EE 746 - Course Project

Effects of Neuron Model Parameters and Synaptic Connectivity on the Performance of a Liquid State Machine

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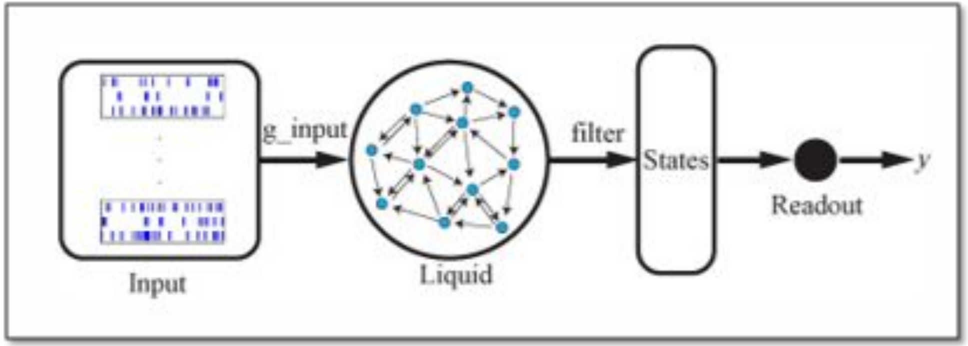
Liquid State Machine

- Biologically plausible model of Mammalian Neocortex
- Three Networks : Input, Reservoir and Readout
- Input Neurons - random connections to reservoir
- Reservoir connections, weights are fixed; Readout weights are trained.
- Universal Computational Power: separation and generalization property



Discussion of Reference Paper

Problem Statement: To investigate the effects of synaptic connectivity defined through the distribution of synaptic strengths and connection density, on the performance of LSM.

Task:

- Poisson spike train classification.
- Each input to the LSM is composed of 4 input spike trains with a duration of 200 ms
- 80 templates are created, each with four 20 Hz Poisson spike trains. 40 templates for each class
- Gaussian jitter with mean zero and a standard deviation of 4 ms is added to these
- A total of 2400 jittered stimuli are generated, 30 from each template.
- 2000 of these are for training and 400 for testing.
- No inherent difference between two classes, LSM has to “memorize” to classify accurately

Discussion of Reference Paper

Network Model: 6x6x15=540 neurons in the network, with a lambda connectivity model. 20% I and 80% E neurons. Each of the 4 input spike trains are connected to 54 random E neurons.

$$p = C.exp\left(-\frac{D(a,b)}{\lambda^2}\right)$$

D(a,b) is the Euclidean distance between the neurons was set at 0.3 (EE), 0.2 (EI), 0.4 (IE), or 0.1 (II)

Neuron Model: LIF neuron

Synapse Model: A dynamic synapse is used here, with synaptic weights changing

Readout Neuron: Single artificial readout neuron

Final state for the mth sample in the in the ith neuron in LSM is

$$s_m^f(i) = \sum_n exp\left(-\frac{t_{sim} - t_i^n}{\tau}\right)$$

Final state of all neurons is sent over to the readout neuron, which produces an output for the mth sample through a linear combination. The weights are obtained through training.

$$O(m) = W^T \left[s_m^f(1) \quad s_m^f(2) \ldots s_m^f(N) \right]^T = W^T S(m)$$

Discussion of Reference Paper

Experiment:

Check the LSM performance for different values of lambda (the connection density parameter) and synaptic weights

Metrics:

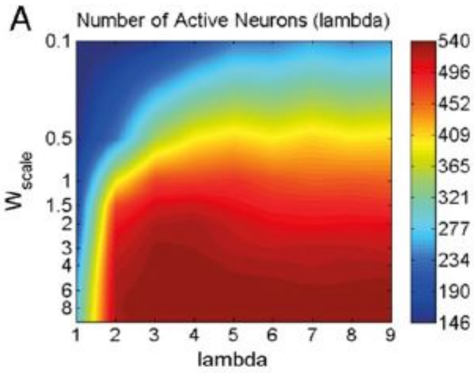
i) Accuracy on classification task

ii) Number of active neurons (that spike at least once) for each input

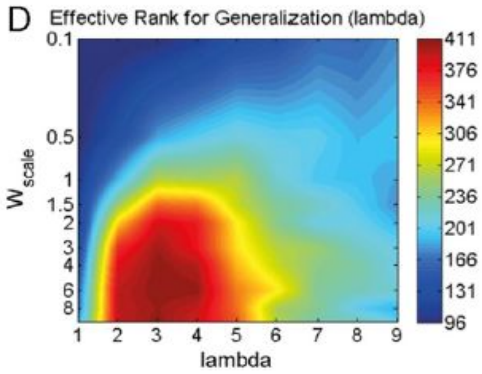
iii) Separation rank: effective rank of final state matrix with a total of 500 different input templates

iv) Generalization rank: effective rank of final state matrix with 500 jittered versions of 4 templates

