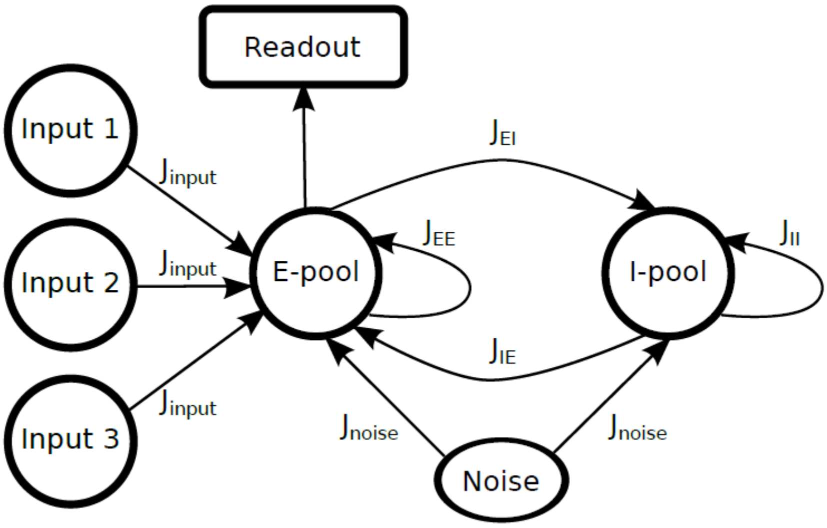
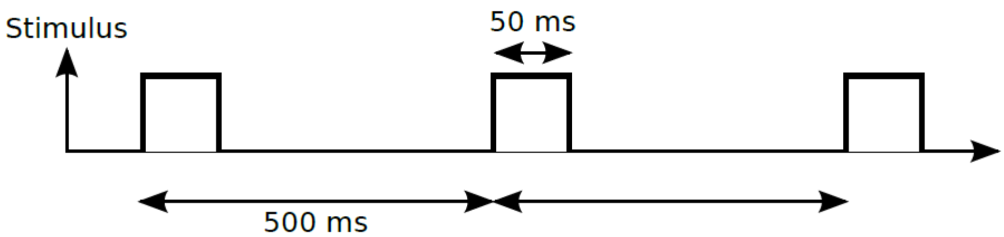
5 Liquid State Machines

This exercise is to study and understand the principle the multiple perceptron-like readout elements can be trained to perform different tasks and that once trained, each readout element can perform the task on novel inputs, because each readout can learn to define its own notion of equivalence of dynamical states within the system. Primarily, to simulate the paradigm of recurrent network of integrate-and-fire neurons to carry out basically any real-time computation on spike trains, in fact several such real time computations in parallel.

Model details





Where, in the model the input function input1, input2 and input3 can be a continuous sequence of disturbances and the readout can be a target output that provides a real-time analysis of this sequence. And in between these states occur a function that generates, at every time as a response to preceding input perturbations.

And the stimulus in the form of three inputs being received where each stimulus lasts 50 ms and is hit at every 500 ms. For each individual stimulus, each input neuron fires either at a high firing rate (200 Hz), or it remains silent. Thus, 3 bits x_0, x_1 and x_2 with $x_j \in \{0, 1\}$ $\forall j$ is given to the networks stimulus. Using the response of the recurrent networks, we

perform simple computations on these inputs by computing some
$y = f(x_0, x_1, x_2)$.

