
MACHINE LEARNING WITH SPIKES

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ACKNOWLEDGEMENTS

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ABSTRACT

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1 ~ INTRODUCTION AND THEORY

The concept of intelligence, how it arises and what needs to be in place for it to occur, is probably been some of the longest standing questions in human history. How and if it can be reproduced artificially is a particularly hot topic today. Getting answers to these questions will not only help us understand our own minds but also brings the promise of unlocking new technology discovering new drugs or materials, it may be the last invention humans ever need to make. In recent years we have crept ever closer to answer some of these questions. New state of the art artificial intelligence systems have achieved remarkable success like the sophisticated language capabilities of GPT models and the protein-folding predictions of AlphaFold.

Despite these triumphs, a significant gap persists between artificial systems and their biological counterparts. Evidently, these AI systems might possess superhuman capabilities in one or a few domains but none of them surpass humans in all, what we call Artificial General Intelligence (AGI). Also more relevant to this thesis is that current state-of-the-art ANNs, require vast amount of data, computation and energy resources. This demand stands in stark contrast to the biological brain—an extraordinarily complex and efficient organ estimated to operate on merely 20-30 Watts while also sitting comfortably in the AGI category. This profound difference in efficiency and capability suggests that contemporary ANN paradigms, might be missing or oversimplifying fundamental principles crucial for truly intelligent and scalable computation.

In this thesis we explore new approaches that first and foremost might solve the critical limitations of scalability and energy efficiency in artificial intelligence. But also hopefully lay the foundation for systems that might eventually unlock true AGI. This likely requires moving beyond current mainstream ANN architectures. We will explore the potential of incorpo-

rating more sophisticated biological principles into AI design. This involves investigating alternative computational paradigms, inspired by mechanisms such as sparse, event-driven processing observed in Spiking Neural Networks (SNNs), the role of temporal dynamics in neural coding, or the potential computational advantages of systems operating near critical states. The central challenge lies in identifying and abstracting the truly essential biological mechanisms for intelligence and efficiency, distinguishing core principles from intricate biological details that may not be necessary for artificial implementation. Concretely this thesis wants to

- Explore how information-flow based on sparse event might be implemented in a network, encoding
- Explore learning algorithms suitable for such a network

In the succeeding sections we will lay down the theoretical foundations that we base our methods on

Established Methods. We will get familiar with the current AI methods

Neuroscience 101. Review neuroscience literature

Method. Outline the methods and how you can recreate the work

Results. bla bla bla

Discussions. blabla bla future work bla bla

1.1 ~ ESTABLISHED METHODS

The term Artificial Intelligence forms an umbrella over many different techniques that make use of machines to do some intelligent task. The most promising way to achieve AI today is through deep neural networks. The neural networks of today are almost exclusively based on the simple perceptron neuron model. It is a fairly old idea based on a simple model on how the brain processes information. The model of the neuron that it is based on has synapses just like the biological one, the synapses function as inputs which when firing will excite the receiving neuron more or less depending on the strength of the connection. If the receiving neuron gets excited above a threshold it will fire and pass the signal downstream to another receiving neuron. Which is conceptually similar to how real neurons operate.

$$z = a\left(\sum xw\right)$$

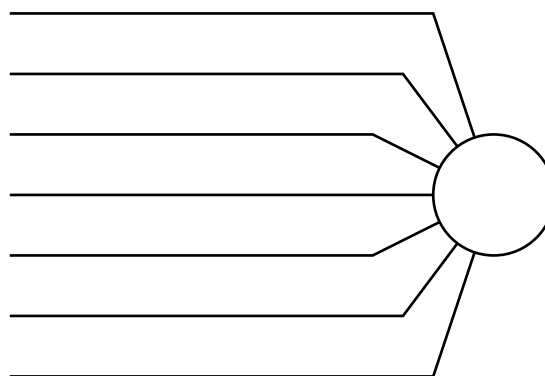


Figure 1: perceptron

This simple model is called a perceptron, which introduced a learning rule for a single computational neuron capable of classifying linearly separable patterns. However, to the MLP was the understanding that stacking multiple layers of these perceptron-like units could overcome these limitations by creating more complex decision boundaries. The critical breakthrough enabling the practical use of MLPs was the independent development and subsequent popularization of the backpropagation algorithm. Backpropagation provided an efficient method to calculate the gradient of the error function with respect to the network's weights, allowing for effective training of these deeper, multi-layered architectures. This combination—multiple layers of interconnected units¹, typically using non-linear activation functions, trained via backpropagation—defines the MLP, which became a foundational architecture for neural networks and paved the way for the deep learning revolution. GPT, alphafold, etc. all use these fundamentals with different variations of architectures which boils down to how many layers how large layers how dense layers and how they should be connected (attention, RNN, CNN, resnet)

1.1.1 ~ PROBLEMS WITH THE ESTABLISHED METHODS

We mentioned in the introduction that the deep learning technique is inefficient compared to the brain. The reason why is not clear, from a hardware standpoint the brain simply has better hardware much more connections per area and the computation is baked into the hardware. From an algorithmic standpoint there may also be room for improvement, In order to compute with deep learning and perceptron networks we need to compute all the entries even tho they might not contribute or are zero. Take an image for example, the human visual system is really good at ignoring unimportant details and we only have a tiny area of focus. even then we don't process much unless something interesting happens like movement. In deep learning we have to process the entire image. The status quo needs global synchronization, every previous layer need to finish computing before the next can start, this can be hard to scale for large systems where multiple processors need to talk to each other. The same applies to backpropagation it requires freezing the entire network and separates computation and learning into two separate stages, local connections that should be independent of each other have to wait extreme quantization models (1bit) also highlight the inefficiency