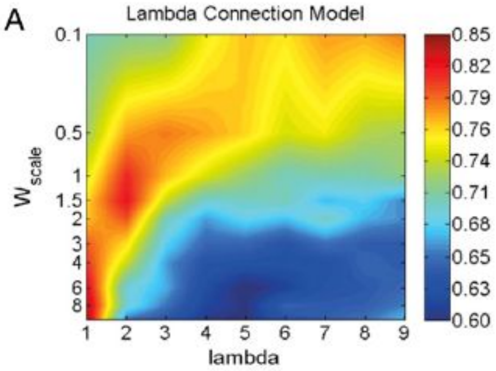
Discussion of Reference Paper



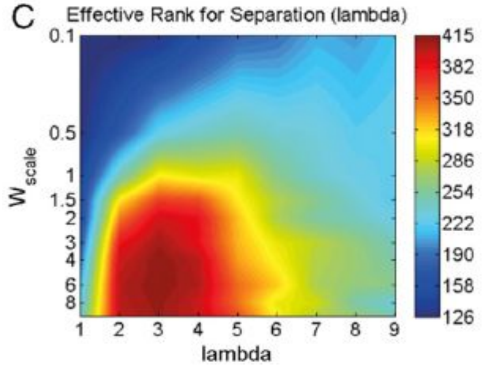
Active Neurons



Generalization Rank



Accuracy



Separation Rank

Discussion of Reference Paper

Results:

- When the number of synapses in the liquid filter is fixed (keeping lambda constant), larger synaptic weights increase the number of active neurons. For constant synaptic weights, larger lambda means more active neurons.

- Poor performance was observed when the number of active neurons was either too large or too small. Optimum performance was achieved using an intermediate number of active neurons, at the ‘edge of chaos’

- The performance of the LSM was highly related to the number of synapses in the liquid filter. When the number of synapses was large (small), smaller (larger) values of W scale were needed to obtain satisfactory performance.

- The separation and generalization rank also have their transition at the points of optimal performance.

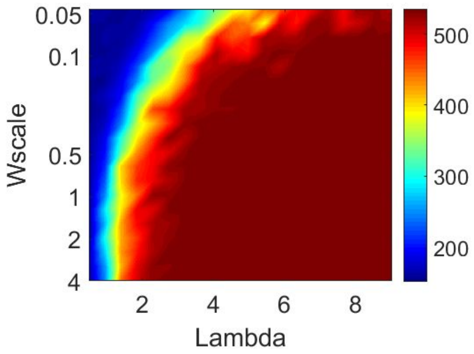
Replication of paper

Network Model, Neuron Model, Readout Neurons and the Metrics are the same as specified before in the discussion of reference paper. A static synapse model is used instead of the dynamic one. The task performed is also different.

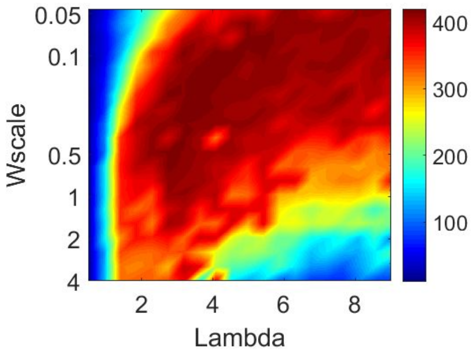
Task:

- Poisson spike train classification.
- Each input to the LSM is composed of 4 input spike trains with a duration of 200 ms
- The input has been changed to have two input classes with spiking rates of 20 and 60 Hz
- We use a total of 50 templates, with 25 of each class.
- Gaussian jitter with mean zero and a standard deviation of 4 ms is added to these
- A total of 500 jittered stimuli are generated, 10 from each template.
- 400 of these are for training and 100 for testing.

