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Reinforcement Learning: From Theory to Applications

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Abstract

In artificial intelligence, reinforcement learning (RL) has become a dynamic and revolutionary paradigm that has the potential to enable intelligent decision-making in dynamic and complicated contexts. By investigating its surroundings at random and drawing on past experiences, RL keeps learning new things. Because of its many features—including self-improvement, online learning, and little programming effort—Reinforcement Learning has emerged as one of the most intelligent agents. Examine the current works that address innate difficulties and those that concentrate on a variety of applications. Because reinforcement learning is self-improving, web-based, and requires less programming work, it may function as an intelligent agent in core technologies. Even with the development of more reliable and effective algorithms, more work has to be done. Artificial intelligence concepts are becoming simpler and less universal due to the influence of reinforcement learning.

Keywords: Reinforcement learning, Artificial intelligence, Algorithms, Supply chain management.

1 Introduction

Over the last few decades, reinforcement learning, or RL, has gained popularity in a variety of domains, including as robotics, recommender systems, resource allocation, video compression, smart grids, finance, autonomous driving, and communication and networks. It has also been extensively used in a broad range of other disciplines, including "edge computing, satellite docking, energy management, wireless security, traffic signal control, transportation scheduling, and chemical processes". But how to ensure safety when RL is used in practical applications is a difficult issue in this field. After all,

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neglecting to consider safety during RL applications in real-world circumstances might result in intolerable tragedies. Safeguards against human injury caused by robot interactions in human-machine interaction settings, the restriction of recommender systems from making recommendations to users that are inaccurate or biased based on race, and the operation of self-driving cars in real-world settings are all examples of such measures. More precisely, we provide a number of safety concepts from several angles that may be useful for safe reinforcement learning studies [1].

RL's original idea was based on trial-and-error using lessons learned from animal behavior. In- vented neural-analog reinforcement calculators based on trial-and-error learning. Later, advancements such as Q-learning turned reinforcement learning into a computer model. An important turning point was the development of deep reinforcement learning (DRL), which allowed agents to deal with high-dimensional issues and partially overcome the dimensionality curse. DRL's versatility is shown by applications in a range of domains, such as robotics and gaming [2].

A subclass of machine learning techniques called reinforcement learning (RL) is rapidly gaining traction in a number of HEMS applications. The dual capacities of learning at higher levels of abstraction and learning from experience are included into this learning paradigm. Algorithmic agents may now assume the role of human beings in real-world settings, such as houses and buildings, in uses that were previously believed to be beyond the existing technological capabilities. With reinforcement learning (RL), an algorithmic creature may form decision sequences and behave based on experience much like a person. DNN has shown to be an effective technique in RL as it allows the RL agent to adapt to a wide variety of complex real-world applications. Furthermore, it has been suggested that RL may achieve artificial general intelligence, which is the ultimate aim. As a result, RL is now deeply ingrained in a wide range of application disciplines. Robotics has seen a great deal of its application. Particular uses for this field of work include [3].

2 Literature Review

(Ning & Xie, 2024) [4] An extensive overview of MARL and its applications is presented in this work. We follow the development of MARL throughout time, point out its advancements, and talk about associated survey efforts. We review task categorization, MARL means, spatial forms of MARL, and a few example stochastic games. Next, look at some problems that occur in MARL applications in detail. We also discuss important operational issues that are crucial to real-world MARL implementations, such computing complexity and hyperparameter tweaking. We next provide a thorough analysis of MARL's applicability to healthcare, biotechnology, chemical engineering, intelligent machines and gadgets, and societal concerns. This demonstrates MARL's broad potential and applicability in both present and future technological settings. We also provide a thorough analysis of benchmark settings from MARL research, which are useful for assessing MARL algorithms and showing how flexible MARL is for various use cases. Finally, we provide our outlook for MARL and talk about their associated methods and possible further uses.

