CAN ARTIFICIAL NEURAL NETWORKS LEARN LIKE BRAINS?

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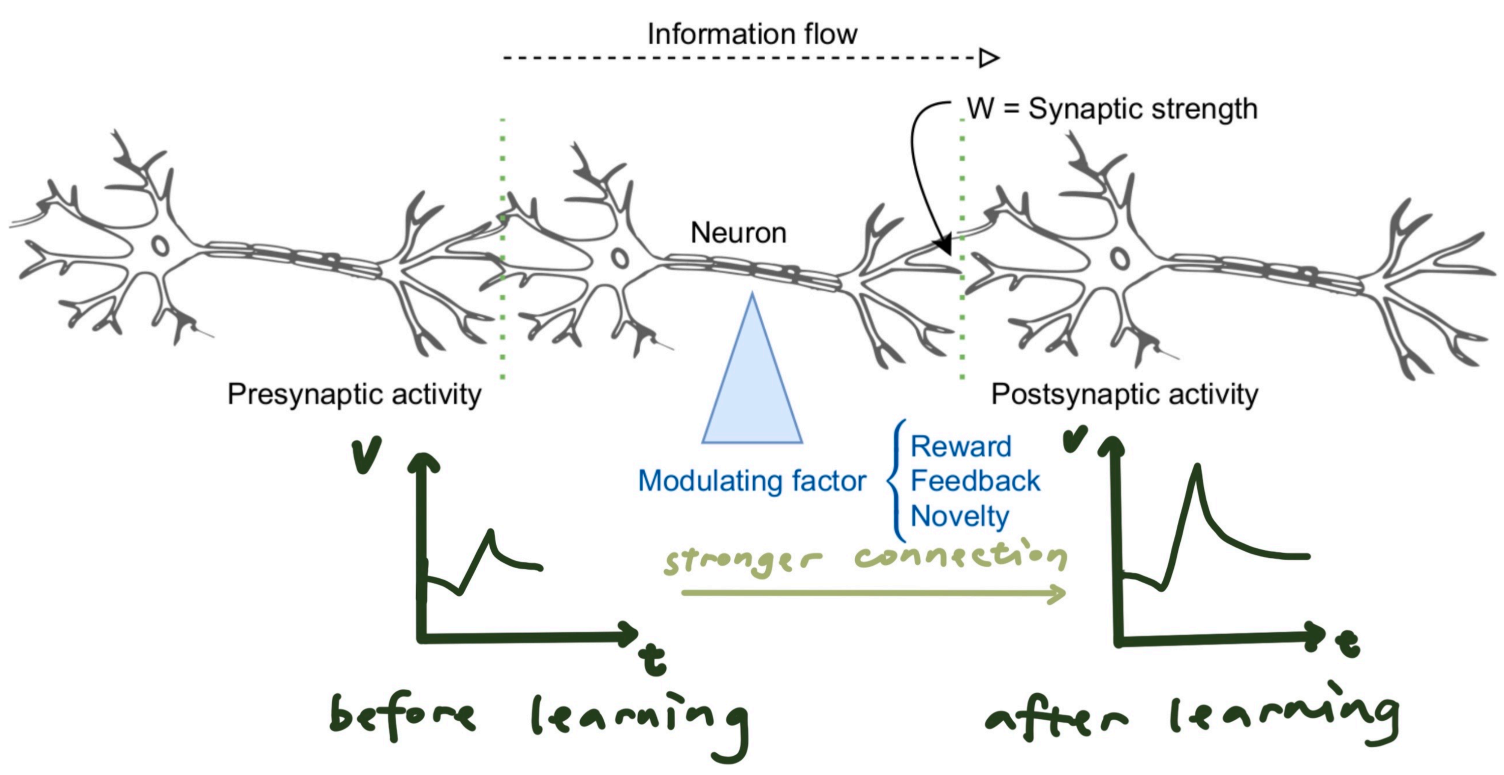
Introduction: The Brain's Plasticity and Artificial Neural Networks

