs from supervised learning in that labeled input/output pairs need not be presented, and sub-optimal actions need not be explicitly corrected. The environment is typically stated in the form of a Markov decision process (MDP), because many reinforcement learning algorithms for this context utilize dynamic programming techniques. The main difference between the classical dynamic programming methods and reinforcement learning algorithms is that the latter do not assume knowledge of an exact mathematical model of the MDP and they target large MDPs where exact methods become infeasible. Reinforcement learning has been applied successfully to various problems, including robot control, game playing, and resource management. In game playing, reinforcement learning has achieved remarkable results, such as defeating world champions in chess, Go, and poker. In robotics, it has enabled robots to learn complex tasks like walking, grasping objects, and navigating through environments. Key concepts in reinforcement learning include the agent, the environment, states, actions, rewards, and policies. The agent is the learner or decision-maker. The environment is everything the agent interacts with. States are situations in which the agent finds itself. Actions are what the agent can do. Rewards are the feedback from the environment. Policies are the strategies that the agent employs to determine the next action based on the current state.