Propagation of spike errors in networks of biophysical neurons

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Abstract

Understanding how synaptic errors impact neural network behavior is crucial for deciphering both normal and pathological brain functions. This study employs computational simulations to investigate the propagation of spike-timing errors across different neural network architectures—namely, Feed-Forward, Scale-Free, and Small-World networks—using the NEURON simulation environment. We introduced random synaptic timing errors to each network and quantified the impact on network behavior using the Victor-Purpura distance metric. Our results demonstrate that resilience does not depend on network types but depend on the network sizes. Small size networks showing a significant amplification of errors as they propagate through layers, while large size networks exhibited greater robustness and error mitigation capabilities. These findings were interpreted in the context of each network's structural connectivity, highlighting the role of network architecture in error propagation. The study faced limitations related to model simplification and the scope of synaptic error types, suggesting areas for further research. Overall, our work contributes to a deeper understanding of how synaptic variability influences neural processing and offers insights into the structural features that enhance network resilience against errors.

Introduction

Spike train data from neurons consist of sequences detailing when a neuron fires its action potentials (spikes), represented as timestamps. Neurons primarily communicate through spikes, making the analysis of spike train data essential for understanding how information is transmitted within the brain. This analysis is fundamental for decoding processes ranging from basic sensory

perception to complex cognitive functions. For instance, spike timing plays a crucial role in the auditory cortex for decoding complex sound environments, suggesting that temporal coding is vital for auditory scene analysis (Huetz et al., 2016). Han et al. (2001) emphasizes the critical role of precise spike timing in modulating neural circuits in the primate brain, highlighting its importance for functional connectivity and behavior.

However, factors such as external radiation or fluctuations in neurotransmitter concentration and their diffusion dynamics can cause errors in synaptic transmission, manifesting as time shifts in spike trains (Barbour, 2001). As neuron spikes propagate through the biophysical neuron network, a pertinent question arises: How do these errors affect network behavior? Using the NEURON neural simulator, we employ computational methods to simulate multiple cohorts of neuron networks with random errors introduced at synapses. These networks include types such as Feed-Forward Networks, Scale-Free Networks, and Small World Networks. We utilize the Victor-Purpura distance to quantify the error in the network.

Method

In this study, we use only point cells with Hodgkin-Huxley model (Hodgkin, Huxley 1952) are used to construct the neuron network. For modeling error, a time shift is applied at the intercell synaptic transmission. The time shift follows a gaussian distribution with standard deviation from 0ms to 1ms with 0.05ms apart. We included three types of representative networks scheme in our simulation: Feed-Forward Network, Scale Free Network, and Small World Network.

Feedforward networks in neuroscience are a class of neural network architectures where connections between the units do not form cycles. This is analogous to feedforward architectures in artificial neural networks. In the context of the brain, these networks involve a unidirectional flow of information from sensory inputs to subsequent processing stages, ultimately leading to an output. This structure is crucial for the processing of sensory information, where each layer of neurons extracts increasingly complex features of the input data. One typical example is the visual system, where information flows from the retina through various layers of the visual cortex, with each layer processing different aspects of the visual input (Sporns, 2010). We randomly generated 10 Feedforward networks of 30, 40, 50, 60 cells per layer for 10 layers, and 10 networks

of 200 cells per layer for 5 layers due to limited computational capacity, with 20% dropout rate in network connection.

Small-world networks are a type of network topology characterized by high clustering and short path lengths, which are prevalent in various biological systems, including the human brain. This configuration allows for efficient information processing and robustness against disturbances. In neuroscience, small-world networks have been identified in the structural and functional brain networks obtained from neuroimaging data, supporting theories about the efficiency of brain connectivity and its role in cognitive function (Watts et al, 1998). We randomly generated 10 small-world networks of size 30, 40, 50, 60, 200 cells.

Scale-free networks are characterized by a power-law distribution of node connectivity, meaning a few nodes (hubs) have a high number of connections, while most have few. In neuroscience, this topology has been observed in the structural and functional brain networks and is thought to underlie various aspects of neural dynamics and brain function. The presence of hubs in scale-free networks enhances both the robustness and vulnerability of the brain, providing resilience against random failures but susceptibility to targeted attacks (Barabási et al, 1999). We randomly generated 10 scale-free networks of size 30, 40, 50, 60, 200 cells.

