

On Infantile Amnesia and Network Structure

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Commentary on "Emergent stability in complex network dynamics."

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Understanding infantile amnesia is crucial to unraveling the intricate mechanisms that underpin memory formation. The enigmatic phenomenon of infantile amnesia, where early childhood memories fade into obscurity, poses a puzzle within the realm of cognitive development. Exploring this phenomenon not only sheds light on memory retention but also holds the key to comprehending the intricate workings of the human brain.

In this letter, we endeavor to draw an intriguing analogy between synaptic density—specifically in the hippocampus, a pivotal brain region for memory—and the stability of neural networks. Synaptic density, much like the stability of computational models, undergoes dynamic changes during early development. This analogy offers a unique lens through which to explore the developmental stages of memory formation and retention.

Analogous to the synaptic proliferation and subsequent pruning observed in the hippocampus, the stability of the connectivity matrix in computational models mirrors a similar trajectory. During early stages, the brain, akin to a network with exuberant synaptogenesis, showcases a homogenous and unstable connectivity matrix. This stage corresponds to a highly connected initial state (similar to a Hopfield network)—chaotic, oscillatory, and lacking persistent memory formation. However, as the brain matures, a phase of synaptic pruning ensues, leading to a more heterogeneous and stable connectivity matrix, enabling the formation of persistent memories. The decline in neurogenesis in the hippocampus was hypothesized to be the cause of infantile amnesia [Josselyn2012]. Reduction in the dimension of the connectivity matrix may have an effect on stability, but not as much as synaptic pruning.

Sufficiently large and heterogeneous network structure guarantees stability independent of its microscopic parameters and external perturbation [Meena2023]. Spectral analysis of the adjacency and Laplacian matrices may reveal significant insight. Stable matrices tend to have heterogeneous eigenvalue distribution. This is evident in power (von Mises) iteration. As the iteration number increases it converges to the greatest eigenvalue, which corresponds to stability. On the other hand, if the two greatest eigenvalues are equal or close, then iteration will oscillate and never converge.

For random matrices, whose entries are independent and identically distributed with zero mean, circular law states that the eigenvalue distribution converges to uniform distribution over the unit disc as the dimension goes to infinity. Complete randomness diminishes structural heterogeneity.

Von Neuman and Gibbs Entropies of graphs can be used to analyze the structural and external excitation requirements to have a stable network. Von Neuman Entropy captures the structural characteristics, whereas Gibbs Entropy measures the uncertainty related to the latent states of a graph. The uncertainty should not be high (corresponding to uniform eigenvalues and instability) or zero (corresponding to full or no connectivity). There should be a heterogeneous structure in order to have a stable operation.

Consider block diagonal matrices. Typically they have heterogeneous eigenvalues, which will lead to stability. Here, we can draw an analogy with the compartmentalization of the brain. A compartmentalized brain will guarantee stable functioning. Pruning excessive connections formed during infancy is a prerequisite for stability and hence permanent memories. Unpruned excessive functions not only prevent persistent memory formation, will also disturb the regional interaction stability, which may cause or exacerbate psychiatric disorders. Therefore, spectral analysis of connectivity may constitute a measure for them.

Let's model the brain connectivity as a Restricted Boltzmann machine. Above a certain connectivity rate, the spiking network will fire forever, even if the input excitation is canceled. To have stability and memory, the number of recurrent connections should be decreased. Otherwise, the spiking will oscillate and never converge to a stable state (i.e. no memory).

In essence, artificial neural networks are function approximators. Any function can be approximated with an adequate number of parameters. For instance, shallow networks with high dimensions can successfully represent words and consequently enable the success of current large language models. However, fully connected layers become practically untrainable for high dimensions. Unlike shallow networks, more layers with limited dimensions are utilized in deep structures. Furthermore, special structures (Convolutional Neural Network, Recurrent Neural Network, and Transformer architectures) are imposed to achieve stable structures that can be trained more easily. We think the incorporation of these specific structures makes the network more heterogeneous, prevents oscillations, enables memorization, and hence makes it trainable more easily. In this case, pruning is not performed during training but provided within the network structure implicitly at the beginning. After training, deep artificial networks tend to have unnecessary redundancy that can be removed by reducing weight precision or pruning without noticeable performance degradation. Pruning during train as in human brain may be more efficient. There should be a mechanism in the brain that performs synaptic pruning modulated by the inputs.

Proposing the analysis of stability of connectivity matrices as a future research direction holds promise in elucidating the nuances of memory formation. Exploring how the transition from homogeneous to heterogeneous connectivity impacts memory retention within computational models might yield profound insights mirroring the developmental stages observed in the brain.

The proposed analogy between synaptic density dynamics and connectivity matrix stability provides a compelling framework to delve deeper into the mechanisms underlying memory formation. While infantile amnesia remains a captivating enigma, this conceptual linkage beckons further exploration, offering a potential avenue for unveiling the mysteries of memory retention and cognitive development.

References

[Josselyn2012] Josselyn, Sheena A., and Paul W. Frankland. "Infantile amnesia: a neurogenic hypothesis." *Learning & Memory* 19.9 (2012): 423-433.

[Meena2023] Meena, Chandrakala, et al. "Emergent stability in complex network dynamics." *Nature Physics* (2023): 1-10.