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

Overall Gaps:

1. Performance Evaluation of Oscillating Activation Functions: There is a scarcity of empirical data on the utility of oscillating activation functions in DQNs by comparing their performance with that of conventional activation functions in standardized control environments.
2. Mixture Activation Functions' Efficacy: While mixture activation functions have been proposed, their comparative analysis, especially using the traditional and oscillating counterparts in the context of DQNs, remains under-explored.
3. Adaptive Activation Functions in DQNs: The application and impact of adaptive activation functions, which dynamically adjust their behaviour during learning, have not been thoroughly investigated in DQNs, particularly in combination with both traditional and oscillating functions.

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.