EE-746 Project Presentation

Equilibrium Propagation for MNIST Classification

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Greetings!

- Our project presentation showcases Spike Based Equilibrium Propagation in Neural Networks.

- The papers we surveyed for the same are as follows -

- Scellier B, Bengio Y. Equilibrium Propagation: Bridging the Gap between Energy-Based Models and Backpropagation. Front Comput Neurosci. 2017 May 4;11:24. doi: 10.3389/fncom.2017.00024. PMID: 28522969; PMCID: PMC5415673.
- Martin, Erwann, Maxence Ernoult, Jer´ emie Laydevant, Shuai-shuai Li, ´ Damien Querlioz, Teodora Petrisor and Julie Grollier. “EqSpike: spike driven equilibrium propagation for neuromorphic implementations.” iScience 24 (2020): n. Pag.

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Back-Propagation and its Shortcomings

- Backpropagation is **not biologically plausible** in terms of the need for labeled data and the backward flow of error signals.

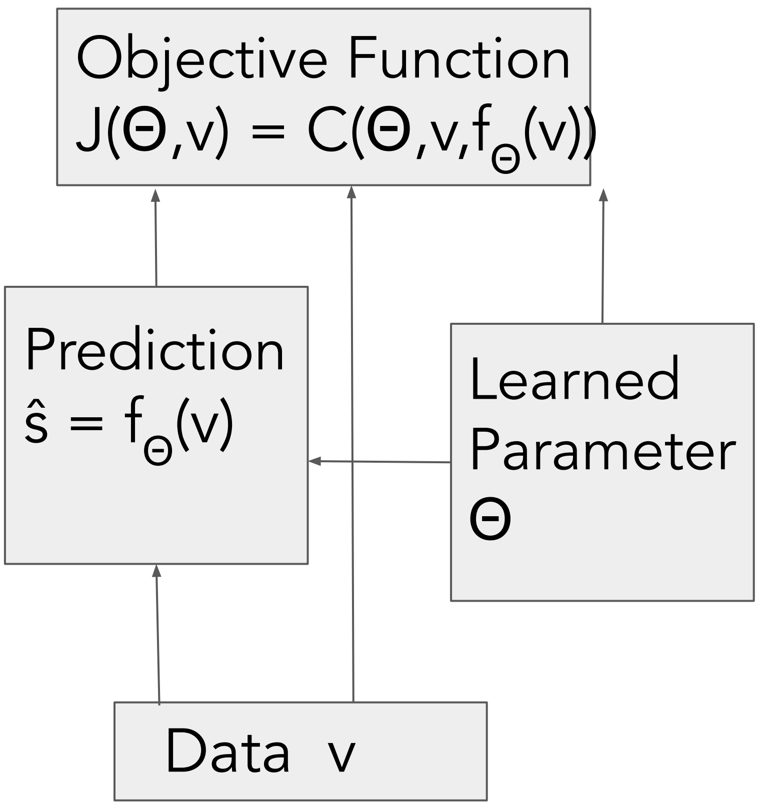
- Plain Vanilla Back-Propagation relies heavily on precise gradients when training deep neural networks on large datasets leading to **high power consumption**.