Task 5a

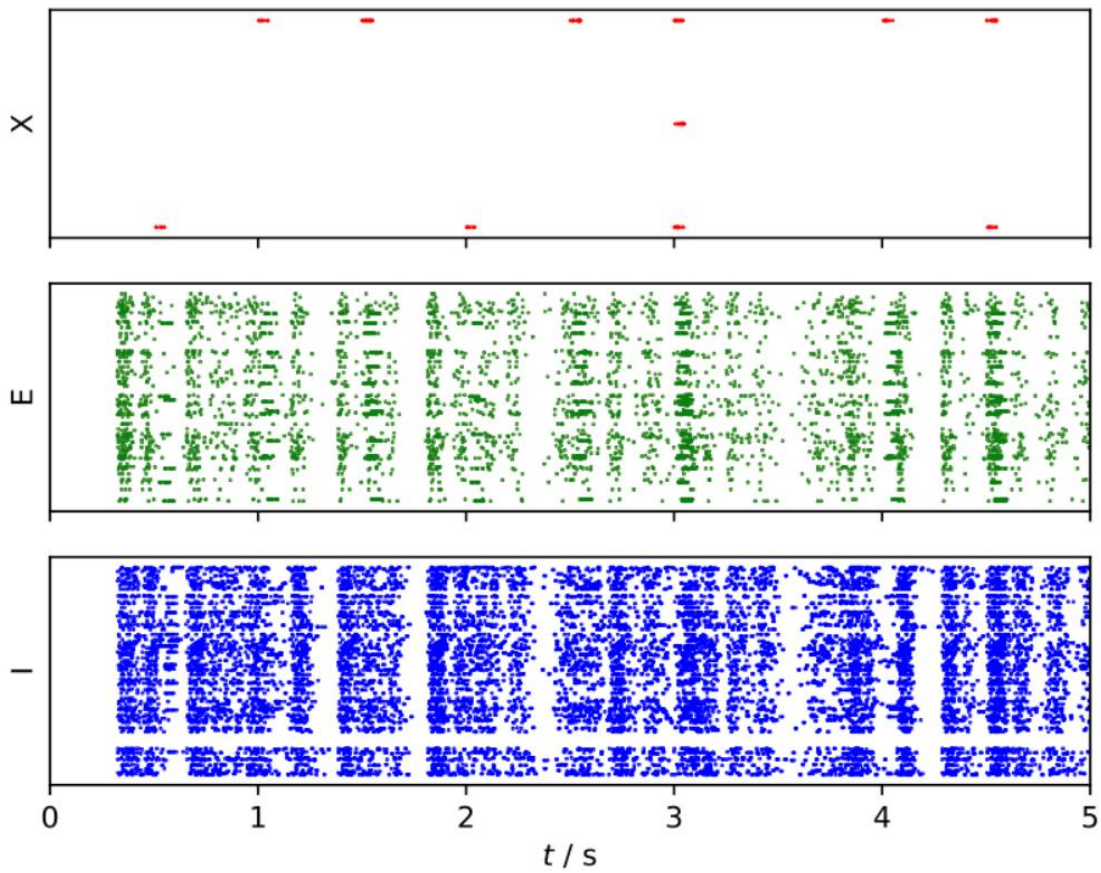


Figure 1
Network activity of LSM.

As different input spike patterns lead to different liquid state trajectories. The sum of spikes of different input source constitute the cumulative firing to the presence of stimuli of each input spike frequency of 200 Hz give raise to the above learning mechanism where nearly after few milliseconds because of the amplitudes of the input synapses were chosen from the Gaussian distribution so, that each neuron in the liquid received a slightly different input. However, the readout neurons are trained within a short span from the receiving of stimulus which can be observed in the graph. And also makes use of two properties for the better response to a stimulus which is separation and approximation property. Compared to other tasks, with sum task the readout neuron is learning much quicker once after the extraction of the liquid states which is done every 20 ms after stimulus presentation has ended.

Task 5b

As far as xor task is concerned it is observed from fig.1 that since the third input bit is not being considered as relevant for the readout perceptron-like-learning, the liquid states are only dependent on the firing of combination of input-1 & input-2. Additional to which they are fired at frequency of 200 Hz and amplitudes of the input synapses which are chosen from the Gaussian distribution. Implies the learning rate related to other two tasks is quite slow. However, when regularization parameter is increased, the average number of connections and the average spatial length of connections is regulated which improves the performance of perceptron-like-learning of readout neuron to perform respective task based on the prior stimulus. However, further increasing regularization parameter leads to chaotic behaviour of microcircuit which decreases the performance and increases the latency before reaching a given level of certainty in the task.

