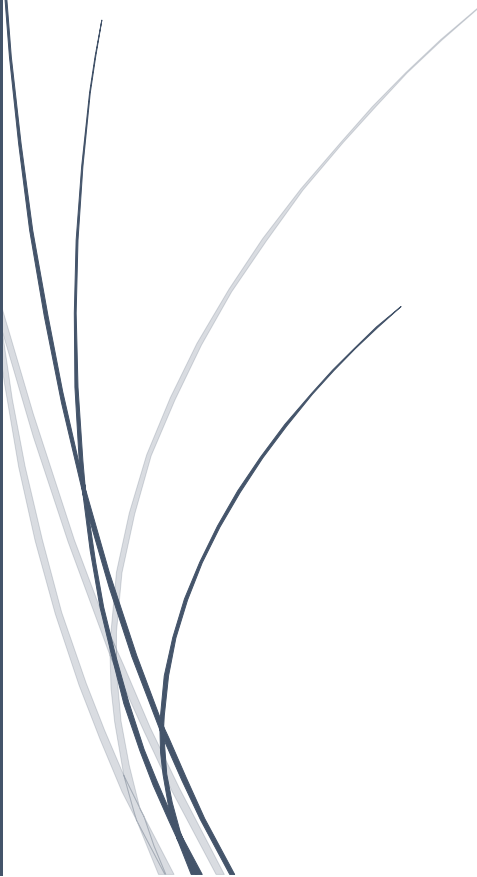


The logo consists of a dark blue vertical bar on the left and a blue arrow pointing right, containing the text "RADemics".

RADemics

Curriculum Learning Strategies for Accelerating Policy Development in Autonomous Decision Systems

An abstract graphic in the bottom left corner featuring several thin, curved lines in dark blue and light grey, resembling stylized grass or reeds.

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7. Curriculum Learning Strategies for Accelerating Policy Development in Autonomous Decision Systems

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Abstract

This chapter explores the integration of Curriculum Learning (CL) strategies with Reinforcement Learning (RL) to accelerate policy development in Autonomous Decision Systems (ADS). By leveraging a structured learning progression, CL enhances the efficiency of RL algorithms, enabling autonomous systems to master complex tasks more effectively and reliably. The chapter delves into key methodologies such as task difficulty scaling, dynamic environment adaptation, and the incremental introduction of complexity, offering practical insights for various applications. Case studies across domains like robotics, healthcare, and autonomous vehicles highlight the synergy between CL and RL, demonstrating their potential to optimize decision-making, improve generalization, and reduce training time. The chapter further emphasizes the transformative impact of CL-RL integration on real-world systems, pushing the boundaries of autonomous decision-making in uncertain and dynamic environments. This research contributes to advancing the capabilities of autonomous systems through intelligent learning strategies, with implications for both theory and practice.

Keywords: Curriculum Learning, Reinforcement Learning, Autonomous Decision Systems, Policy Development, Task Complexity, Real-World Applications.

Introduction

Autonomous Decision Systems (ADS) are revolutionizing industries by enabling machines to make decisions without human intervention [1]. These systems are employed in applications ranging from robotics and autonomous vehicles to healthcare and smart cities [2,3]. The goal of ADS was to create systems that can learn and adapt in real-time, processing vast amounts of data to make accurate decisions [4,5]. However, the complexity of real-world environments presents significant challenges for these systems [6]. must navigate uncertain conditions, make decisions based on incomplete or noisy data, and adapt to dynamic and evolving scenarios [7]. Traditional learning methods, while effective, often struggle to meet the demands of these highly complex systems, particularly in terms of efficiency and adaptability [8-10]. The need for robust learning

strategies that can handle increasing task complexity and uncertainty was crucial to the success of autonomous systems [11].

Curriculum Learning (CL) has emerged as a promising solution to address the challenges faced by ADS [12]. CL draws inspiration from human learning, where individuals gradually acquire skills by starting with simpler concepts and progressively moving to more difficult ones [13,14]. In the context of ADS, CL offers a structured framework for training these systems by first introducing easy tasks and then incrementally increasing their difficulty as the system's performance improves [15-18]. This staged approach ensures that the system develops foundational skills before tackling more complex and higher-stakes decision-making scenarios [19]. By providing a clear progression of learning, CL helps prevent systems from becoming overwhelmed by the intricacies of challenging tasks, allowing them to learn more efficiently and effectively [20-22]. This methodology ensures better generalization of learned behaviors and helps autonomous systems handle real-world complexities with greater accuracy [23].

The integration of Curriculum Learning (CL) with Reinforcement Learning (RL) offers a powerful approach for enhancing the capabilities of Autonomous Decision Systems (ADS) [24,25]. While RL enables systems to learn optimal policies through trial-and-error, where rewards are used to reinforce desired behaviors, it often faces challenges related to sample inefficiency and slow learning speeds. CL addresses these limitations by providing a structured learning pathway, starting with simple tasks that progressively build toward more complex ones. By combining CL with RL, autonomous systems can learn faster and more effectively. RL optimizes decision-making in dynamic environments, while CL ensures that the learning process was gradual, allowing systems to refine their understanding and adapt to increasingly difficult scenarios. This synergy leads to improved performance, particularly in environments that require long-term decision-making and real-time adaptation. The combination of CL's progressive learning structure and RL's reward-based feedback mechanism forms a comprehensive approach for accelerating the training of ADS, leading to better performance in real-world applications.