For every randomly generated network, each connection is either excitatory synapse or inhibitory synapse. For many areas of the cortex, the ratio of excitatory to inhibitory synapses has been reported to be around 4:1 or even higher, depending on the specific brain region and the method of measurement. For example, in the neocortex, excitatory synapses, which primarily use the neurotransmitter glutamate, vastly outnumber the inhibitory synapses, which mainly use gamma-aminobutyric acid (GABA) (Markram et al 2004). In our simulated network, a connection is random assign to be either excitatory or inhibitory with ratio of 1:4.

In the brain neurons usually have a mean firing rate of 30 Hz – 50 Hz. For many neurons in the brain under non-stimulated, resting conditions, firing rates can range from a few spikes per second to around 20 Hz. This low-frequency baseline activity is typical of neurons that are not actively engaged in processing specific sensory inputs or motor outputs. When neurons are actively engaged, such as during sensory stimulation or while performing a task, firing rates can increase significantly. Rates from 20 Hz to as high as 100 Hz or more can be observed, especially in sensory or motor areas where neurons may be responding directly to external stimuli or

commands for movement. Certain specialized neurons can have higher or lower typical firing rates. For instance, fast-spiking interneurons in the cortex can exhibit very high rates of up to 100 Hz or more, while other types of neurons might operate at lower frequencies even during active states (Softky et al, 1993; Dayan et al, 2001). In our analysis, the connection weights are randomly generated from uniform (0, X) distribution, where the X is tuned to enable the cell to have average firing rate between 30 Hz – 50 Hz, with some extreme case which cell can firing at as low as 20Hz or as high as 100Hz.

Each network receiving input to makes the cell to begin firing. For feedforward network, only the first layer is receiving input, and the following layers receive synapses input from prior layer to fire; thus, signal propagate from first layer to the last. The first layer of feedforward network receive stimulus following poisson process with average interval of 1.5ms, which would make the first layer of feedforward network firing at rate between 30Hz to 50Hz. For Small-world and Scale-Free network, each cell is receiving stimulus following poisson process with average interval of 3ms, which would make the cells in the network to fire at 20Hz without network effect. When network connection is included, the cells in the networks will fire at frequence from 20Hz to 100 Hz.

Each set up of the network (Network Type x Network Size in number of Cells x 10 randomly generate network) receives 10 different sets of randomly generated input following scheme describe above. The random errors in the form of shifting in synaptic transmission follows a gaussian distribution with standard deviation from 0ms to 1ms at 0.05ms interval. Due to the random error involves in the network running at the synapses, each set up with each set of input is ran for 10 seconds under different random errors distribution 10 times to see how the random errors effects the network behaviors. In total, 3 network types x 4 network size x 10 randomly generate network x10 randomly generate sets of input x 21 random error of different standard deviation x 10 times running network, 25200 simulations are run.

Here is an example of running one of the networks. Firgure1 show a feedforward network of 30 cells per layer, 10 layers in total. The connection map shows the connectivity and weight of the connection propagation each layer, with negative meaning inhibitory synapse connection and positive meaning excitatory synapse connection. The input goes to the first layer, which is randomly generated following poisson process with 1.5ms mean interval.

