Astrocyte Modulated Synaptic Plasticity in Liquid State Machines

BTech Project-1
Nivedya S Nambiar
Guided by Prof. Udayan Ganguly and Anmol Biswas

Outline of the presentation

- NALSMs - Theory
    - Introduction
    - Motivation and biological plausibility
    - Existing implementation for MNIST-784 handwritten digits
- Results for NALSM framework extended for Google mini speech commands dataset
- Refactoring code and testing with TI-46 dataset
    - Tuning LSM network parameters
    - Experiments with STDP and results
- Hypothesis for observations
- Future work
- References

Neuron-Astrocyte Liquid State Machine (NALSM)

- NALSMs were introduced in [1] as an improvement over regular LSMs using STDP (spike timing dependent plasticity)

$$\frac{dw}{dt} = A_+ T_{pre} \sum_o \delta(t - t^o_{post}) - A_- T_{post} \sum_i \delta(t - t^i_{pre})$$

Weight update equations, A^+ is the potentiation rate and A^- is the depression rate

$$\tau^*_+ \frac{dT_{pre}}{dt} = -T_{pre} + a_+ \sum_i \delta(t - t^i_{pre})$$

$$\tau^*_- \frac{dT_{post}}{dt} = -T_{post} + a_- \sum_o \delta(t - t^o_{post})$$

Image source : [1]

Astrocyte modulation

A^- | A^-_{astro} | A^+ | b_{astro}

$$\tau_{asto}\frac{dA_-^{astro}}{dt} = -A_-^{astro} + w_{astro}\sum_{i\in N_{liq}}\delta(t-t_i) - w_{astro}\sum_{j\in N_{inp}}\delta(t-t_j) + b_{astro}$$

decay

reservoir spike count

input spike count

dc term

Image source : [1]

Biological plausibility of NALSM

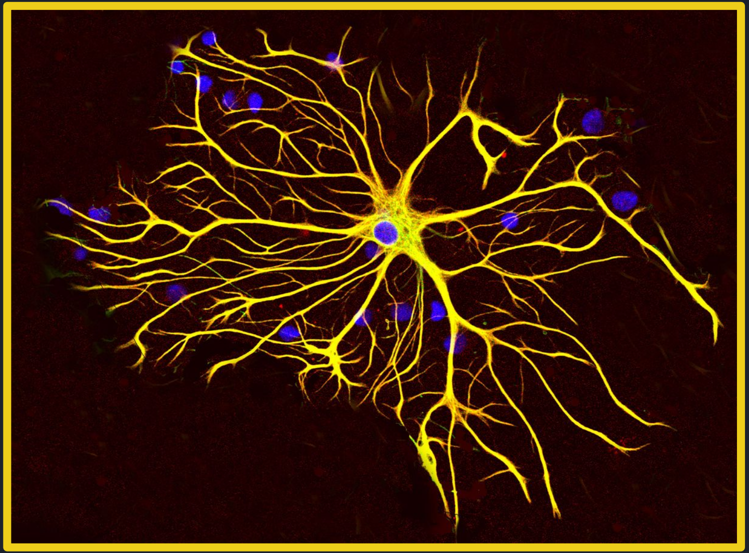
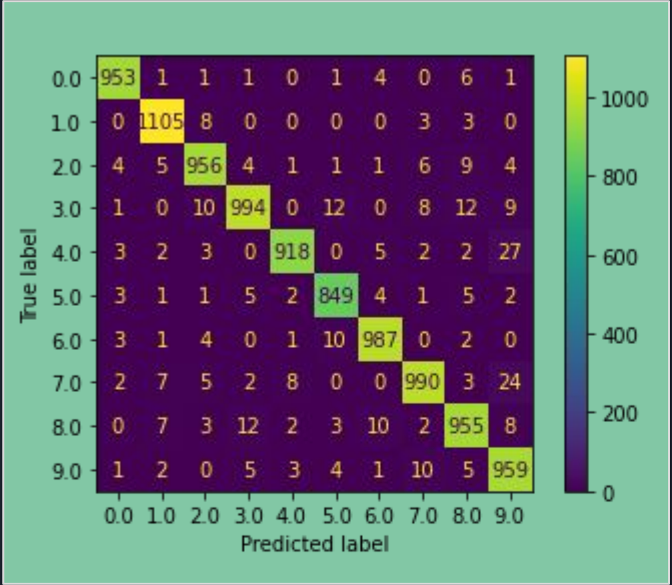


image source:
https://upload.wikimedia.org/wikipedia/commons/thumb/6/63/Astrocyte5.jpg/1200px-Astrocyte5.jpg