Equilibrium Propagation

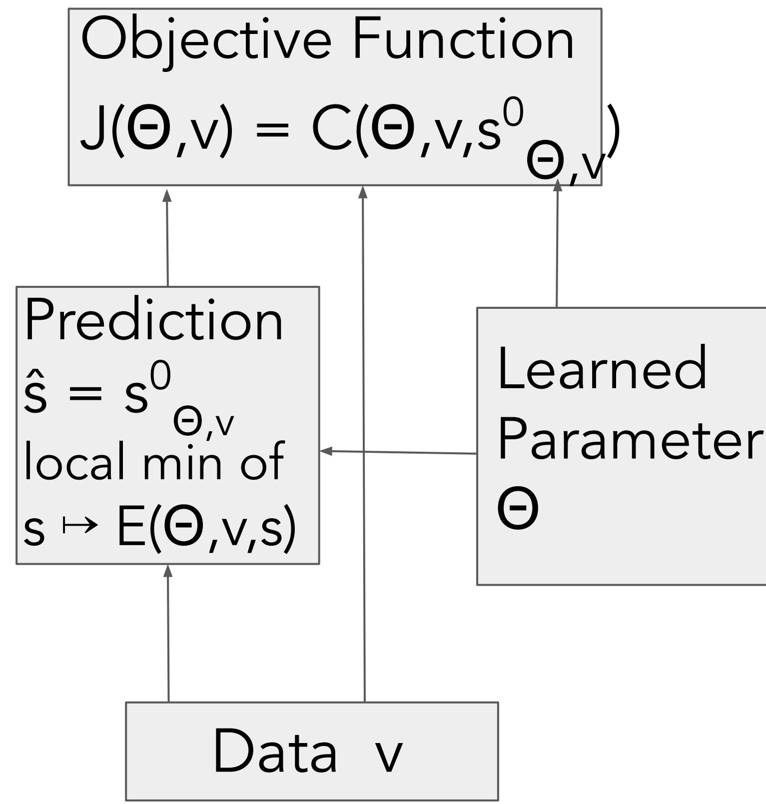
- Equilibrium propagation frames learning as an **energy-minimization** problem.
- Learning minimizes the difference between the current state and the target state through an iterative process.
- Spike-based neuromorphic computation proves to be outstandingly energy efficient on inference tasks.

IT IS BIOLOGICALLY FEASIBLE :)

Frameworks



Back-Propagation



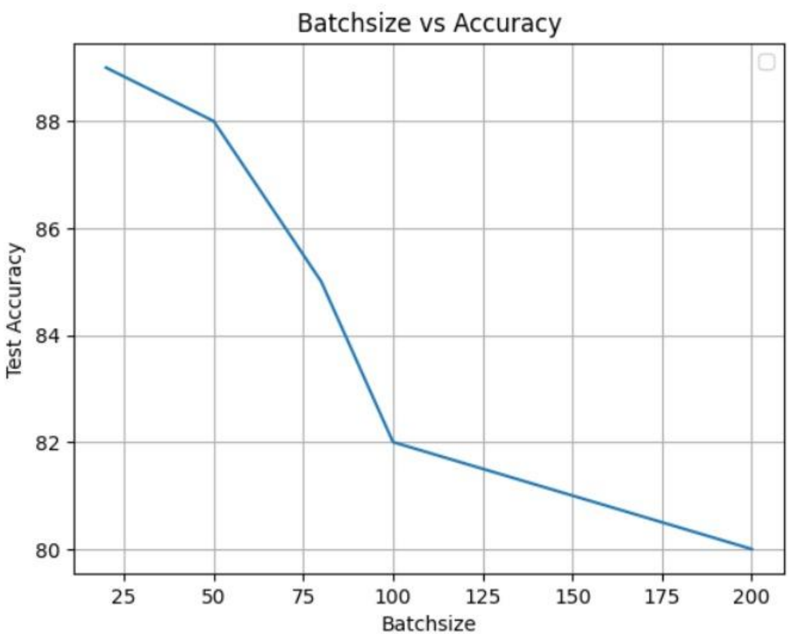
Equilibrium propagation

Implementation

- We use one hidden layer with 1024 neurons.
- There are 5 important hyper-parameters:
  - Batch Size
  - Forward Pass Time
  - Backward Pass Time
  - Clamping Factor - β
  - Learning Rate
- The entire code has been written from scratch without the use of any SOA NN model or optimization