Figure 1. Example connection Map and Example Input

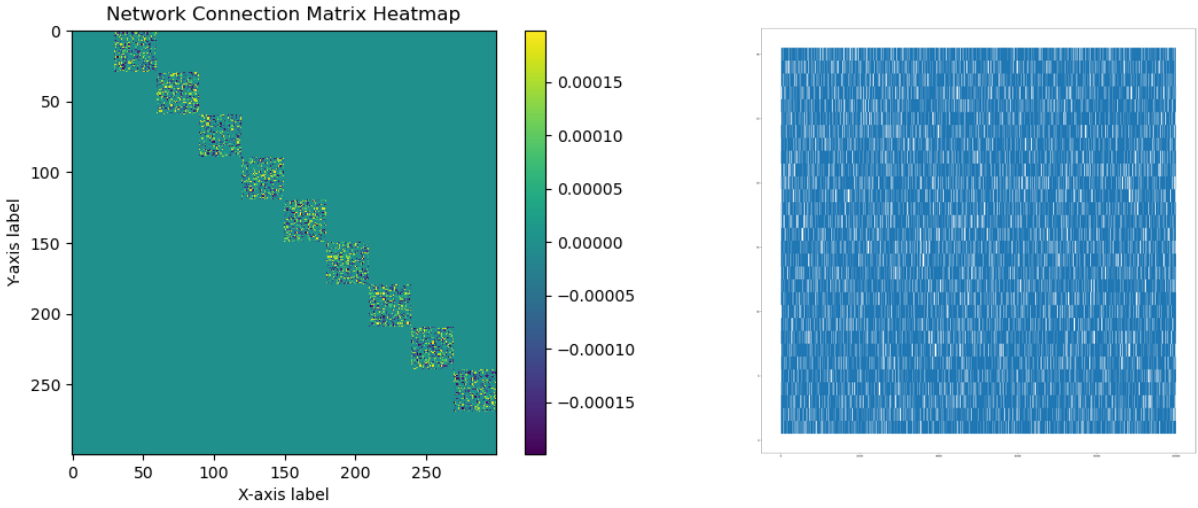
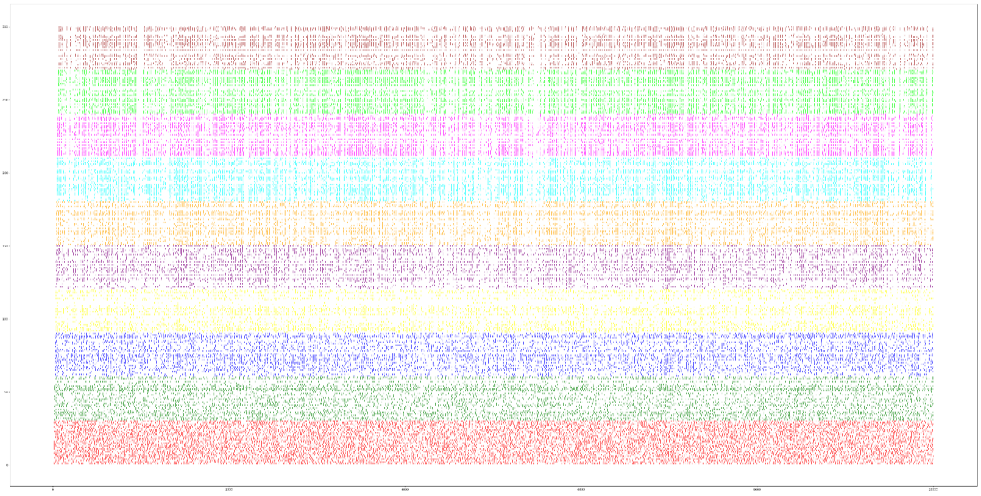


Figure 2 shows the spike train data of each neural firing across layer from bottom as layer 1 and top as layer 10.

Figure 2. Example output of the Network



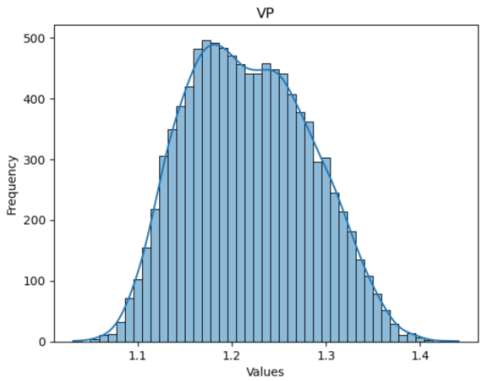
Results

We use Victor-Purpura distance to describe difference in network behavior. The Victor-Purpura distance, also known as the spike-time metric, is a way to quantify the similarity between two

