May 8th, 11:00 AM

Computational Capabilities of Leaky Integrate-and-Fire Neural Networks for Liquid State Machines

Amin Almassian
Portland State University

Christof Teuscher
Portland State University

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Amin Almassian
teuscher.:Lab | Department of Computer Science | Maseeh College of Engineering and Computer Science
www.teuscher-lab.com | amin2@pdx.edu

Abstract

We analyze the computational capability of Leaky **Integrate-and-Fire (LIF)** Neural Networks used as a reservoir (liquid) in the framework of **Liquid State Machines (LSM)**. Maass et. al. investigated LIF neurons in LSM and their results showed that they are capable of noise-robust, parallel, and real-time computation. However, it still remains an open question how the network topology affects the computational capability of a reservoir. To address that question, we investigate the performance of the reservoir as a function of the average reservoir connectivity. We also show that the dynamics of the LIF reservoir is sensitive to changes in the average network connectivity, which is consistent with the results taken from RBN reservoirs. Our results are relevant for understanding of the computational capabilities of reservoirs made up of biologically-realistic neuron models for real-time processing of time- varying inputs.

Questions Addressed

- How long does it take for the input signal to perturb the reservoir well enough to change the output of the readout layer?
- How does the connectivity of the reservoir contribute in the performance of the LSM?
- How much does a reservoir of LIF neurons need to be perturbed to adequately distribute the input signal?

LSM's Components

Reservoir (liquid)

- An excitable component that consists of a general purpose and non-task-specific recurrent neural network (RNN).
- Inputs perturb the reservoir such that a state of the reservoir is a transformation of its input history while a none-recurrent trained readout layer interprets the dynamics of the reservoir.

Leaky Integrated-and-Fire Neuron

- A simplified mathematical model of a spiking neuron inspired by biologically realistic neuron models.
- LIF neuron is the building block of the reservoir.
- None linear dynamics of this neuron transforms continuous time input signals to spikes – a short-lasting rises and falls in the electrical membrane potential of the neuron cell and then stimulates the afferent connected neuron.

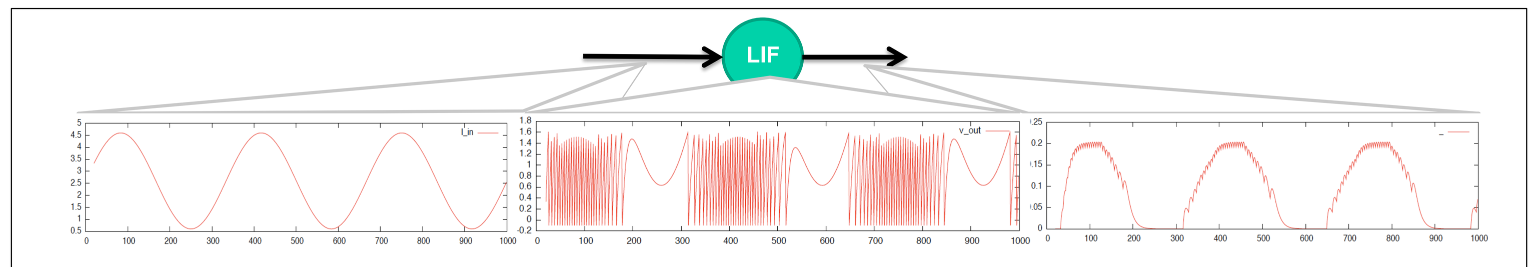
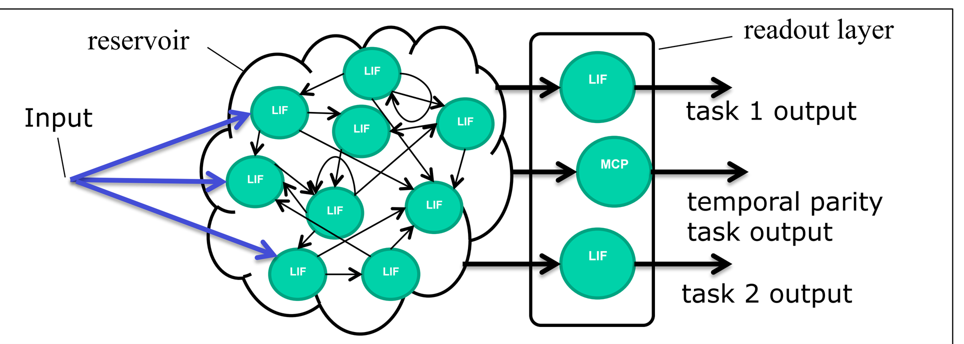


Figure 1:left: input signal induced directly to an LIF neuron. Center: The membrane potential resulted from the input signal. Right: Consequent post synaptic current induced to the afferent neuron through a synaptic connection.

