COMP4082 Autonomous Robotic System

University of Nottingham Malaysia

Reinforcement Learning using Gymnasium Environments

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Redefining Activation Dynamics: An Empirical Comparison of Oscillating, Mixture, and Adaptive Activation Functions in Deep Reinforcement Learning

Research Paper:

1. Biologically Inspired Oscillating Activation Functions can Bridge the Performance Gap between Biological and Artificial Neurons
2. A survey on recently proposed activation functions for Deep Learning
3. Adaptive activation functions in convolutional neural networks

Background Studies

In the realm of neural networks, recent studies have delved into the untapped potential of oscillating and adaptive activation functions. One notable paper, "Biologically Inspired Oscillating Activation Functions," introduces oscillating functions that mimic the dynamics of biological neurons, challenging conventional activation methods. These novel functions, inspired by the complex behaviour of biological neurons, are proposed to narrow the performance gap between biological and artificial neural networks. The paper's empirical evaluations suggest these biologically inspired functions could enhance artificial neural network performance in specific tasks, paving the way for more sophisticated architectures.

Another significant contribution is the comprehensive survey "A Survey on Recently Proposed Activation Functions for Deep Learning." This work compiles and analyzes the latest advancements in activation functions, providing insights into their theoretical underpinnings and practical applications. It serves as a crucial guide for practitioners and researchers, helping them navigate the evolving landscape of neural network activation functions.

In the context of convolutional neural networks (CNNs), the study "Adaptive Activation Functions in Convolutional Neural Networks" investigates the impact of adaptive functions that dynamically adjust during learning. This research explores various strategies, including mixed, gated, and hierarchical activation functions, highlighting their potential to improve CNNs' learning efficiency and accuracy.

Overall Gaps that have been found:

Despite these advancements, several gaps remain in the field. Firstly, there's a lack of comprehensive performance evaluation of oscillating activation functions in Deep Q-Networks (DQNs), particularly in comparison with traditional functions in controlled environments. Secondly, the efficacy of mixture activation functions, which combine traditional and oscillating types, is yet to be thoroughly analyzed in the context of DQNs. Lastly, the application and impact of adaptive activation functions in DQNs need more exploration, especially regarding their integration with both traditional and oscillating counterparts. Addressing these gaps could significantly advance our understanding and application of activation functions in neural networks.

Research question:

1. How do oscillating activation functions compare to traditional activation functions in terms of enhancing Deep Q-Network (DQN) performance in standardized control tasks?
2. What performance differences, if any, are observable when employing mixed activation functions in DQN architectures?
3. In the context of DQN, do adaptive activation functions with different mechanisms like gated activation and hierarchical demonstrate significant performance enhancements over static activation functions, particularly when utilizing gating mechanisms and hierarchical structures?

Justification:

The exploration of oscillating activation functions could provide a critical link in advancing artificial neural networks towards the complexity of biological neural computation. If such functions can indeed mirror or surpass the capabilities of traditional activation functions, they could significantly contribute to the development of more biologically plausible models. This is particularly relevant for DQNs, which stand as a robust empirical framework for evaluating activation function performance due to their success in various control tasks provided by OpenAI Gym benchmarks.This research will also aim to explore whether mixture activation functions will provide better performance in an artificial neural network. Additionally, this research will explore whether the integration of adaptive Gated mechanisms and Hierarchical structure can render DQN architectures more flexible and efficient in learning. Through comprehensive experiments involving environments such as the Cart Pole, we will assess whether these innovative activation functions can lead to performance improvements, thereby guiding future neural network design strategies.

Classic control:

Classic control to be used is the **Cart Pole environment** for creating a DQN algorithm for the minesweeper. Both environments have been used to train DQN agents. DQN agents have been successfully trained to solve both the Cart Pole environment and the Acrobat environment.