spike trains. This measure is particularly useful in computational neuroscience for analyzing how neurons encode information through the timing of their spikes. The metric allows for the comparison of spike trains by incorporating the cost of transforming one spike train into another through a series of basic operations such as shifting a spike in time or adding or deleting a spike. The key aspect of the Victor-Purpura distance is that it allows for temporal precision to be adjusted through a parameter q. This parameter sets the cost of shifting spikes relative to the cost of adding or deleting spikes. When q is low, the cost of moving a spike is small compared to adding or deleting spikes. This treats spike timing with less precision. When q is high, the cost of moving a spike is greater, emphasizing precise spike timing. The distance between two spike trains is computed by finding the minimum cost required to transform one spike train into the other using three types of operations: inserting a spike into a spike train, deleting a spike from a spike train, and shifting a spike, which involves moving a spike to a new time point within the spike train (Victor, Purpura 1996). In our analysis of Victor-Purpura distance, the q value is 0.1, as we would like to look at the analysis is more forgiving of small timing differences between spikes, which can be advantageous in studies where the coding information is primarily carried by the rate of firing rather than the precise temporal pattern (Kreuz et al 2007). We use Electrophysiology Analysis Toolkit to calculate the victor-purpura distance of each network outputs.

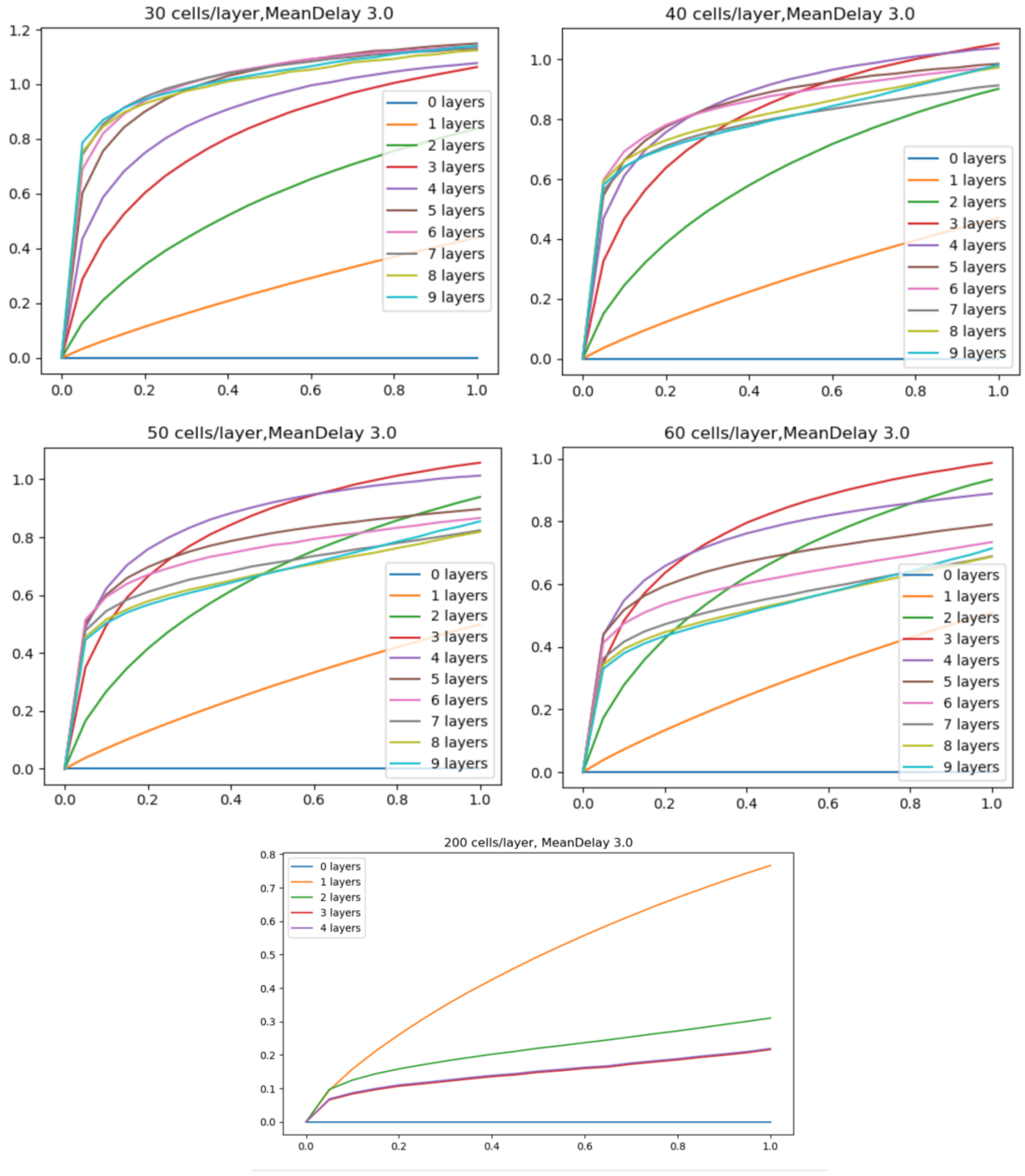
For the baseline of analysis, two same cell spike trains data will give a VP distance of 0. To understand what the VP distance of completely different spike train data is, we simulate 10,000 randomly generate spike train data, and the VP distance distribution is shown in Figure 3. From the distribution, we can see that if a cell spikes completely randomly, it will mostly like have a VP distance greater than 1.1.