Task 5c

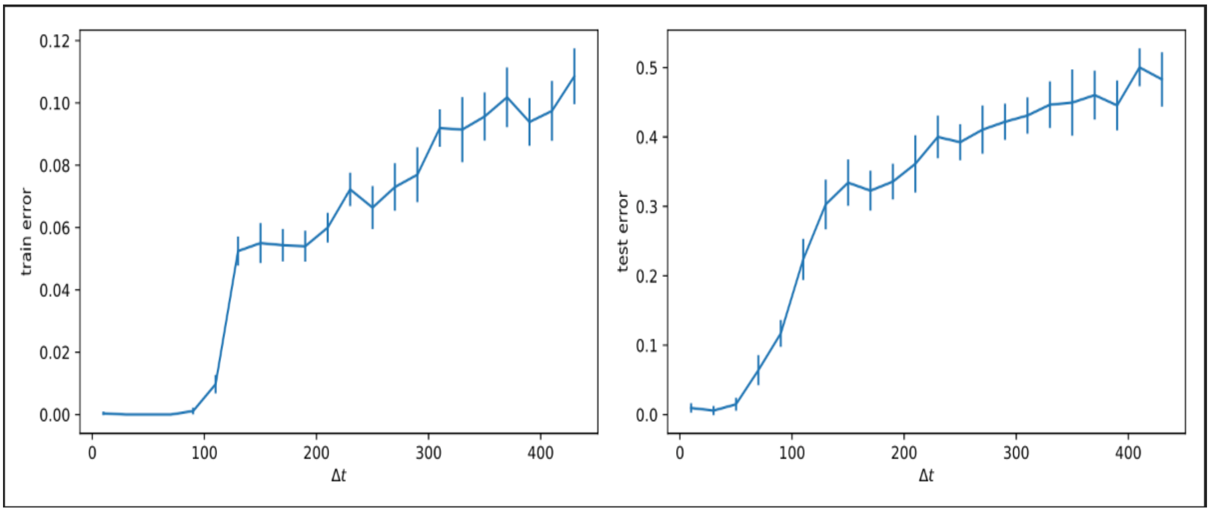


Figure 2.1

Train readouts for mem1 task

From the fig 2.1 it can be assessed about the fading properties that for varying delay in extraction after each stimulus, the time required to learn the liquid states also varies resultant to which there is a variance in the remembering of stimulus state causing the error in remembering the stimulus which is as above. But with less or more error the readout neuron still trying to remember the stimulus for varied delay in extraction. Compared to memall task the error in the fading properties of mem1 is a bit less where it is at max of 0.12 - train error and 0.5 – test error.

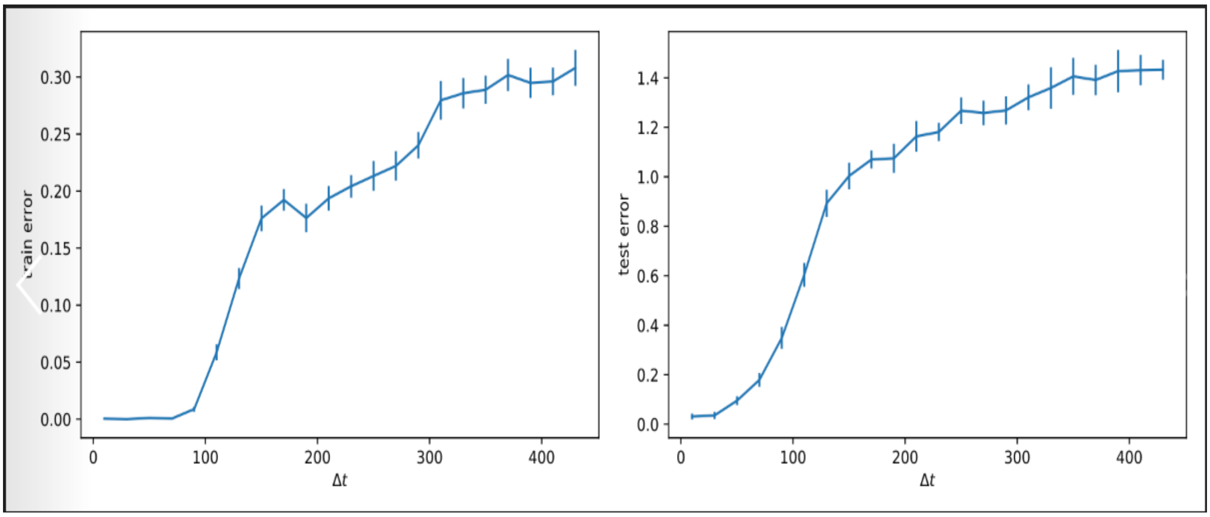


Figure 2.2
Train readouts for memall task

If we observe the fading properties for memall task because here it is intended to extract all 3 input bits simultaneously by mapping each possible input bit combination to an integer, the erroneous behaviour is a bit more in terms of remembering the stimulus than with mem1 task. And especially if it is looked at the time course of the test error on two tasks, the difference from memall task to mem1 task is the error in remembering the stimulus for memall increases rapidly for change in delay of information extraction compared to mem1 task. Especially, when memall task is concerned the fading property diminishes for delay in time 200 ms where the error is at maximum implies the neuron has lost the capability of fading properties and keeps increasing with increase in delay wherein w.r.t mem1 task even at delay of 400 ms the error is still at 0.5 which tells that fading property has not completely diminished.