- This modulation of the rate of depression is inspired from the astrocyte cells in the biological nervous system
- These cells are unlike neurons in that they do not spike, but play a crucial role in modulating the synaptic plasticity of neuronal networks, hence influencing learning
- Astrocytes integrate the activity of multiple synapses into a slow intracellular continuous signal modulating synaptic plasticity by feeding back to neurons [2]

Implementation of NALSM for MNIST-784



The existing implementation of NALSM+STDP shared had been implemented for the MNIST-784 handwritten images

The accuracy was 96.64% for the train set and 91.9% for the test set.

Shown alongside is the resulting confusion matrix

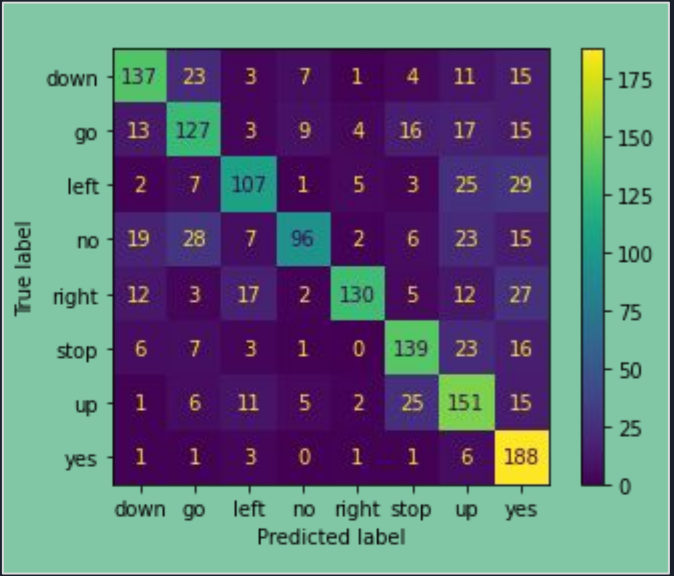
Duplicating NALSM for Google mini speech commands dataset

The same NALSM+STDP framework was used for classification of spoken commands in the Google mini speech commands dataset

To generate the spike patterns from the audio .wav files the waveform was converted to a cochleogram using the Lyon ear model and the cochleogram was used to generate spikes using the BSA encoding algorithm. Existing packages in Python, lyon and pyspikes were utilised for the same

train score=0.9385

test score=0.6718



Refactoring Code and Testing with TI-46

LqW	2
in_conn_density	0.08
inh_fr	0.35
λ	3

train score = 0.89587
test score = 0.865248

- Testing the existing implementation on TI-46 dataset having 19038 samples yielded poor results - train score of 0.5952 and test score of 0.4963
- Hence the code for LSM state update and the STDP rule were reimplemented from scratch based on update equations in [1]
- The LSM network parameters were tuned to maximise the accuracy without STDP and hence create a set point that STDP could improve on, tuned parameters are shown alongside

Experiments with STDP

- The update equation for the depression rate A^-_{astro} was modified as

$$\tau_{astro}\frac{dA^-_{astro}}{dt} = -A^-_{astro} + w_{astro}\left(\frac{1}{N_{liq}}\right)\Sigma_{i\in N_{liq}}\delta(t-t_i) - w_{astro}\frac{1}{N_{inp}}\Sigma_{j\in N_{inp}}\delta(t-t_j) + b_{astro}$$

