PROPOSAL FOR A MASTER'S THESIS SUBJECT

SUBJECT: Exploring Plasticity-Driven Spiking Neural Networks for Enhanced Machine Learning

Description:

Keywords: artificial neural-networks, spiking-neural-networks, synaptic plasticity, genetic-algorithms, machine learning.

Context

Spiking Neural Networks (SNNs) are highly valuable in machine learning due to their ability to capture temporal dynamics and process events, making them well-suited for tasks like event recognition and real-time processing. Furthermore, integrating brain-inspired local plasticity rules into SNNs can significantly enhance adaptability, particularly in autonomous and lifelong learning systems. However, the optimization of SNN architectures with plasticity for specific tasks is a complex endeavor, involving the intricate management of numerous parameters and dynamics. This project aims to tackle this challenge by implementing an SNN architecture generated through an optimization mechanism that leverages plasticity for learning and solving a particular task, ultimately with the aim of advancing the state of the art in this field.

Objectives

The objective of this thesis is to formulate a SNN architecture capable of incorporating a plasticity rule for acquiring the ability to solve a predefined task. To achieve this aim, an optimization approach, such as a genetic algorithm, will be employed to identify an architecture that effectively harnesses a local plasticity rule within the framework of an SNN. In our experimental setup, we will utilize the OpenAI Gym environment, which provides a selection of problem scenarios for evaluating machine learning solutions, such as the challenging Mountain Car problem. Within the scope of this research, our objective is to examine and compare the performance of the SNN plasticity-based solution against two other counterparts: a fixed (without plasticity) SNN architecture and architectures based on artificial neural networks (ANNs).

The proposed approach to achieve our goal is structured into five key steps:

1. **Understanding General Concepts**: Begin by gaining a comprehensive understanding of essential concepts, including the Leaky Integrate-and-Fire (LIF) model, Spiking Neural Networks (SNN), and Artificial Neural Networks (ANN).
2. **Tool Installation and Exploration**: Install and explore simulation tools, namely NEST for modeling SNN and PyTorch for modeling ANN. This step entails familiarizing oneself with the functionalities and capabilities of these tools.
   a. **Simulation Experimentation**: Conduct experiments using the NEST simulator to observe various aspects of neuron dynamics. This includes the examination of excitatory and inhibitory postsynaptic potentials (EPSP and IPSP), inducing direct currents (DC), and stimulating neurons using spike generators. Visualize both individual neuron behavior and collective network activity by generating raster plots of spikes.
   b. **Simple SNN Architecture Implementation**: Implement a basic SNN architecture in NEST, drawing upon the insights gained from step 3. Analyze the dynamics of the network based on this initial implementation.
3. **SNN Architecture for Mountain Car Challenge**: Develop and train an SNN architecture capable of solving the OpenAI-Gym Mountain Car challenge. Compare the performance of this SNN solution to other approaches employing ANNs as referenced in the existing literature.
4. **Local Plasticity Rule Implementation**: Implement a simple SNN architecture using a local plasticity rule.
5. **Optimization for Mountain Car Challenge**: Employ an optimization algorithm to search for an SNN architecture capable of successfully tackling the Mountain Car challenge through the utilization of local plasticity.

These steps collectively form the comprehensive strategy for achieving our research objectives.

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DESIRED SPECIFICITIES