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The Liquid State Machine is Not Robust to Problems in its Components

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ABSTRACT

The Liquid State Machine has been proposed by Maass and others as a computational framework for brain function that focuses on reverberating temporal activity as opposed to attractors.

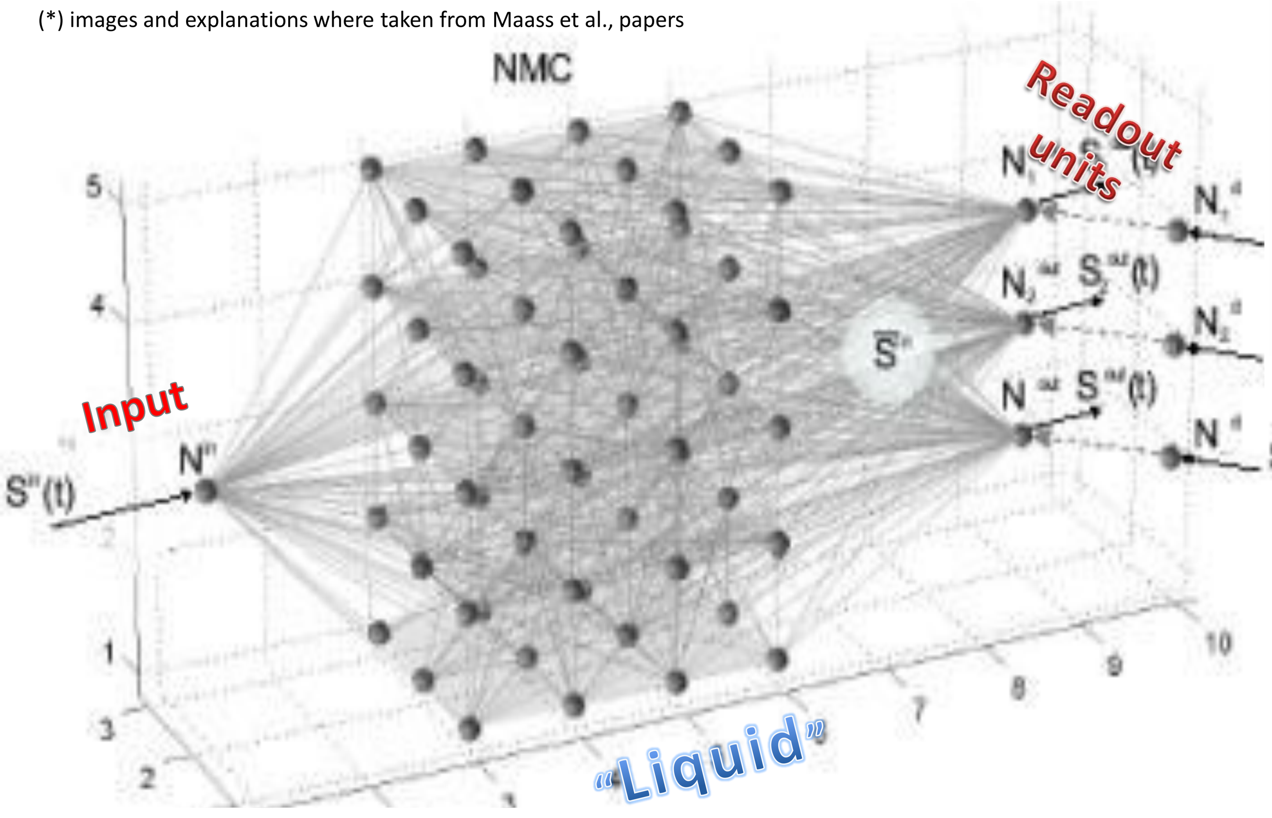
First, we show that the Liquid State Machine in its basic approach cannot serve as a natural model for brain function. This is because they are very vulnerable to failures in parts of the model. Thus, for example, a small number of neurons that respond differently than they did during learning (e.g. a substantially different threshold) causes the activity pattern of the liquid to change so much that it can no longer identify trained signals. This result is in contrast to the work by Maass and others which showed that these models are robust to noise in the input data.