- The timescale of decay of A^-_{astro} was changed from 10 to 5 to enable faster decay of the term

train score = 0.8578

test score = 0.7583

train score= 0.8847

test score= 0.7848

Introducing decay in $b_{astro} = A^+$

$\Delta A^+ \propto A^+$

$\Delta A^+ \propto (A^+)^2$

$\Delta A^+ \propto (A^+)^3$

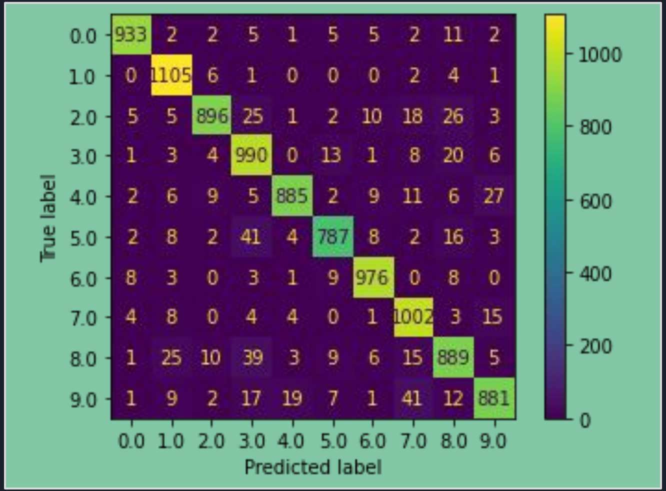
Introducing a decay in the potentiation rate improved the accuracy, and as opposed to an increase which deactivated the reservoir entirely

Update equation	train score	test score
$A^+=0.99A^+$	0.87184	0.8308
$A^+=A^+(1-1/10^6)$	0.9042	0.851
$A^+=A^+(1-A^+/10^5)$	0.9002	0.8547
$A^+=A^+(1-(A^+)^2/10^5)$	0.91024	0.8581

More non-linear the decay equation, higher the accuracy

Crucial to regulate decay of b_{astro} to ensure learning doesn't stop too early

Extending for MNIST-784



The refactored code when extended to MNIST-784, without any hand tuning yielded a train score of 0.97556 and test score of 0.9344

Conclusion - An overview of experiments

Refactoring of NALSM+STDP code with hand tuning of network parameters

Update of equation for A^{+}_{astro} decay

Introducing a decay in b_{astro}

A naïve hypothesis

- In all experiments, the common theme was aiding the decay of A^-_{astro}, either by speeding up the timescale, normalising the spike counts, or decaying b_{astro}
- In effect, this modulates the synaptic plasticity by regulating the magnitude of weight decrease in anti-STDP as well as the magnitude of weight increase through STDP by directly impacting the potentiation rate A^+ and the depression rate A^-
- Hence there is a short term depression that this astrocyte modulation introduces which aims to regulate the effect of long term potentiation

Future Work

- The follow-up question to these experiments is asking how these mechanisms improve the reservoir’s capabilities, by visualising the results and the reservoir dynamics
- This would aid in testing the hypothesis of the effect of short term depression on performance of the reservoir
- Another avenue to explore is fatiguing STDP - scaling the effect of presynaptic spike on synaptic weight by a factor depending on the normalised coordinated firing rate [2]

Code links

Refactored code for TI-46

https://colab.research.google.com/drive/1yuPJn_CZTJtRGs2duJ1VF71Z3oCDeH82?usp=sharing

Extending for MNIST-784

https://colab.research.google.com/drive/1qrsK2kfm8xyaErMLGRC3AITvnPS9fbAz?usp=sharing

References

[1] Vladimir A. Ivanov and Konstantinos P. Michmizos. Increasing liquid state machine performance with edge-of-chaos dynamics organized by astrocyte modulated plasticity. CoRR, abs/2111.01760, 2021.

[2] Timoleon Moraitis, Abu Sebastian, and Evangelos Eleftheriou. The role of short-term plasticity in neuromorphic learning: Learning from the timing of rate-varying events with fatiguing spike-timing-dependent plasticity. IEEE Nanotechnology Magazine, 12(3):45–53, 2018.