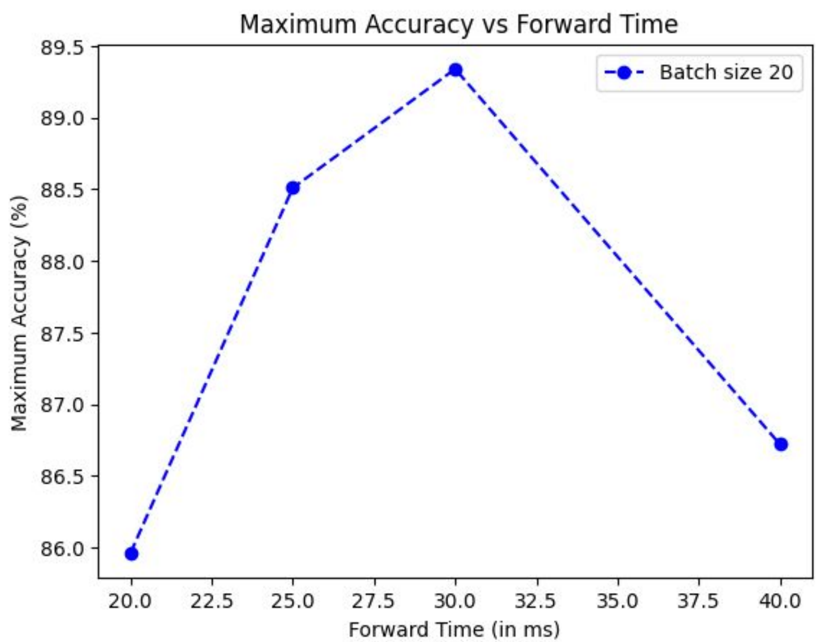
Experiments - Batch Size

- Firstly we find optimum batch size - the one that serves the trade off between variance and computation time



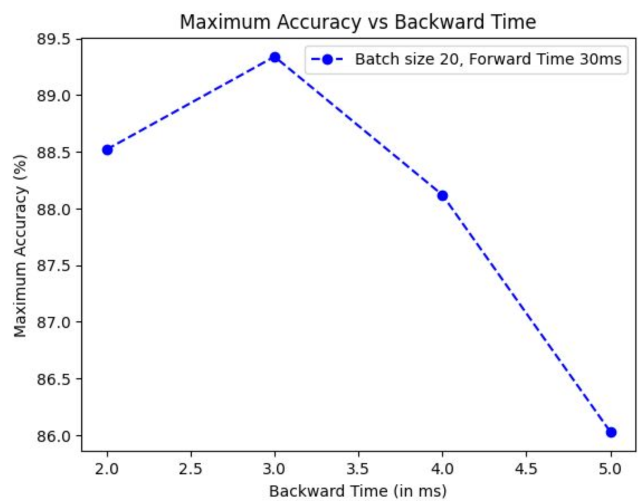
Forward Pass Time

- Next we try to find optimal forward pass time - again we have computation time as the expense



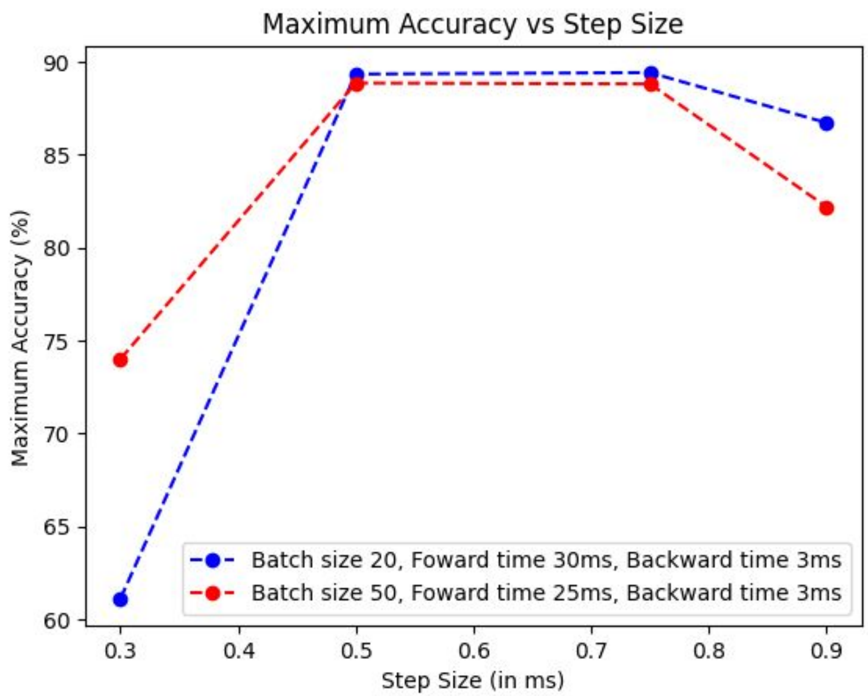
Backward Pass Time

- We have one heuristic that time taken to propagate neuronal information "just once" is the backward time!
- "Just once" - because once you let information flow backwards once, then it will propagate in the future itself.