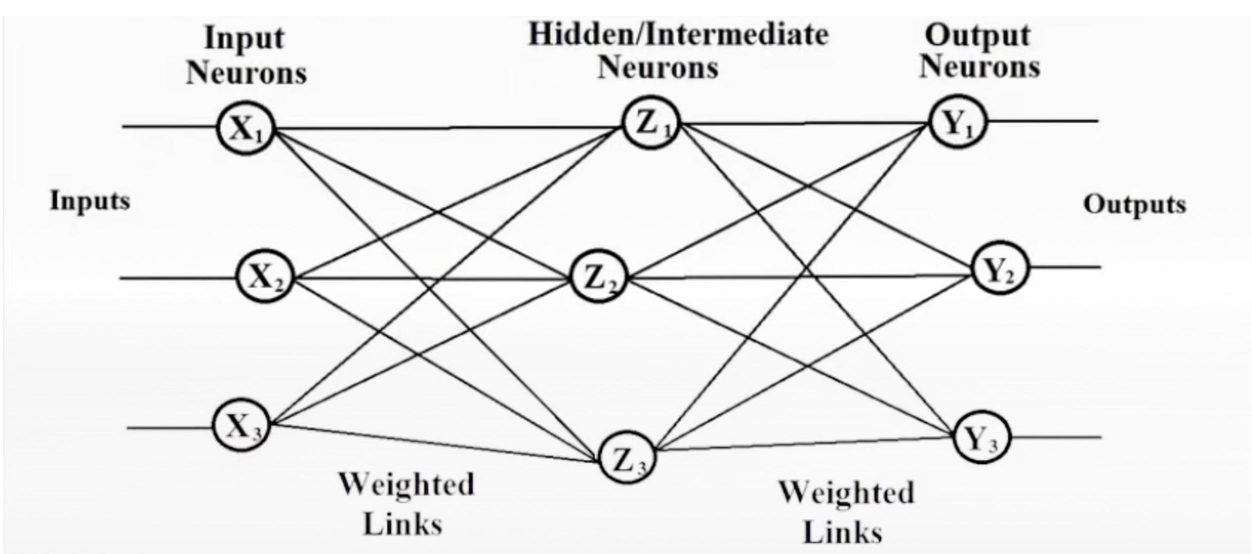
Discover the fascinating world of artificial neural networks inspired by the brain's plasticity, the ability to change and adapt as we learn. Researchers strive to create artificial neural networks that can learn and adapt like the human brain, unlocking their full potential and enabling groundbreaking applications, including computational psychiatry.

Hebbian Learning: The Cornerstone of Neural Network Learning

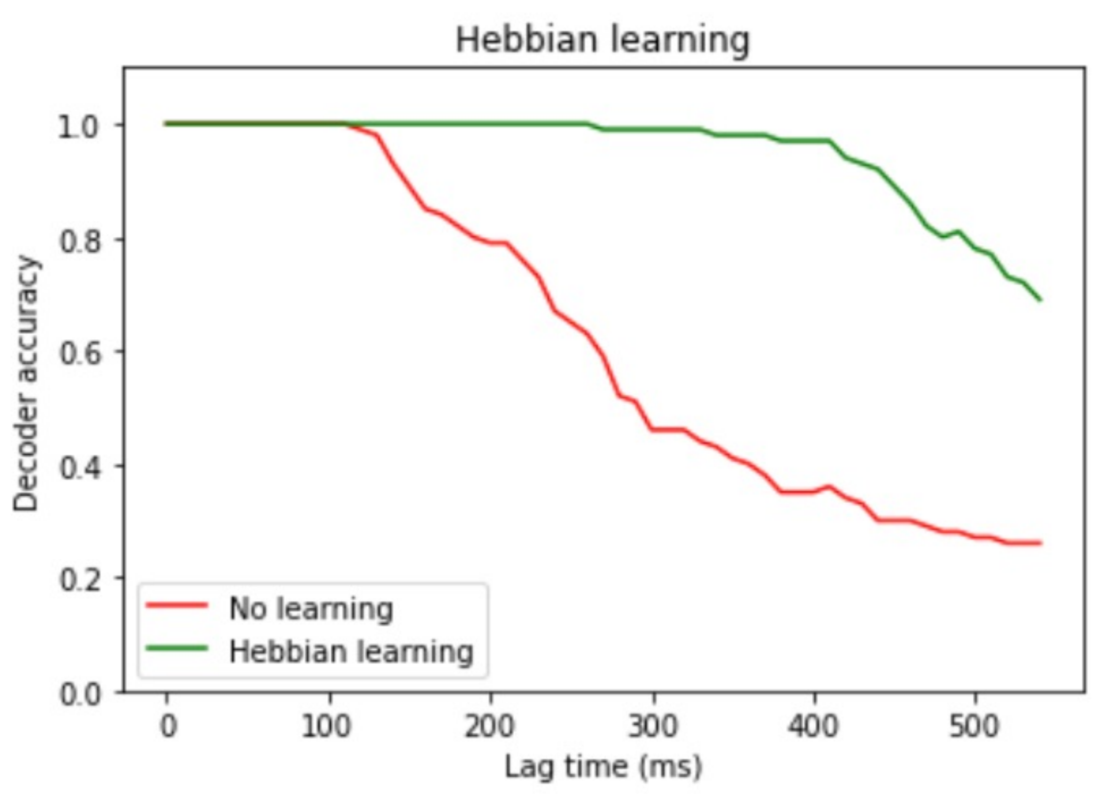
Hebb's rule, "cells that fire together wire together," laid the foundation for neural network learning. Hebbian learning is a process that strengthens connections between neurons that consistently activate together. By applying this principle to artificial neural networks, researchers can improve their performance by increasing the weight between interconnected neurons that are both activated at the same time (Hebb, 1949).