Readout layer

- A layer of nodes with no lateral or recurrent connections.
- Each node interprets the dynamics of the reservoir simultaneously and in parallel.
- Each readout node can be an LIF neuron, McClutch-and-Pitts (MCP) neuron, etc.
- In order for the readout neuron to be trained a gradient descent technic is used.

Figure 2: A schematic view of LSM. Inputs are injected to a portion of nodes in the the reservoir and all nodes in the reservoir are connected to each readout bode in readout layer.



Relation of the network topology and computational capability in LSMs

- Two properties of the reservoir are crucial for real-time computing [1]:

1) Separation between the internal states caused by two different extraneous inputs.

2) Approximation property: Capability of the readouts in distinguishing and transforming different internal states of the liquid into the target outputs

- These two properties are dominated by reservoir's recurrences, data propagation delay, average connectivity, nodes' dynamics, etc.
- We investigate the role of the network connectivity in real-time computing of a temporal parity task. See Figure (3).

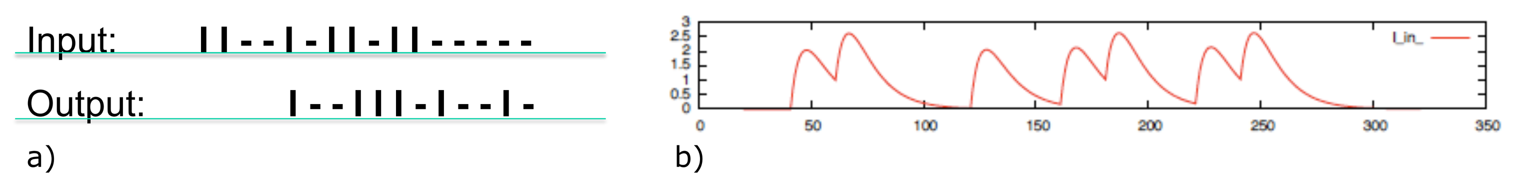


Figure 3: a) A sample temporal stream of a particular binary input and it's resulting temporal parity over time with sliding window of 5. b) Spike train corresponding to the binary input in (a)

Approximation property of LSM

The input spike train is projected to a higher dimensional space thereby providing a linear separable representation of the input signal. Consequently, a better approximation property is obtained. See Figure (4).