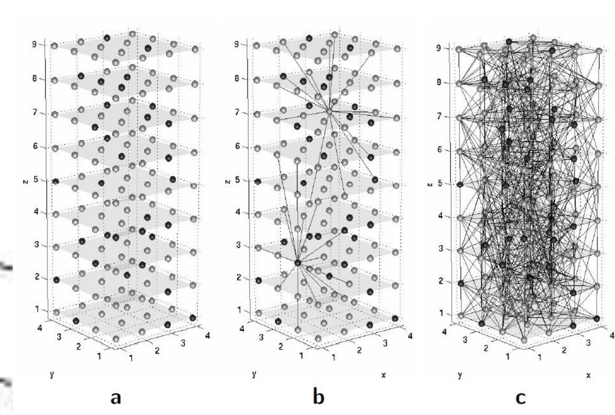
Second, we show that, on the other hand, if the LSM, while retaining a random connectivity, nonetheless has certain internal topological structures related to "hubs" or "small world topology", it can then perform reliably even under conditions of damage. Since it has been argued in other works that these topologies arise naturally, this modified version can then be considered as a possible model.

WHAT IS LIQUID STATE MACHINE FRAMEWORK?

A liquid state machine (LSM) consists of a large collection of units/neurons. The units are randomly connected to each other. Each unit receives an input from other units, some units are chosen randomly from the pull to receive additional input from external stimuli. The recurrent nature of the connections turns the input into a spatio-temporal pattern of activations in the network units. The spatio-temporal patterns of activation are read out by linear discriminate units like: Perceptron, Back-Propagation, etc.

(*) images and explanations where taken from Maass et al., papers





From Maass et al., papers
Construction of a generic neural microcircuit model.
(a) 20% of the neurons are inhibitory.
(b) Randomly chosen postsynaptic targets are shown for two of the neurons. The underlying distribution favors local connections.
(c) Connectivity graph of a generic neural microcircuit model (for λ=2).

Connectivity structure:
The probability of a synaptic connection from neuron a to neuron b (as well from b to a) was defined as $C \times \exp(\lambda D^2(a;b)/\lambda^2)$, where λ is a parameter which controls both the average number of connections and the average distance between neurons that are synoptically connected (we set λ = 2).

ROBUSTNESS OF THE LSM COMPONENTS

Maass et al., showed that the LSM is robust to variants in the input, but when considering the LSM as a biological model like the brain or as a computational model in a noisy environment, one need to consider that the LSM itself has inflicted temporary damage (like all biological systems that are dynamic by nature and not acting like accurate electronic devices, i.e., neuron that failed to fire at given time, or neuron that fired not according to plan). As a result the activity of the LSM is not reliable any more, i.e., the readout unit will experience a disturbed activity that is not normally shown for the same input.