Figure 3 Victor-Purpura Distance for Random Spike Train Data



We calculate the VP distance between the spike train data of every cell of very run of a setup with the spike train data of that cell with the same network connection map and input with no random error happening at the synapses.

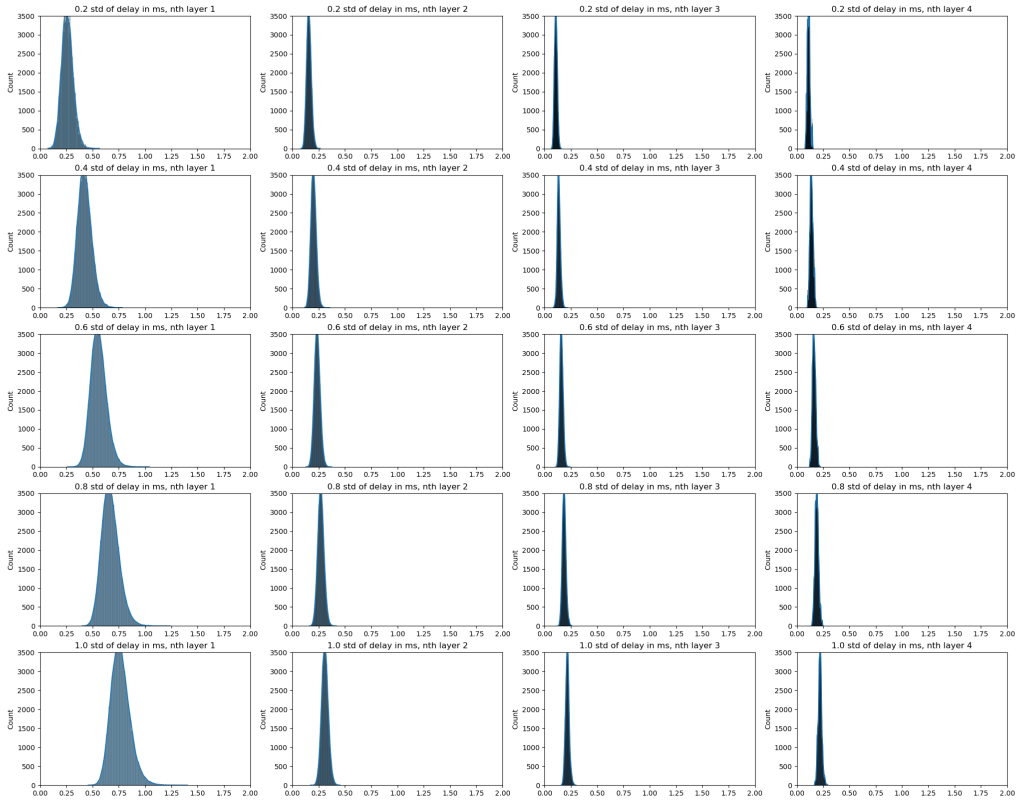
Figure 4.



Feedforward network gives us a view of how network error propagates though layers. We averaged the VP distance of each cell of each set up across layer with different standard deviation of gaussian spike error at synapses. In figure 4, x-axis representing the standard deviation of

gaussian noise introduce at synapses, y-axis representing the average Victor-Purpura distance of a layer. The layer is organized from Layer 0 – Layer 9 for network size 30 -60, and layer 0 – Layer 4 for network size 200. It is expected that layer 0 always has 0 average VP because no synaptic transmissions have happened yet. For Layer 1, the average VP distance scales linearly, as the error has only introduced once at synapse transmission, and for layer two, the average VP distance starts to scale non-linearly. One key observation is that average VP distance scales dramatically for layer 3 and above when tiny error was introduced for network of size 30 cells per layer, and when the errors are larger, the networks nearly loose all information as average VP distance approach 1.1, which is determined to be totally random.
The average VP distance rate of scaling for layer 3 and above gradually decrease when the network size gets larger. This means that larger neural networks are more resistant to errors.