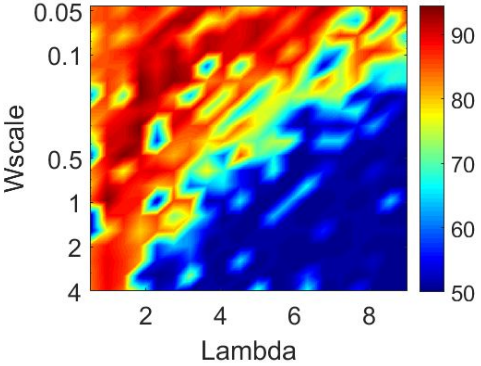
Replication of paper



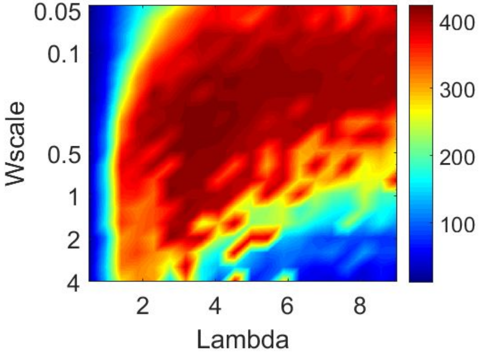
Active Neurons



Generalization Rank



Accuracy



Separation Rank

Replication of paper

Results:

- Since the task attempted in the paper is different from the one we attempted, and since the synapse model is also distinct, we expect these plots to be different from the paper. However, the key takeaways here are similar to those from the reference paper as highlighted before.

- One important distinction we notice is that the drop in accuracy from the maxima in the low-weight, low-lambda regime is not as large as before

- This phenomenon is seen in our results because the task performed here is simpler than the task attempted in reference paper hence just the spike pattern from the input neurons are enough to provide the information required for classification

Novel Ideas and Experimentations

Inspiration:

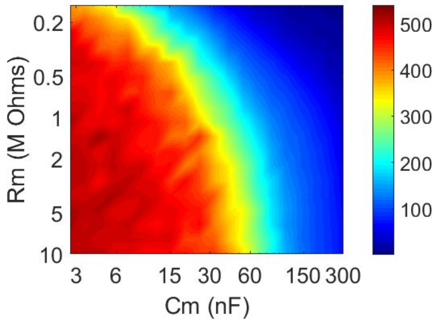
- There are a multitude of neurons in various parts of the mammalian neocortex and their properties vary with their specific functionality in different biotic systems.
- The LIF Neuron model can be used to approximate the behaviour of a large variety of neurons by varying their capacitive and resistive properties
- Finding optimal C_m and R_m would give us a Biological understanding of important properties found in better performing Neurons

$$C_m \frac{dV_m}{dt} = -(V_m - V_{resting})/R_m + I_{syn} + I_{inj}$$

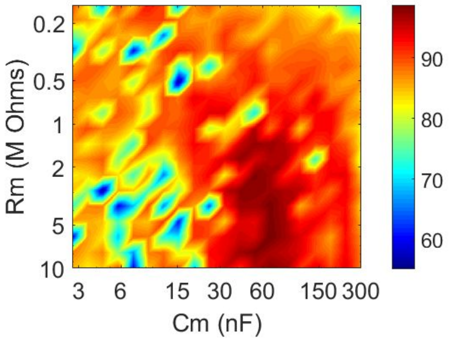
Experiment: The performance of LSM is checked for different values of LIF Neuron parameters R_m and C_m for 4 different chosen connectivity parameters [W_{scale}, λ]:

i) [0.2 , 2]
ii) [0.2 , 5]
iii) [1 , 2]
iv) [1 , 5]