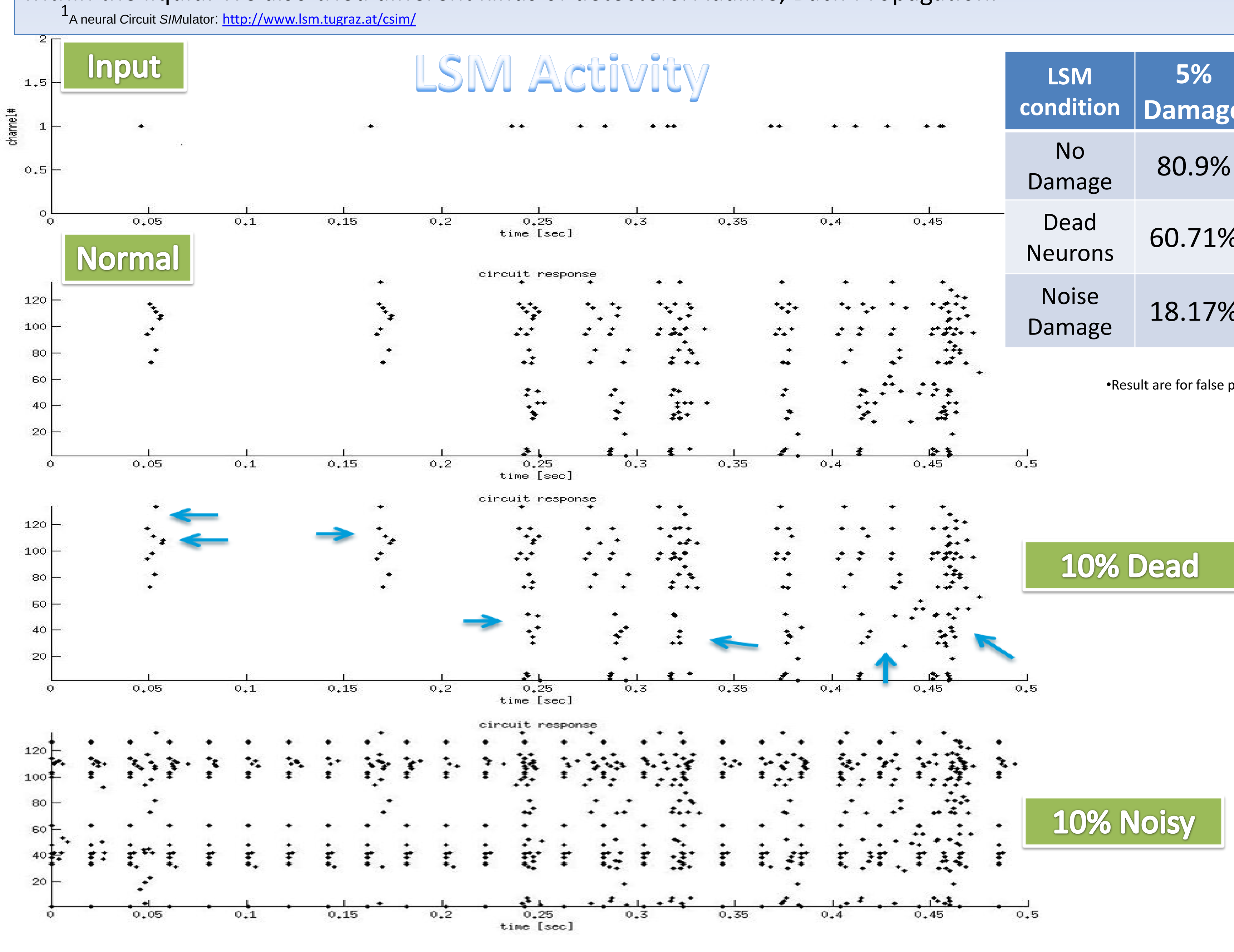
The experiments

To test this resistance to noise, we downloaded the code of Maass et al., from his lab site[1] and then implemented two kinds of damage to the liquid: A. The percentage of neurons damaged. B. The kinds of damages.

The kinds of damages were either transforming a neuron into a "dead" neuron (i.e., one that never fires) or transforming a neuron into a "generator" neuron, (i.e., one that fires as often as its refractory period allows it, regardless of its input).

We did experiments from 1% until 10% damage and with different connectivity (i.e., average random connectivity) within the liquid. We also tried different kinds of detectors: Adaline, Back-Propagation.

[1] A neural Circuit SIMulator: http://www.lsm.tugraz.at/csim/



LSM condition	5% Damage	10% Damage
No Damage	80.9%	84.03 %
Dead Neurons	60.71%	20.64 %
Noise Damage	18.17%	7.8%

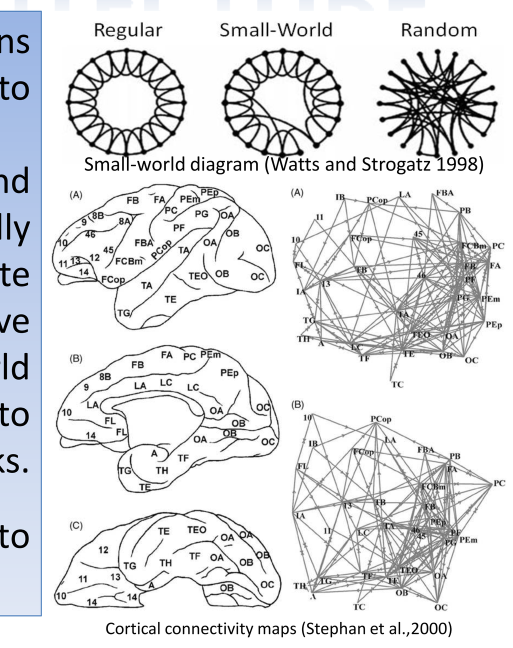
•Result are for false positive

SMALL WORLDS & LSM ARCHITECTURE

Small-world topology is characterized by dense local clustering of connections between neighboring units. Nevertheless from each unit there is a relatively short path to any other unit, utilizing rare units that have a relatively big number of connections.