Figure 5. VP distance of 200 cells Feedforward network



Another observation is that, for feedforward networks of size 60 cells, layer 7, 8, 9 have smaller average VP distance when the error of standard deviation 0.3ms above. For feedforward networks of size 200 cells, the average VP distances are lower for layer 2, 3, 4 compare with layer 1 across all different magnitude of errors. This means that the larger networks are not only resistant to error, but they are correcting the errors happened during synapses. This conclusion is further

confirmed by Figure 5, which shows the VP distance distribution of 200 cells Feedforward network. The distribution gradually gets concentrate at lower VP distance from layer 1 to 4, meaning the signals in the later layers are more robust against error, even though larger error has been accumulated. This might be due to higher connectivity in the larger networks which may mitigate the effect of single errors.

Figure 6, VP distance distribution of Scale Free across time and magnitudes of errors

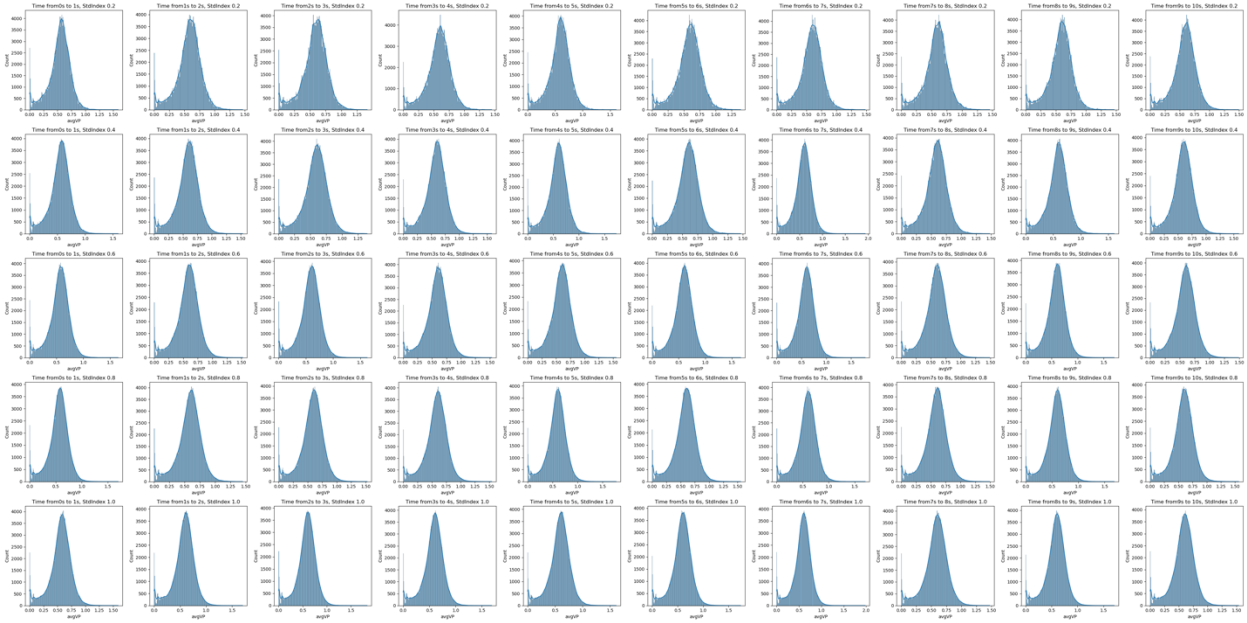
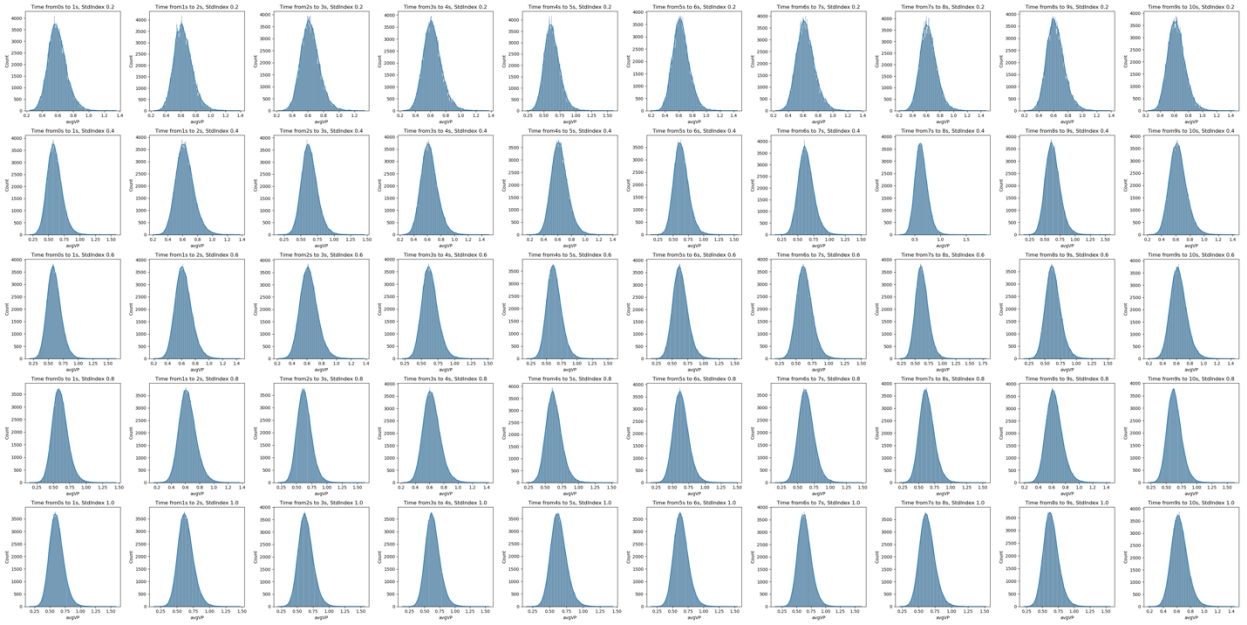


