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Editorial

Why Reinforcement Learning?

Mehmet Emin Aydin [1,*], Rafet Durgut [2] and Abdur Rakib [3]

[1] School of Computer Science and Creative Technologies, University of the West of England, Bristol BS16 1QY, UK
[2] Crystalloids BV, 3013 AK Rotterdam, The Netherlands; durgutrafet@gmail.com
[3] Centre for Future Transport and Cities, Coventry University, Coventry CV1 5FB, UK; ad9812@coventry.ac.uk
* Correspondence: mehmet.aydin@uwe.ac.uk

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The term Artificial Intelligence (AI) has come to be one of the most frequently expressed keywords around the globe. Machine learning (ML) continues to gain popularity in the provision of solutions to both industrial and everyday problems, and advancements in infrastructure computing technologies have driven a surge of interest in AI, ML, and particularly large language models (LLMs). This involves huge data stocks and bulky data processing. However, many real-world problems lack the necessary existing data for modelling and model training. Furthermore, numerous dynamic problems do not retain data for later use due to constantly evolving circumstances, resulting in significant challenges in identifying or uncovering patterns (domain knowledge) within such dynamic structures and situations. These problems remain as significant and outstanding challenges.

Reinforcement learning is a type of active learning whereby a trainee agent learns by performing desired tasks. This is very useful, especially when labelled data are unavailable or difficult to obtain beforehand but can only be accessed while running the system. Moreover, it is particularly useful for dynamic and non-stable problems, as well as online and ever-changing cases. Robotic and gaming applications are two well-known areas of application, and researchers are increasingly focusing on numerous emerging use cases [1].

Reinforcement learning (RL), a modern machine learning paradigm, enables an AI-driven system (known as an agent) to learn in an interactive environment via trial and error using feedback from its own actions and experiences [2]. The basic idea behind RL is to train the agent by a reward-and-punishment mechanism [3] whereby the agent receives rewards for performing correct actions and is punished for incorrect ones. Through this process, the agent aims to maximize appropriate choices while minimizing incorrect ones. This has paved the way for allowing learning agents to adapt to changing circumstances in order to fulfil a specific goal, as, based on the feedback responses, the agent assesses its performance and responds appropriately [4].

The well-known application domains of RL appear to be self-driving cars, robotics for industrial automation, business strategy planning, trading and finance, aircraft and robot motion control, healthcare, and gaming, among others [1,5,6]. In fact, research on RL has expanded in a variety of areas, making it a prominent topic in studies of AI, ML, multi-agent systems, and data science. RL researchers have developed theories, algorithms, and systems to address real-world problems that require learning through feedback over time.

Although RL is not yet widely used in real-world applications, research on RL has shown promising results. In the creation of this Special Issue, we received several submissions and have successfully accepted five application articles along with one review article, which can be seen in the list of contributions below. The application articles—listed as contributions 1, 2, 3, 4 and 5—detail the approaches/methodologies employed to utilise the emerging capabilities of reinforcement learning for targeted application scenarios. Each application case is very distinct, ranging from economic models to continuous control problems. Additionally, the review article—contribution 6—elaborates how inverse reinforcement learning can help design and develop the theory of mind, as it is recognised to help identify the preferences of decision makers from their behaviours, thereby unveiling the cognitive maps of decision makers.

We would like to extend our heartfelt gratitude to the anonymous reviewers for their invaluable contributions to the review process in this Special Issue. Your excellent evaluations, constructive feedback, and unwavering commitment to academic excellence have significantly enhanced the quality and rigor of the published works.

Conflicts of Interest: The authors declare that they have no conflict of interest.

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