Student name - Logan Place

Enrolment number - 30138122

Your course - MSc Artificial Intelligence

Your Project

Project Title - Continual Learning in Reinforcement Learning Environments using Liquid Neural Networks

Project Aim - Evaluate the effectiveness of Liquid Neural Networks (LNNs) in adaptation and addressing the problem of catastrophic forgetting during continual learning within reinforcement learning (RL) environments.

Project Objectives

- Conduct a literature review on continual learning as well as LNNs
- Develop a baseline RL agent for comparison with LNN model
- Implement an RL agent using LNN architecture, utilizing the npcs Python library
- Incrementally introduce tasks to RL agents for on-demand adaptation
- Evaluate the adaptability and memory retention of both RL agents for comparison

Project Artefact type - Implementation (software prototype of an RL agent using LNNs).

Brief description of your project (no more than 500 words), this should try and address the lifecycle of a project e.g. analysis (research), design, development, evaluation/testing, what will you do in each of these areas:

This project aims to evaluate the performance of Liquid Neural Networks (LNNs) in a reinforcement learning environment with continual learning tasks, aiming to address the problem of catastrophic forgetting, which is prevalent in this domain. Continual learning is a field in which AI models are incrementally given new tasks and are forced to adapt and solve them without training from scratch. Spawning from this domain is the catastrophic forgetting problem, in which AI agents can adapt to new information/tasks, but when evaluated on previously learned tasks, any previous knowledge is forgotten, and performance plummets. Transfer learning in image classification is a fine example of how, after adapting a model to a new group of classes, any previously learned classes will be completely forgotten, and accuracy will drop off steeply.

LNNs are biologically inspired neural network models that process information in continuous time, showing great promise in dynamic environments, proving to be a promising architecture in continual learning scenarios. Even after training, LNNs have demonstrated the ability to adapt to new information without the need for fine-tuning the way traditional models would need to be updated. The core hypothesis is that LNNs and their time-based functionality would make them much better at adapting to tasks, and more resilient in forgetting previously learned tasks.

The project lifecycle:

Analysis/Research - An extensive and comprehensive literature review of current approaches in continual learning, identifying core problems (such as catastrophic forgetting) within the domain and steps taken to mitigate them. There is a limited amount of research on LNNs in general, so a focus will be put on similarly biologically inspired architectures such as Spiking Neural Networks (SNNs), which show great promise in the field of continual learning and addressing catastrophic forgetting.

Design - The architecture for the baseline agent and LNN-based agent will be planned. This includes choosing RL environments such as CartPole, MiniGrid, or similar OpenAI Gym tasks that can be modified to simulate new task introductions over time.

Development - The implementation will begin by developing a traditional RL agent that will be used as a comparison/reference model for both adaptability and memory retention. A LNN-based agent will then be developed with the ncps Python library, containing pre-written definitions for LNN neurons that can be easily integrated with existing PyTorch or TensorFlow frameworks. OpenAI Gym environments will be modified to introduce tasks (e.g. pole length change in CartPole) incrementally over time.

Evaluation/Testing - Each RL agent will be evaluated for accuracy, adaptability, and memory retention on previously seen/learned tasks. Continual learning strategies like task replay and weight freezing may be implemented to improve memory retention. Domain-specific metrics will be used to ensure proper evaluation of each model.

The outcome is to result in a functioning LNN-based RL agent capable of continual learning with memory retention to combat the catastrophic forgetting problem, suggesting LNNs to be a viable alternative to current/traditional deep learning techniques in continual learning.

Legal, Social, Ethical and Professional Issues -

Since this project doesn’t involve any human participants, personal data, or real-world deployment, the direct legal and ethical risks are very low. All experiments will be carried out in simulated environments using open-source tools like OpenAI Gym and PyTorch, which means there are no concerns around data privacy, informed consent, or participant safety.

That said, there are still some broader ethical and professional responsibilities to keep in mind. Continual learning systems (especially ones that can adapt over time) could have real-world applications down the line, such as in robotics or autonomous systems. If these models aren't carefully designed and evaluated, they might forget important information or behave unpredictably in changing environments. While this project is strictly academic, it's still important to make sure the models are tested fairly, results are reported honestly, and everything is well-documented and reproducible.

All tools, frameworks, and research sources will be properly cited, and the project will adhere to the university’s guidelines for responsible research. Care will be taken to ensure that the work is accurate, ethically conducted, and reflects positively on the institution.

You may find it useful to consider the following aspects when completing this section:

- protect the dignity, rights, safety and well-being of participants
- inform participants about the purpose, methods and use of the research
- obtain informed consent from participants
- safeguard the anonymity of participants
- protect the confidentiality of information relating to participants
- ensure compliance with data protection
- protect researchers, particularly those conducting research off campus
- protect the reputation of the University

Commercial Risk -

There is minimal commercial risk associated with this project. It uses only open-source tools and publicly available environments and is not intended for direct commercial application. However, since continual learning and Liquid Neural Networks are emerging areas in AI, the research could contribute insights valuable to future industry applications.

Project Plan -

Task	Start Date	End Date	Start Day	Duration
Project Planning & Literature Review	2025-06-02	2025-06-15	1	14
Environment Setup & Tool Familiarization	2025-06-09	2025-06-20	8	11
Baseline RL Agent Implementation	2025-06-16	2025-06-30	15	14
Liquid Neural Network Integration	2025-06-23	2025-07-04	22	11
Continual Learning Strategy Design	2025-06-30	2025-07-11	29	11
Report Writing & Documentation	2025-07-01	2025-08-31	31	61
Experimentation & Evaluation	2025-07-07	2025-08-01	36	25
Results Analysis & Interpretation	2025-07-28	2025-08-08	57	11
Final Review & Submission Preparation	2025-08-22	2025-09-05	82	14
Buffer Period & Contingency Planning	2025-09-01	2025-09-12	92	11

References -

Verwimp, T., van der Pol, E., Rajeswar, S., Yildiz, B., Wiggers, K. and Nowé, A., 2023. *Continual Learning: Applications and the Road Forward*. [online] arXiv. Available at: https://arxiv.org/abs/2311.11908

Kim, S., Wang, J., Rathi, N. and Roy, K., 2023. *Investigating Continuous Learning in Spiking Neural Networks*. [online] arXiv. Available at: https://arxiv.org/abs/2310.05343

Bansal, R., Ojha, R., Trivedi, A. and Bera, P., 2024. *Liquid Neural Network-based Adaptive Learning vs. Incremental Learning for Link Load Prediction amid Concept Drift due to Network Failures*. [online] arXiv. Available at: https://arxiv.org/abs/2404.05304

Proposed Project Supervisor (First Choice)

Dr. Mabrouka Abuhmida

Proposed Project Supervisor (Second Choice)

Dr. Carl Jones

Please complete ALL sections.