Figure 7. VP distance distribution of Small World across time and magnitudes of errors



For non-linear neural network (Small World Network, Scale Free Network), there does not exist a layered structure to measure propagation. However, due to the non-linearity, the cell activities

later are under more random synaptic transmission error influence than at an earlier time. As a result, we would like to compare the distribution of VP distance at different times of the simulation. We break the 10s simulation time into pieces of 1s, so there are10 sections per simulation. We compare the distribution of VP distance per section shown in Figure 6 & Figure 7. Across the columns are section from 0 -1s to 9-10s, and across the row are different magnitude of gaussian errors with standard deviation from 0.2ms to 1ms The distribution looks very similar across different times section and across different magnitude of error introduce, consistent with prior finding in the linear case. The resilience of scale-free and small-world networks can be attributed to their structural properties. Scale-free networks, with their hub-like architecture, allow for efficient communication and error distribution across the network, preventing local perturbations from disrupting the entire system. Small-world networks combine efficient local and global communication, enabling them to maintain functionality even when local errors occur. This is consistent with the robust-yet-fragile nature of these networks, where they are generally robust against random errors but can be vulnerable to targeted attacks on their hubs.

Discussion and Limitations

The findings from our simulations suggest that network size influence the propagation and impact of synaptic errors within neural networks, regardless of whether linear networks (Feedforward Network) or non-linear networks (Small World Network, Scale Free Network) is. Larger networks have better resiliency against and are capable reduce the effect of such errors. While exact reasons are not known, it is likely due to their higher connectivity and the presence of redundant pathways which may help in the error correction or mitigation.

These simulation results have significant implications for understanding how biological neural networks process information and maintain functionality despite inherent biological variability and potential synaptic errors. The ability of certain network architectures to buffer against errors might be crucial in neural development and learning, where synaptic modifications are frequent, and errors can be common.