It is already showed that this topology can support both segregated/specialized and distributed/integrated information processing. Nervous systems are anatomically connected as small-world networks at macro and micro scales. This is an appropriate topological solution to the problem of economically delivering complex or adaptive network dynamics. In humans, there have been several recent reports of small-world brain functional networks measured using fMRI or MEG/EEG, but there is much still to learn about the (presumably small-world) topology of human brain anatomical networks.
(Danielle Smith Bassett and Ed Bullmore, DOI: 10.1177/1073858406293182)

We use this assumption to create a "Liquid" network for the LSM framework and to retest our finding.



IMPROVING THE LSM ARCHITECTURAL

In our experiments we used either a "Leaky Integrated and Fire" (LIF) neuron or alternatively an Izhikevich neuron model to build the liquid in the LSM.

The neurons were connected by weights according to the topology of "small-worlds", i.e., we built a cluster of 6 neurons, each of them connected randomly to two of his neighbors and then create 10 clusters with the same concept. We randomly choose 30 neurons and allow each one of them to connect randomly to two other neurons, not from his cluster. The weight of the connections between the connected neurons is 0.5. 75% of the neurons are excitatory and 25% inhibitory.

For input neurons we choose 9 from the 60 neurons (15%) to be the input and we exclude them from being outputs neurons. All other neurons that do not act as an input are output neurons.

To simulate the damage in the liquid, we choose from 1% to 10% random neurons, (those neurons could be an input neuron or an output neuron). To simulate a noise, we choose those neurons to fire, regardless of their current status, and to simulate dead neurons, we reset the current voltage of those neurons to the voltage in the resting stage (-65mv) regardless of their current status. For each iteration we randomly choose different neurons, and the previous neurons return to normal operation.

We use resilient back-propagation networks as detectors, because of their ability to recognize patterns with relatively small training time.