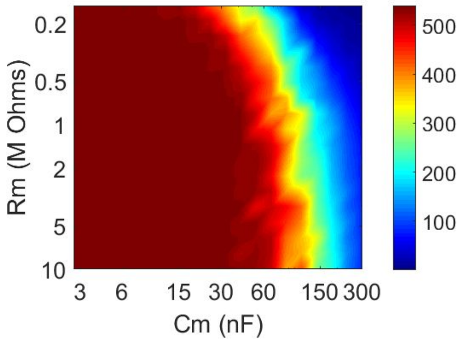
Novel Ideas and Experimentations



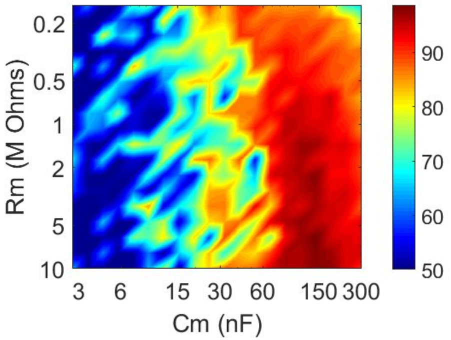
Active neurons
Wscale = 0.2, Lambda = 2



Accuracy
Wscale = 0.2, Lambda = 2

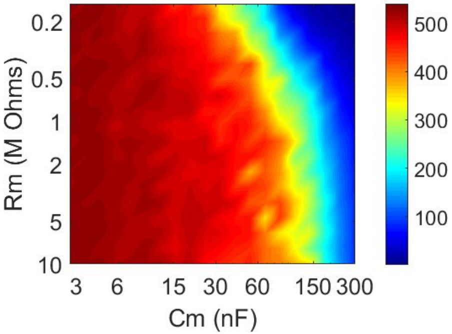


Active neurons
Wscale = 0.2, Lambda = 5

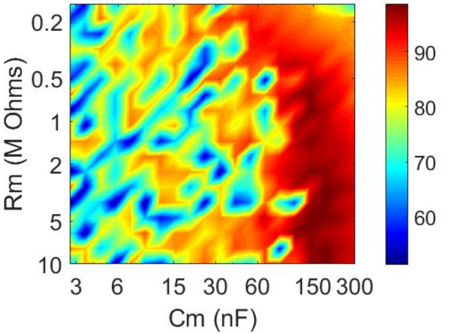


Accuracy
Wscale = 0.2, Lambda = 5

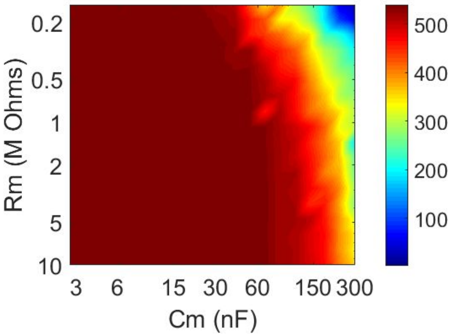
Novel Ideas and Experimentations



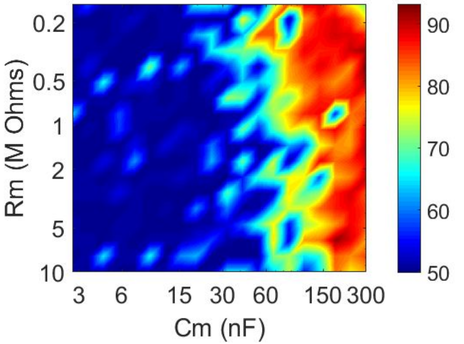
Active neurons
Wscale = 1, Lambda = 2



Accuracy Wscale = 1,
Lambda = 2



Active neurons
Wscale = 1, Lambda = 5



Accuracy
Wscale = 1, Lambda = 5

Novel Ideas and Experimentations

Results:

- We see that the number of active neurons increases when C_m is decreased and R_m is increased.
- We can very clearly observe that the performance is best at the edge of chaos, when just the right number of neurons in the network are active
- Varying Cm and Rm has an effect on all the neurons, including the input neurons. Hence here, we see considerable drop in accuracy from both sides of the optimal edge.
- For each choice of lambda and weight, we notice that the optimal values of Cm and Rm are different. However, the maximum achieved accuracy with a free choice of neuron model is very similar for different connectivity parameters.

Novel Ideas and Experimentations

Conclusions:

- For a given task, a network and it’s connectivity parameters, one can find the best possible neuron, which is again based on the edge-of-chaos.

- An interesting Question : We see wide variety of biologically-observed neurons occuring in different organisms, and specializing in different tasks ; Similarly, there is a large difference in the networks that these neurons are observed in. Since we observe artificially the presence of an ‘optimal’ neuron for different connectivity parameters, Can we expect to see similar correlations between the biological neuron parameters and the networks that they occur in naturally?