Hebbian learning has been found to be particularly useful in pattern classification and working memory. In a random recurrent neural network model of working memory, Hebbian learning has been shown to significantly increase the length of time memory can be maintained (Hebb, 1949). This learning rule's simplicity and effectiveness make it a fundamental component of many neural network models.





Hebbian learning will update the weights of the links between neurons.



The figure shows the effect of Hebbian learning in a random recurrent neural network, which simulate the working memory in our brain. It is easy to notice that Hebbian learning significantly improve the capacity of this working memory model.

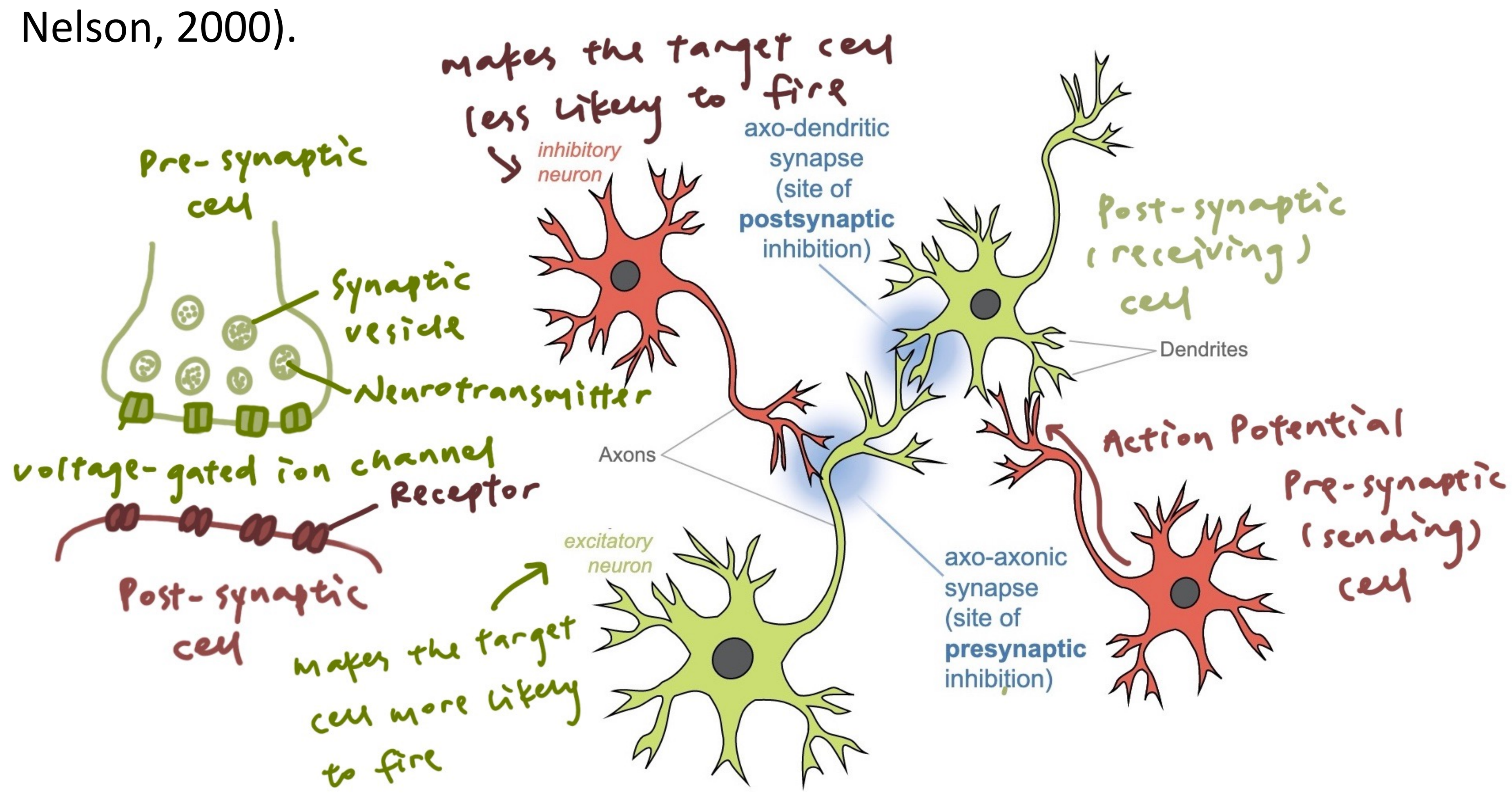
References:
Bi, G.-Q., & Poo, M.-M. (2001). Synaptic modification by correlated activity: Hebb's postulate revisited. Annual Review of Neuroscience, 24, 139-166.
Hebb, D. O. (1949). The Organization of Behavior. New York: Wiley.
Series. (2020). Computational Psychiatry: A Primer.
Siegle, & Hasselmo. (2002). Using connectionist models to guide assessment of psychological disorder.
Turrigiano, G. G., & Nelson, S. B. (2000). Hebb and homeostasis in neuronal plasticity. Current Opinion in Neurobiology, 10(3), 358-364.