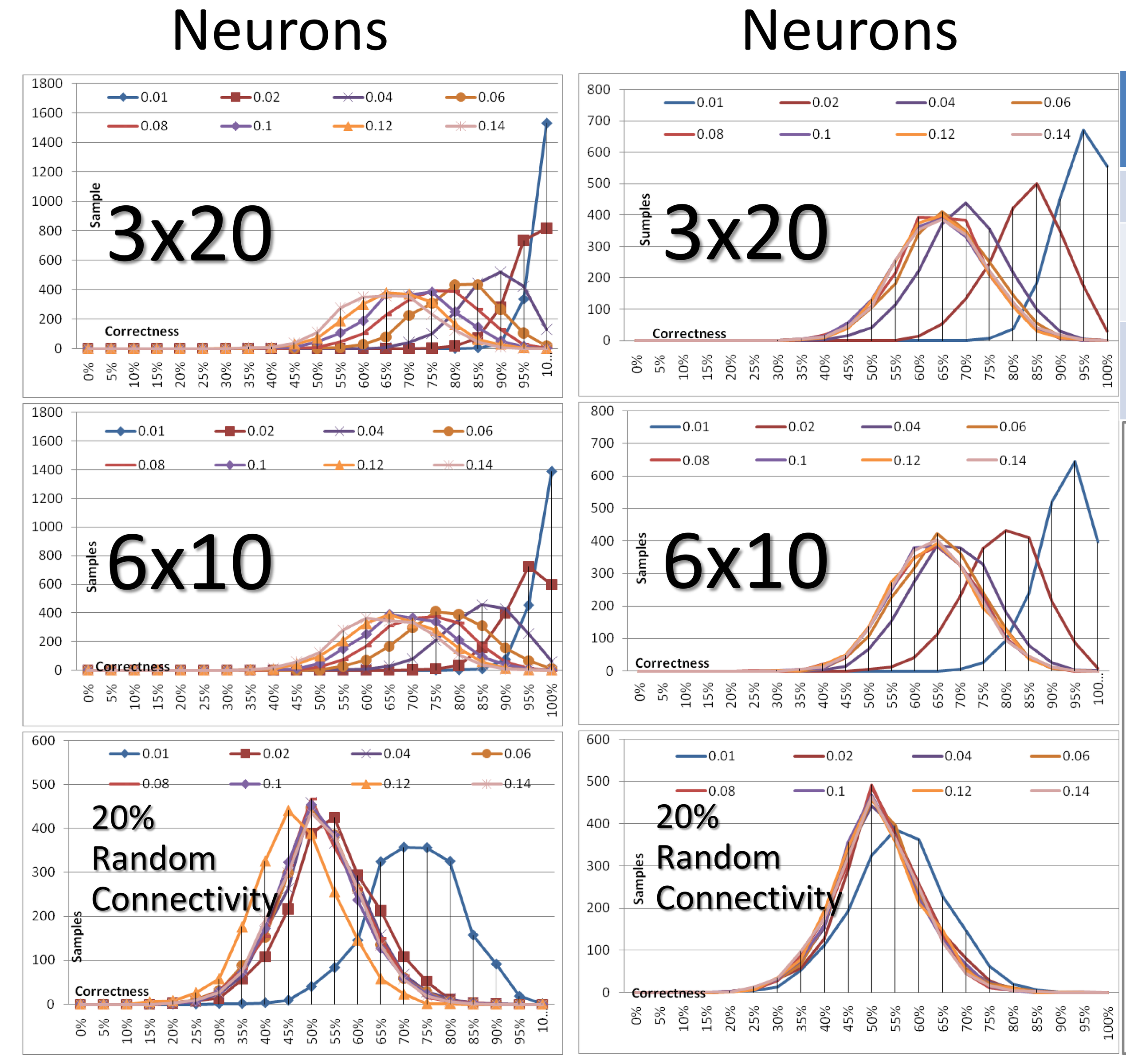
RESULTS

We found that one of the most important features of the LSM framework is the *degree of connectivity* inside the liquid. The ability of the LSM framework to recognize patterns depends on the ability of the liquid to produce a rich activity, i.e., the higher the connectivity, the richer and the more distinguished the patterns; as the connectivity gets lower the liquid will produce less activity and its activity will be less distinguishable. **But as the connectivity increases so does the sensitivity to damage.**

The "small worlds" topology reduces this sensitivity to possible damage without reducing the richness of the activity in the liquid.

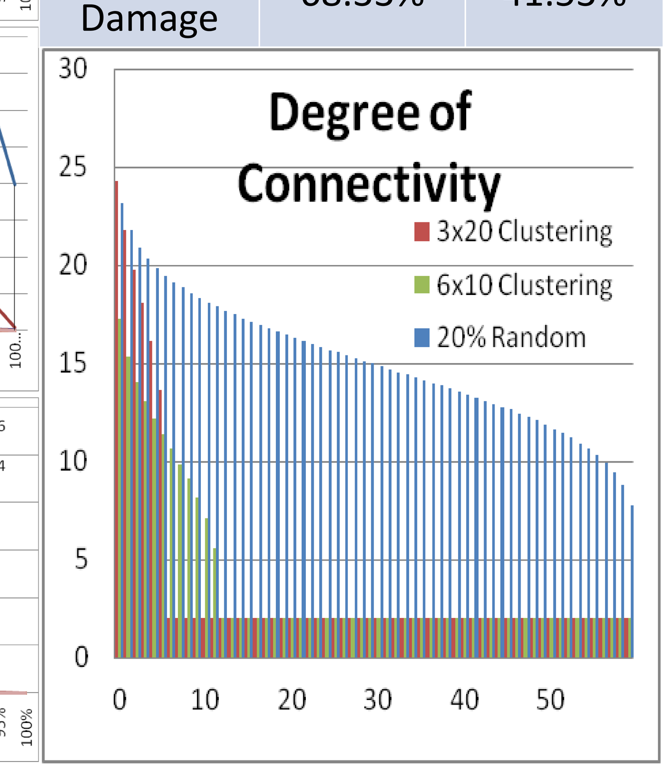
Damage of Noisy Neurons

Damage of Dead Neurons



3x20 Results

LSM condition	5% Damage	10% Damage
No Damage	100%	100%
Dead Neurons	33.60%	28.35%
Noise Damage	68.33%	41.53%



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