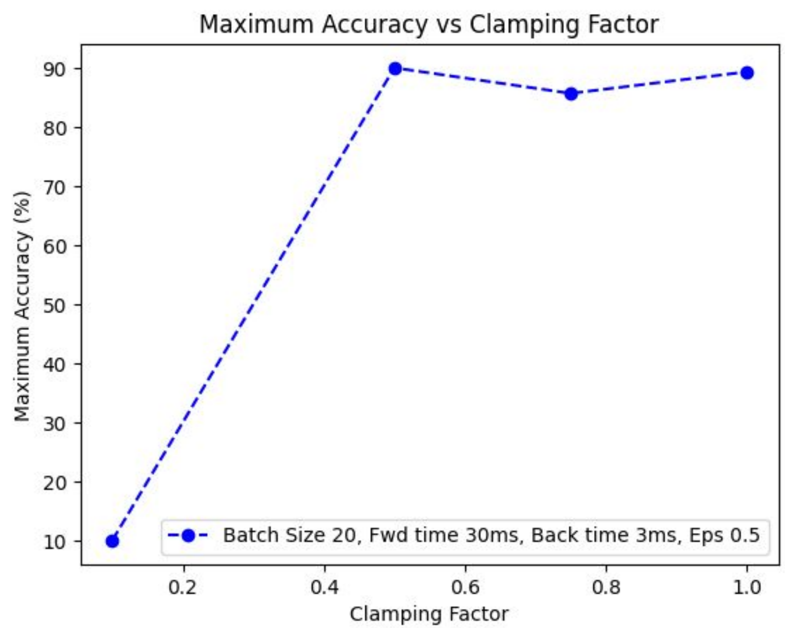
Time Step

- We vary the time-step to influence the convergence of updates.



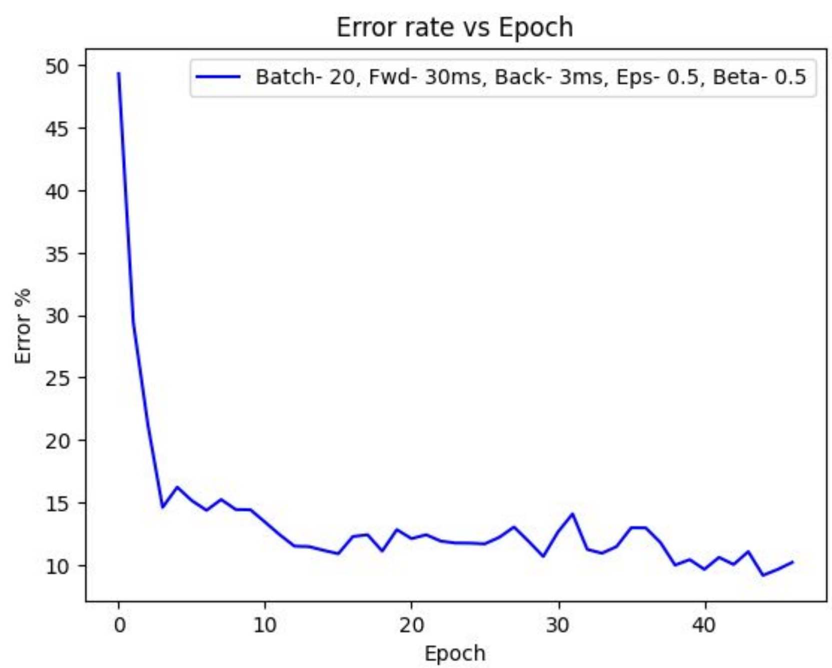
Clamping Factor

- β - Beta is the clamping factor that drives output layer to the target. But a larger β affects the required weight update - in short there is some optimum.



