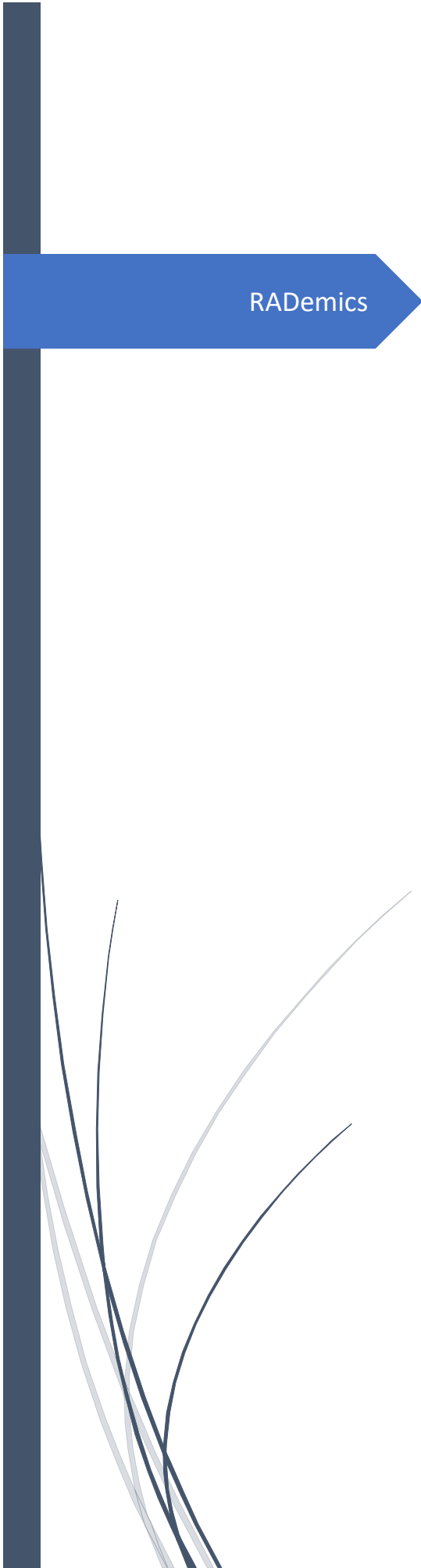




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Multi-Agent Deep Reinforcement Learning for Cooperative and Competitive Autonomous Systems

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Abstract

This book chapter delves into the critical aspects of Multi-Agent Deep Reinforcement Learning (MADRL), focusing on its application in cooperative and competitive autonomous systems. The chapter explores the theoretical foundations of MADRL, highlighting key challenges such as scalability, non-stationarity, and credit assignment. Various learning paradigms are discussed, including Centralized Training with Decentralized Execution (CTDE), and advanced algorithms like Multi-Agent Actor-Critic (MAAC). Emphasizing the importance of communication and coordination, the chapter also investigates decentralized communication mechanisms and their trade-offs in large-scale systems. It covers the essential techniques and algorithms for both cooperative and competitive multi-agent interactions, offering solutions to issues such as stability and convergence. This comprehensive analysis aims to provide valuable insights into the design, optimization, and implementation of MADRL in autonomous systems, addressing both theoretical challenges and practical applications.

Keywords:

Multi-Agent Systems, Deep Reinforcement Learning, Cooperative Systems, Competitive Systems, Stability, Decentralized Communication.

Introduction

Multi-Agent Systems (MAS) have become fundamental in addressing complex decision-making problems in autonomous environments [1]. These systems consist of multiple agents that interact with each other and their surroundings to achieve individual or collective goals [2]. In fields like robotics, transportation, and smart cities, MAS enable more efficient and adaptive solutions by leveraging the collective intelligence of agents [3-5]. In recent years, the integration of Deep Reinforcement Learning (DRL) into multi-agent systems has significantly enhanced their ability to learn complex behaviors [6]. MADRL leverages the power of deep learning models to approximate complex value functions, allowing agents to make informed decisions based on their experiences [7-9]. This approach has gained traction due to its success in various high-dimensional

environments where traditional methods struggle to scale [10]. The ability to model complex interactions, both cooperative and competitive, was crucial for the success of autonomous systems operating in real-world settings [11].

One of the primary challenges was non-stationarity; each agent's actions impact the environment and the other agents, creating a constantly changing dynamic [12]. This contrasts with single-agent environments, where the dynamics are more predictable [13]. In MAS, agents must adapt to not only the environment but also the strategies of other agents [14]. Additionally, credit assignment becomes more complicated in multi-agent settings [15]. It becomes difficult to attribute rewards to individual agents when multiple agents are involved in achieving a collective goal [16]. This problem was exacerbated when agents must collaborate or compete, as the impact of one agent's actions be diffused across the group [17]. These challenges necessitate the development of new techniques and algorithms capable of handling such complexities, making MADRL a vibrant research field [18].

MADRL can be categorized based on the nature of interactions among agents, which are typically classified as either cooperative or competitive [19]. In cooperative multi-agent systems, agents work together towards a shared objective, often requiring complex coordination and communication strategies [20-22]. Cooperative behavior in MADRL aims at maximizing the overall system performance by aligning individual rewards [23]. Key challenges in cooperative settings include managing the credit assignment problem and ensuring effective communication [24,25]. On the other hand, competitive multi-agent systems involve agents with conflicting objectives, where each agent seeks to outperform the others. These systems are often modeled using game-theoretic approaches, where agents are considered to be participants in a non-cooperative game. In such environments, ensuring stability and equilibrium in agent interactions becomes a critical challenge. Addressing these distinct interaction types was essential to the development of MADRL algorithms that can perform effectively in both types of settings.