However, our simulations are limited in following ways:
Model Simplification: Our use of point neurons with the Hodgkin-Huxley model, while computationally feasible, simplifies the complex morphological and biochemical properties of real neurons. This reductionism limits the ability to fully capture the dynamics of synaptic interactions and their impact on neural computation in a more biologically accurate setting.
Synaptic Error Modeling: The Gaussian model for synaptic timing errors, though providing a useful approximation, does not encompass all types of synaptic variability observed in biological systems.

Real synaptic errors might also involve variations in neurotransmitter release, receptor dynamics, and other stochastic biochemical processes that were not modeled in this study.

Network Size and Complexity: The computational constraints that limited the size of the networks and the number of simulations that could be conducted may also restrict the generalizability of our findings. Larger and more complex network simulations might yield different insights into error propagation and network resilience.

Biological Relevance: While the model networks used mirror some aspects of neural architecture in the brain, they are still abstract representations. The extent to which these findings apply to specific neural circuits in vivo, particularly in higher cognitive functions, remains to be validated with empirical data.

Future research should aim to address the limitations noted by incorporating more detailed neuronal and synaptic models, exploring a broader range of error types, and validating findings against experimental data. This would enhance our understanding of neural information processing and the robustness of neural circuits against internal and external perturbations.

Work Cited

1. "Huetz, C., Philibert, B., & Edeline, J.-M. (2016). Precise spike timing and the coding of complex auditory scenes in the auditory cortex. *Journal of Neuroscience*, 36(5), 1158-1170. DOI: 10.1523/JNEUROSCI.3607-15.2016
2. Han, X., Qian, X., Bernstein, J.G., Zhou, H.-H., Franzesi, G.T., Stern, P., Bronson, R.T., Graybiel, A.M., Desimone, R., & Boyden, E.S. (2011). Millisecond Timescale Optical Control of Neural Dynamics in the Nonhuman Primate Brain. *Neuron*, 62(2), 191-198. DOI: 10.1016/j.neuron.2009.03.011
3. Barbour, B. (2001). Variability of neurotransmitter concentration and nonsynaptic diffusion in synaptic clefts of the rat neocortex. *Journal of Neurophysiology*, 86(3), 1126-1136.
4. Softky, W.R., & Koch, C. (1993). The highly irregular firing of cortical cells is inconsistent with temporal integration of random EPSPs. *Journal of Neuroscience*, 13(1), 334-350.
5. Sporns, O. (2010). "Networks of the Brain". MIT Press. In this book, Olaf Sporns discusses the role of different types of neural networks, including feedforward networks, in processing and integrating information in the brain. The text provides a detailed overview of how information flows through structured pathways in various cognitive and sensory systems, highlighting the importance of feedforward networks in the hierarchical processing of neural information.
6. Watts, D. J., & Strogatz, S. H. (1998). "Collective dynamics of ‘small-world’ networks." Nature, 393(6684), 440-442. This seminal paper introduced the concept of small-world networks and has been influential in neuroscience for understanding how brain connectivity facilitates both specialized and integrated processing.
7. Markram, H., Toledo-Rodriguez, M., Wang, Y., Gupta, A., Silberberg, G., & Wu, C. (2004). "Interneurons of the neocortical inhibitory system." Nature Reviews Neuroscience, 5(10), 793-807. This comprehensive review discusses the properties of interneurons in the neocortex and provides insights into the ratio of excitatory to inhibitory synapses, emphasizing the functional implications of this balance in cortical networks.
8. Softky, W. R., & Koch, C. (1993). "The highly irregular firing of cortical cells is inconsistent with temporal integration of random EPSPs." Journal of Neuroscience, 13(1), 334-350. This paper discusses the variability in firing rates among cortical neurons and explores theoretical implications for neuronal computation.
9. Dayan, P., & Abbott, L. F. (2001). "Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems." MIT Press. This textbook provides a comprehensive overview of firing rates across different types of neurons and brain regions, offering insights into the principles of neural activity.
10. Victor, J. D., & Purpura, K. P. (1996). "Nature and precision of temporal coding in visual cortex: A metric-space analysis." Journal of Neurophysiology, 76(2), 1310-1326.
11. Kreuz, T., Haas, J. S., Morelli, A., Abarbanel, H. D. I., & Politi, A. (2007). "Measuring spike train synchrony." *Journal of Neuroscience Methods*, 165(1), 151-161.