(Gu et al., 2024) [1] A wide range of difficult decision-making situations have shown that Reinforcement

Learning (RL) is very successful. However, when RL is used in practical settings, safety issues are brought up, which is why there is an increasing need for safe RL algorithms in situations like autonomous driving and robotics. Although safe control has a long history, safe RL algorithm research is still in its infancy. In this work, we give a review of safe reinforcement learning (safe RL) from the viewpoints of techniques, theories, and applications, hoping to provide a solid basis for future safe RL research. First, we summarize the development of safe reinforcement learning from five perspectives and identify five key issues that need to be resolved before safe RL can be used in practical settings. These issues are dubbed "2H3W." Secondly, we examine the algorithm and theoretical advancements in light of addressing the "2H3W" issues. Specifically, an overview and discussion of safe RL algorithm sample complexity is presented, after which safe RL algorithm applications and benchmarks are introduced. In the hope of spurring more study on this topic, we now open the debate of the difficult issues in safe reinforcement learning. We provide the implementations of the main safe RL algorithms in an open-sourced repository at the link to further the research on safe RL algorithms.

(Al-Hamadani et al., 2024) [5] With simultaneous sampling, assessment, and feedback, RL can handle sequential decision-making issues because to this special characteristic. Consequently, RL approaches are now good options for creating potent solutions across a range of fields. We provide an extensive and methodical analysis of RL techniques and applications in this work. This study begins with an examination of the principles of reinforcement learning. It then goes on to analyze each algorithm in depth and ends with a comparison of RL algorithms based on many factors. The two main uses of RL that are covered in this paper are robotics and healthcare. Reinforcement learning (RL) improves accuracy and flexibility in robotics manipulation tasks including grabbing objects and self-learning. By focussing on the topic of cell growth problems in healthcare, this research clarifies how RL has provided a data-driven approach to enhancing "cell culture growth and developing therapeutic solutions". This paper provides a thorough perspective, illuminating how RL is developing and its promise in two distinct but related disciplines.

(Moerland et al., 2023) [6] "Markov Decision Process (MDP)" optimisation, which is often used to describe sequential decision making, is a major problem for artificial intelligence. Two key approaches to addressing this problem are reinforcement learning (RL) and planning. Model-based reinforcement learning, as it is often called, is the synthesis of both domains in this review. Two major phases comprise model-based RL. First, we go into great detail on dynamics model learning approaches, including topics like managing uncertainty, stochasticity, partial observability, and temporal abstraction. Second, we provide a structured categorisation of the planning-learning insertion, including subjects like how to prepare, how much time and money to allocate to planning and data collection, and how to include strategy into the action and learning loop. Beyond these two components, we also explore included "model-based RL" as a complete replacement for model design and learning, as well as the potential benefits of model-based RL. The survey also makes links along the way to a number of related disciplines in reinforcement learning, including hierarchical RL and transfer learning. The survey provides a broad conceptual picture of planning and learning for MDP improvement, all things considered.

(Rolf et al., 2023) [2] For supply chain decision-makers, high degrees of complexity, a combination of discrete and continuous processes, integrated and interrelated activities, dynamism, and adaptability present difficulties. New opportunities for flexible data-driven decision-making are being created by developments in processing power, intelligent algorithms, and data availability. Among the data-driven methods is the machine learning algorithm family known as Reinforcement Learning. The present status of reinforcement learning in supply chain management (SCM) is examined in this semi-systematic literature review, which also suggests a categorization scheme. Academic articles are categorized by the framework according to data sources, algorithms, supply chain drivers, and industrial sectors. A few important revelations came from the examination that was done. First, the conventional Q-learning algorithm continues to be the most commonly used algorithm. Second, inventory management is the most often used reinforcement learning application in supply chains as it is crucial to supply chain synchronization. Finally, the majority of evaluated publications tackle SCM issues that resemble toys and are fueled by synthetic data. The transition to industry-scale difficulties will thus be a major undertaking in the coming years. Real-time, data-driven decision-making may become a reality if this change is effective.

(Sivamayil et al., 2023) [7] They could thus become inflexible and unable to adapt to new circumstances or unanticipated developments. RL is able to go beyond these obstacles. Using an RL agent to learn to make decisions based on occupancy and temperature sensor data, EMS may be implemented by changing the HVAC system's settings. Reactive learning (RL) is a hot topic in smart building research and has shown promise in reducing building energy use. By developing an ideal control strategy to maximize battery life and fuel economy, reinforcement learning (RL) may be used to enhance energy management in hybrid electric vehicles (HEVs). RL has established a noteworthy presence in gaming applications, robotics, and autonomous vehicles. Most programs linked to security run in a virtualized environment. Recommender systems based on reinforcement learning provide diverse and accurate recommendations. This page helps the layperson understand the principles and uses of reinforcement learning.