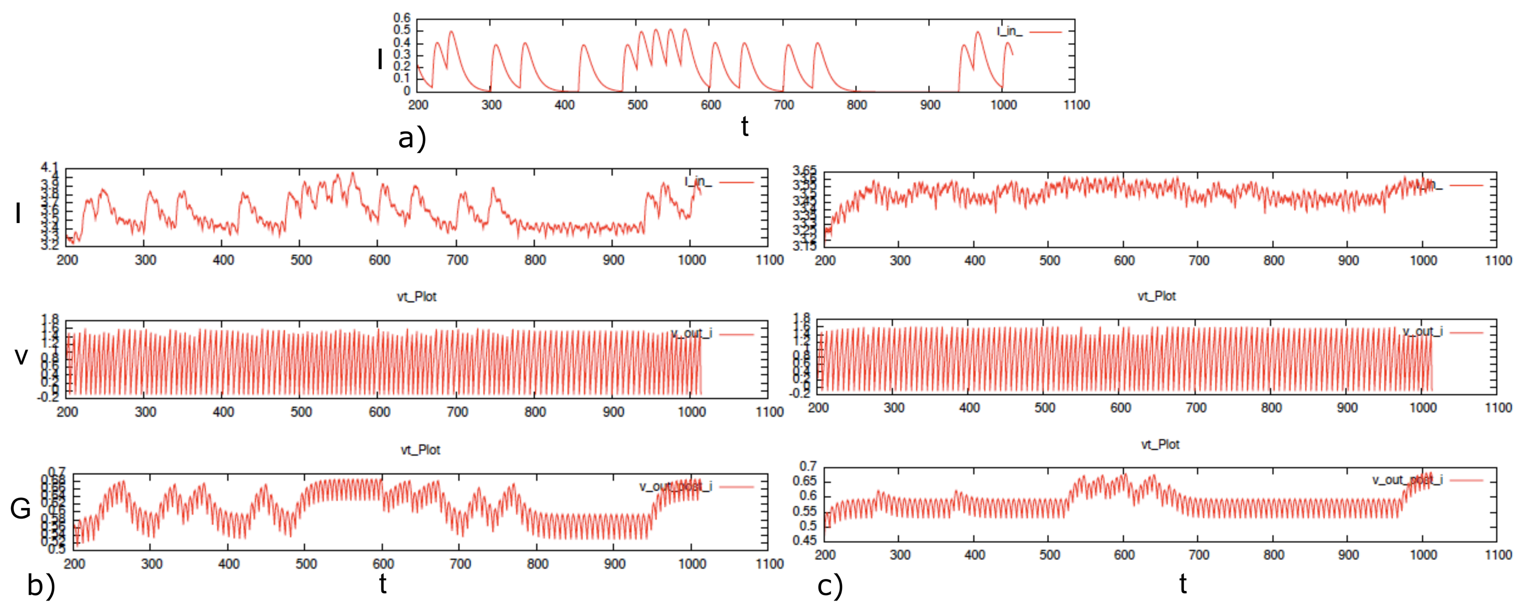


Figure 4: a) The input signal injected to the reservoir over time. b) Time series of a randomly selected LIF neuron from among the nodes of reservoir to which the input signal is induced over time course of 1100 ms. Top: input signal plus other post synaptic currents of other neurons in the reservoir. Center: resulting membrane potential of the same LIF neuron. Bottom: post synaptic current resulted from the membrane voltage of the same neuron c) Time series of a randomly selected LIF neuron from reservoir to which the no input signal is induced. Top: post synaptic currents of other neurons in the reservoir. Center: resulting membrane potential of the same LIF neuron. Bottom: post synaptic current resulted from the membrane voltage of the same neuron. Parameters of the reservoir: number of LIF neurons is 20. Average connectivity is 4/20.

Separation property of LSM

- The amount of separation between dynamics of reservoir resulted from two different input signals should be well above the separation caused by any internal noise or any imposed extraneous noise. Look at figure 5.
- The reservoir should essentially posses a fading memory property to avoid the history of input data from lasting so long that drops the separation property for recent inputs.

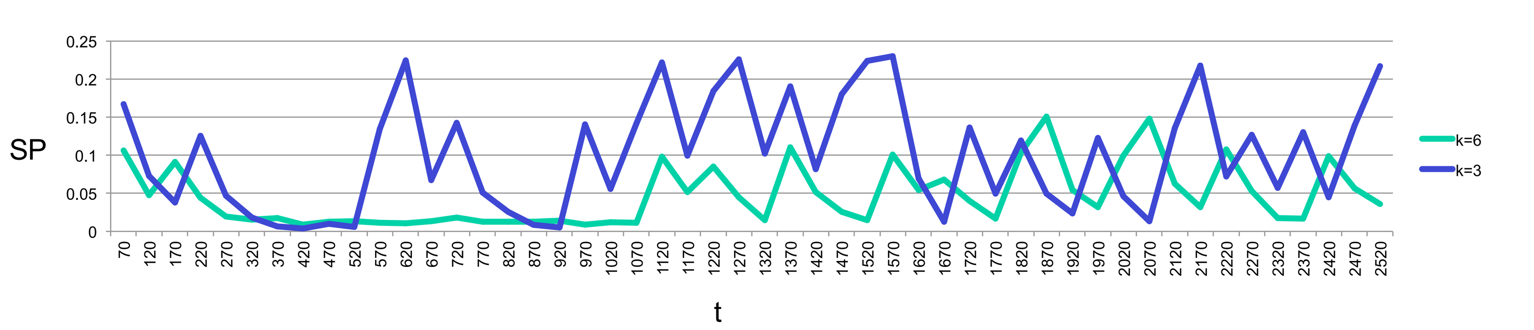


Figure 5: Separation (SP) measured from two different random inputs generated independently from two Gaussian distributions. Blue line: average-connectivity=3/20. Green line: average-connectivity=6/20,

Performance analysis

- We performed a quantitative performance analysis on the temporal parity task with window size of 3 against the average network connectivity.