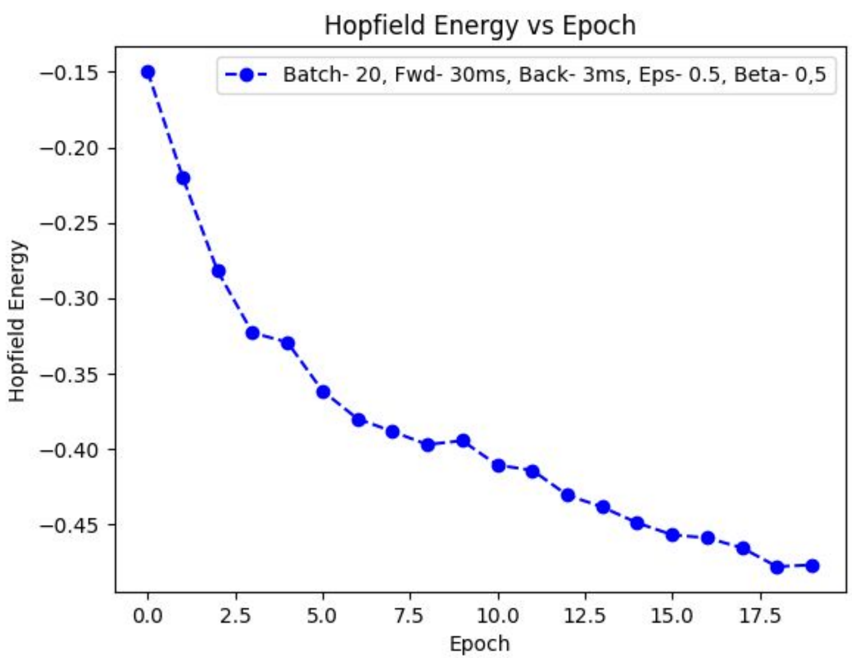
Results

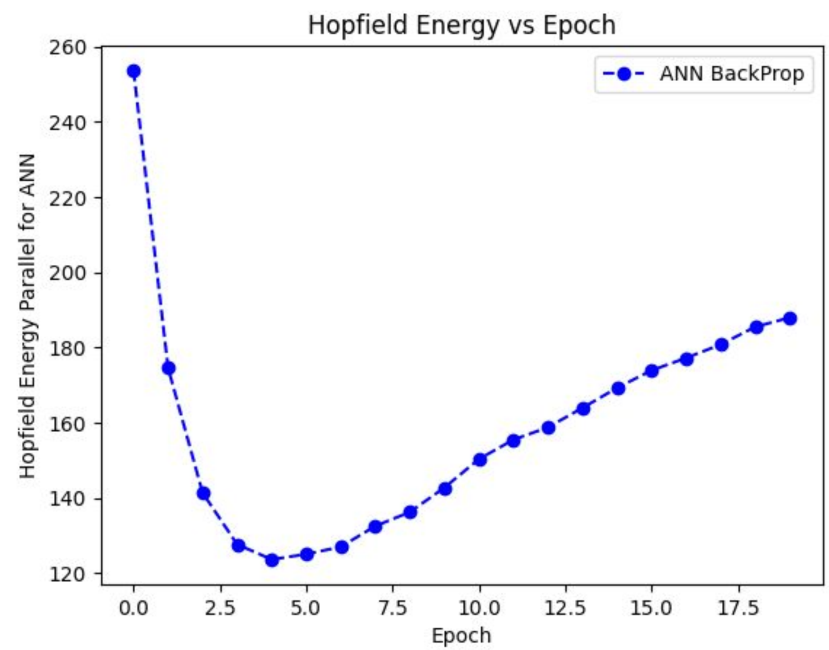
- Through various experiments, the best results gave an maximum accuracy of 90.84%.



Energy Analysis

The biggest flex of Equilibrium Propagation technique is that the system continuously moves towards lower energy.





Conclusion and Future Work

- In conclusion, equilibrium propagation presents a promising approach for MNIST training, demonstrating its potential in leveraging low-powered biologically inspired principles for efficient learning.

- Future work could focus on optimization and multi-layer implementation of our approach.

THANK YOU !!

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