(Al-ani & Das, 2022) [8] This study is motivated by the recent rapid growth of reinforcement learning (RL) in numerous energy applications and the increasing penetration of home automation. It examines how RL is used in different home energy management system (HEMS) scenarios. In reinforcement learning, the focus is on "deep neural network (DNN) models". The paper provides a summary of reinforcement learning. The most recent approaches to deep reinforcement learning (DRL) value, policy, and actor-critic methodologies are then discussed. To help the HEMS community better understand the published content in reinforcement learning, verbal explanations are complemented with mathematical expressions using standard machine learning terminology and with illustrative images. The use of reinforcement learning in several HEMS fields is then covered in depth. An additional consideration in the research is the type of "reinforcement learning algorithms" that are used in each HEMS application. It implies that there is still more to learn about this area of study. In conclusion, the paper suggests four performance measures for assessing RL techniques.

(Singh et al., 2021) [9] AI researchers believe that there is a close relationship between human and artificial intelligence learning patterns. They have determined that self-learning systems may be efficiently created using machine learning (ML) techniques. This paper presents an overview of reinforcement algorithms' use in robotics research. This study provided a thorough analysis based on the following segments: (1) development of RL Actor-Critic, DeepRL, multi-agent RL, and human-centered algorithms are examples of (2) RL algorithm types. (3) a range of RL robotics applications depending on the platforms on which they are employed, such as air, sea, and land; (4) RL algorithms and mechanisms used in robotic applications. Finally, a candid conversation is offered, which may bring up a number of prospective avenues for robotics study in the future. The purpose of this survey is to provide a foundation for further research that will take a more relevant course.

(Gourav & Kaur, 2020) [3] An essential component of artificial intelligence is machine learning. The exploration of projects is what enables computers to communicate in a human-like manner. Machine learning has emerged as a significant technological advancement with a wide range of applications. One of the main uses of machine learning is reinforcement learning, which gives computers and software agents the ability to operate explicitly and decide how to behave in certain scenarios in order to perform as well as possible. Because reinforcement learning is self-improving, web-based, and requires less programming work, it may function as an intelligent agent in core technologies. Even with the development of more reliable and effective algorithms, more work has to be done. Thus, the main objective of this study is to provide an overall description of reinforcement learning along with its uses using a range of machine learning techniques.

(Hammoudeh, 2018) [10] This paper aims to present, assess, and summarise many research findings and articles on reinforcement learning. Artificial intelligence includes reinforcement learning, which has shown promise in the development of artificially intelligent systems and the resolution of sequential decision-making issues. In recent years, reinforcement learning has made many remarkable strides, surpassing human ability in several domains, including gaming and winning in different games. In the past, reinforcement learning has proven successful in addressing specific problems with control systems. These days, its variety of uses is expanding. This paper contains an introduction to reinforcement learning that illustrates both the basic ideas and the intuition behind reinforcement learning. The astounding achievements of reinforcement learning are then emphasized. As a result, strategies and specifics for resolving issues with reinforcement learning are compiled. From this point forward, information from a large number of papers in many applications of reinforcement learning was examined. Lastly, the potential and difficulties of reinforcement learning are explored.

3 Conclusion

With a rich theoretical foundation, many applications, a lengthy history, notable accomplishments, innovative algorithms, and a plethora of unsolved issues, reinforcement learning is a vast field. This research examines many methods for reinforcement learning that may reduce the number of states in a test, increase learning productivity at the start of the test, and speed up convergence. In order to build the likely field of artificial intelligence and establish the Q values based on the prior knowledge, multi-agent

Q-learning algorithms are also covered. By enhancing the link between the theoretical aspects of "Multi-agent Reinforcement Learning (MARL)" as well as its practical implementation in many real-world contexts, this review has the potential to greatly accelerate the development of MARL research and technology. In supply chains, inventory management is the most popular use of reinforcement learning as it is crucial to supply chain synchronization. Artificial intelligence concepts are becoming simpler and less universal due to the influence of reinforcement learning.

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