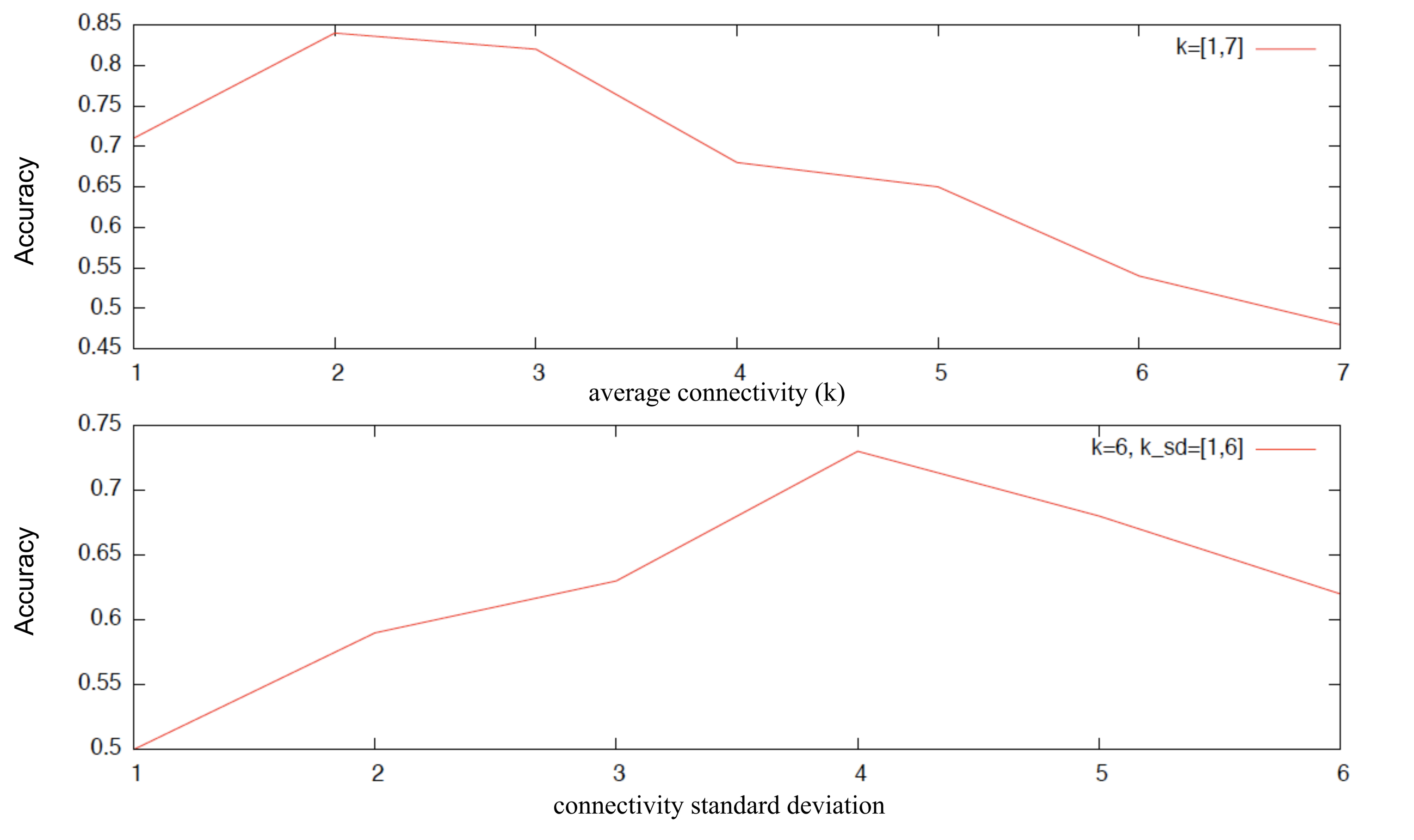


Figure 5: a) Accuracy of the temporal parity task as a function of average network connectivity of the reservoir. b) Accuracy of the temporal parity task as a function of standard deviation of network connectivity of the reservoir (with average in-degree of 6).

Concluding remarks

- In order for the input signal to contribute in producing the output, the reservoir requires a short period of time to be perturbed accordingly.
- The performance of the LSM depends on the network connectivity of the reservoir to a considerable extent.
- The standard deviation of the the network connectivity in the reservoir can augment the separation property of the reservoir by making the connection distribution of the reservoir heterogeneous.
- The connectivity and weights of the input connections to the reservoir should be in an optimum range.
- Our result is consistent with the result obtained form Random Boolean Network (RBN) reservoir [3] in the sense that the reservoir's computational capability is sensitive to the average network connectivity of the network.

Next Steps

- Investigation of the computational capabilities of the reservoir made up of LIF neurons under the influence of complexity of the reservoir [2].
- Comparison of our results with the same measures taken from a reservoir made up of an RBN [2].
- Learn what role the dynamics of the nodes in the reservoir might be playing in overall network performance.

References

[1] Maass, W., Natschläger, T., & Markram, H. (2002). Real-time computing without stable states: A new framework for neural computation based on perturbations. Neural computation, 14(11), 2531-2560.

[2] Natschläger, T., Bertschinger, N., & Legenstein, R. (2004). At the edge of chaos: Real-time computations and self-organized criticality in recurrent neural networks. Proc. Advances in Neural Information Processing Systems.

[3] Snyder, D. R., Goudarzi, A., & Teuscher, C. (2012). Computational Capabilities of Random Automata Networks for Reservoir Computing. arXiv preprint arXiv:1212.1744.

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