RADemics

Asynchronous Deep Reinforcement Learning for Real-Time Adaptation in Resource-Constrained Autonomous

Asma Anjum, Sangeetha R
VISVESVARAYA TECHNOLOGICAL UNIVERSITY, VELALAR COLLEGE OF ENGINEERING AND TECHNOLOGY

8. Asynchronous Deep Reinforcement Learning for Real-Time Adaptation in Resource-Constrained Autonomous

[1]Asma Anjum, Assistant Professor, Department of Computer Science and Engineering, HKBK College of Engineering, Visvesvaraya Technological University, Bangalore 560045, Karnataka, India, asmacs13@gmail.com

[2]Sangeetha R, Assistant Professor, Department as Information Technology, Velalar College of Engineering and Technology, Erode, Tamil Nadu, India, sangeetha8189@gmail.com

Abstract

This chapter explores the transformative role of Asynchronous Deep Reinforcement Learning (A-DRL) in optimizing resource allocation within resource-constrained environments, specifically focusing on its application in autonomous systems. As the complexity of real-time adaptation in dynamic settings grows, A-DRL emerges as a powerful tool for overcoming computational limitations while ensuring efficient decision-making. The chapter delves into the key advantages of A-DRL, including reduced synchronization costs, enhanced scalability, and the ability to handle high-dimensional state and action spaces. Additionally, the discussion highlights its impact on smart cities, where A-DRL optimizes energy distribution, traffic flow, waste management, and other urban resources. The benefits of A-DRL for real-time feedback loops and efficient resource utilization in autonomous systems are underscored, presenting it as a critical approach for the future of sustainable, adaptive technologies.

Keywords:

Asynchronous Deep Reinforcement Learning, Resource-Constrained Environments, Autonomous Systems, Real-Time Adaptation, Smart Cities, Resource Allocation.

Introduction

Asynchronous Deep Reinforcement Learning (A-DRL) has emerged as a transformative approach in enhancing the efficiency and adaptability of autonomous systems operating in resource-constrained environments [1,2]. The rise of such systems has led to an increased demand for technologies that can handle real-time decision-making while minimizing computational overhead [3,4]. Traditional deep reinforcement learning (DRL) methods often face challenges when deployed in environments where resources, such as processing power and memory, are limited [5,6]. These constraints often lead to inefficient decision-making, which was problematic in real-world applications that require rapid responses [7,8]. A-DRL mitigates this challenge by enabling asynchronous updates in learning processes, significantly improving efficiency and responsiveness [9-12]. Through this technique, systems can adapt to environmental changes without waiting for global synchronization, making it a perfect fit for autonomous systems [13].

Autonomous systems, such as self-driving cars, drones, and smart city infrastructures, rely heavily on real-time adaptation to make decisions that affect their performance [14,15]. These systems must react dynamically to changes in their environment, whether it's adjusting traffic signals in a smart city or altering the flight path of a drone [16]. Real-time adaptation was particularly important in environments with limited resources, as these systems need to operate efficiently without overburdening the available computational resources [17,18]. A-DRL facilitates this by allowing multiple agents to learn and adapt independently, which reduces the strain on system resources and ensures faster, more efficient decision-making [19-21]. This decentralized approach ensures that each agent focuses on local adaptation, thus improving overall system performance and reducing the time needed for synchronization [22].

By allowing agents to update their policies asynchronously, the learning process becomes much more efficient [23]. Agents can continue learning and improving even when other agents are processing data or updating their policies [24]. This asynchronous process prevents the bottleneck that occurs in traditional DRL methods, where all agents must synchronize before making any updates [25]. A-DRL enables better handling of high-dimensional state and action spaces, which are often encountered in complex autonomous systems. These systems need to make decisions based on vast amounts of data, and A-DRL allows them to process this data more efficiently, leading to faster and more accurate decision-making.