Beyond Hebbian Learning: Bio-Inspired Learning Algorithms

Researchers have developed advanced bio-inspired learning algorithms to further improve the learning capabilities of artificial neural networks. These algorithms aim to capture more complex aspects of brain learning processes:

A) Spike-timing-dependent plasticity (STDP): STDP is a learning rule that refines the learning process by considering the timing of neuron activation. It modifies the strength of connections between neurons based on the precise timing of spikes in their activity. This allows for more accurate and efficient learning in neural networks (Bi & Poo, 2001).

B) Homeostatic plasticity: Homeostatic plasticity is a mechanism that maintains the stability of neural networks by regulating overall activity. By balancing excitatory and inhibitory inputs, homeostatic plasticity ensures that the network operates within an optimal range, preventing over-excitation or inhibition and promoting efficient learning (Turrigiano & Nelson, 2000).

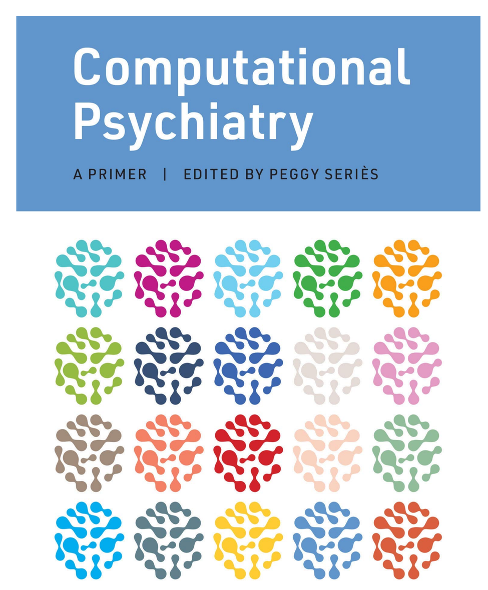


Homeostatic plasticity improves the performance of neural networks by finding the optimal ratio of inhibitory and exhibitory neurons.

Computational Psychiatry: Using Artificial Neural Networks to Investigate Mental Disorders

Computational psychiatry is an emerging field that significantly benefits from employing neural networks to create mechanistic and behavioral models for mental health disorders. These networks examine massive amounts of data, decoding intricate patterns in brain activity, behavior, and cognition. This leads to enhanced decision-making models for both healthy individuals and those with psychiatric conditions. By incorporating various data sources, such as neuroimaging, genomics, and clinical records, neural networks facilitate a comprehensive understanding of psychiatric disorders, laying the groundwork for more effective diagnostic and treatment approaches.

Siegle and Hasselmo (2002) employed neural networks to investigate emotional processing impairments in depression. Their model successfully emulated the typical behavior of depressed patients, including the faster recognition of negative information. By retraining the network with positive information, akin to cognitive behavioral therapy, the model's response was normalized. This underscores the potential of neural networks in deepening our understanding of depression and treatment outcomes (Series, 2020).



Conclusion: Pioneering the Fusion of AI and neuroscience

Our journey to create artificial neural networks that learn like the human brain is just beginning. As we continue to explore bio-inspired learning algorithms, and foster collaboration between AI, neuroscience, and psychiatry, we unlock the mysteries of the human brain and related diseases while revolutionizing AI.