1.2 ~ NEUROSCIENCE 101

Although the perceptron captures common key aspects of biological neuron models A lot is left on the table. A lot of progress and new ideas has surfaced since the invention of the perceptron. The simple neuron previously thought to be simple like the perceptron model turns out to be more complex, the information encoding is also a key research topic not explored by older models. How the brain learns is also entirely different than what deep learning uses, changing the models and information encoding forces us to rethink how the learning algorithms in the brain work. Network architecture, fully asynchronous

¹While often conceptualized in layers (e.g., layers of the neocortex), the brain's connectivity is vastly more complex than typical feedforward ANNs, featuring extensive recurrent connections, feedback loops, and long-range projections that make a simple 'unrolling' into discrete layers an oversimplification

1.2.1 ~ NEURON MODELS

The neuron is the fundamental building block of the brain. Comprised of an axon synapses dendrites. When presynaptic neurons fire the postsynaptic neuron increases in potential if it reaches a threshold it will itself fire. Neurons communicate with neurotransmitters such as dopamine and glutamate. There are ion channels and some calcium idk.

1.2.2 ~ ENCODING

It is observed that neurons fire in short bursts called spikes. Experiments show that neurons fire repeatedly. A sequence of spikes is called a spike train, and exactly how information is encoded in a spike train is a topic of hot debate in neuroscience. A popular idea is that information is encoded in the average value of spikes per time called rate encoding

1.2.3 ~ LEARNING

Spikes Do Not Play Nice With Gradients. While models like Spiking Neural Networks (SNNs) offer greater biological plausibility and potential advantages in processing temporal information and energy efficiency, their adoption faces significant challenges, primarily stemming from the nature of their core computational element: the discrete spike.

A cornerstone of the success of modern deep learning, particularly with Multi-Layer Perceptrons (MLPs) and related architectures, is the backpropagation algorithm. Backpropagation relies fundamentally on the network's components being differentiable; specifically, the activation functions mapping a neuron's weighted input sum to its output must have a well-defined gradient. This allows the chain rule of calculus to efficiently compute how small changes in network weights affect the final output error, enabling effective gradient-based optimization (like Stochastic Gradient Descent and its variants). These techniques have proven exceptionally powerful for training deep networks on large datasets.

However, when we transition from the continuous-valued, rate-coded signals typical of MLPs to the binary, event-based spikes used in SNNs, this differentiability is lost. The spiking mechanism itself—where a neuron fires an all-or-none spike only when its internal state (e.g., membrane potential) crosses a threshold—is inherently discontinuous. Mathematically, this firing decision is often represented by a step function (like the Heaviside step function), whose derivative is zero almost everywhere and undefined (or infinite) at the threshold.

Consequently, standard backpropagation cannot be directly applied to SNNs. Gradients calculated using the chain rule become zero or undefined at the spiking neurons, preventing error signals from flowing backward through the network to update the weights effectively. This incompatibility represents a substantial obstacle, as it seemingly precludes the use of the highly successful and well-understood gradient-based optimization toolkit that underpins much of modern AI.

Surrogate Gradients: A popular approach involves using a “surrogate” function during the backward pass of training. While the forward pass uses the discontinuous spike generation, the backward pass replaces the step function's derivative with a smooth, differentiable approximation (e.g., a fast sigmoid or a clipped linear function). This allows backpropagation-like algorithms (often termed “spatio-temporal backpropagation” or similar) to estimate gradients and train deep SNNs, albeit with approximations.

1.2.4 ~ NETWORK

However, this abstraction, while powerful, significantly simplifies the underlying neurobiology. Decades of rigorous neuroscience research reveal that brain function emerges from complex electro-chemical and molecular dynamics far richer than the simple weighted sum and static activation. While it's crucial to discern which biological details are fundamental to computation versus those that are merely implementation specifics², moving beyond the standard MLP model is necessary to capture more sophisticated aspects of neural processing.

A primary departure lies in the nature of neural communication. Unlike the continuous-valued activations typically passed between layers in an MLP (often interpreted as representing average firing rates), biological neurons communicate primarily through discrete, stereotyped, all-or-none electrical events known as action potentials, or 'spikes'. Information in the brain is encoded not just in the rate of these spikes (rate coding), but critically also in their precise timing, relative delays, and synchronous firing across populations (temporal coding) (Gerstner et al., 2014). For instance, the relative timing of spikes arriving at a neuron can determine its response, allowing the brain to process temporal patterns with high fidelity – a capability less naturally captured by standard MLPs. Spikes can thus be seen as event-based signals carrying rich temporal information.

Furthermore, neural systems exhibit complex dynamics beyond simple feedforward processing. Evidence suggests that cortical networks may operate near a critical state, balanced at the 'edge of chaos,' a regime potentially optimal for information transmission, storage capacity, and computational power. Systems like the visual cortex demonstrate this complexity, where intricate patterns of spatio-temporal spiking activity underlie feature detection, object recognition, and dynamic processing. These biologically observed principles—event-based communication, temporal coding, and complex network dynamics—motivate the exploration of Spiking Neural Networks (SNNs), which explicitly model individual spike events and their timing, offering a potentially more powerful and biologically plausible framework for computation than traditional MLPs.

²Disentangling core computational mechanisms from biological implementation details is a major ongoing challenge in neuroscience and neuromorphic engineering. Some complex molecular processes might be essential for learning or adaptation, while others might primarily serve metabolic or structural roles not directly involved in the instantaneous computation being modeled.

2 ~ METHODOLOGY

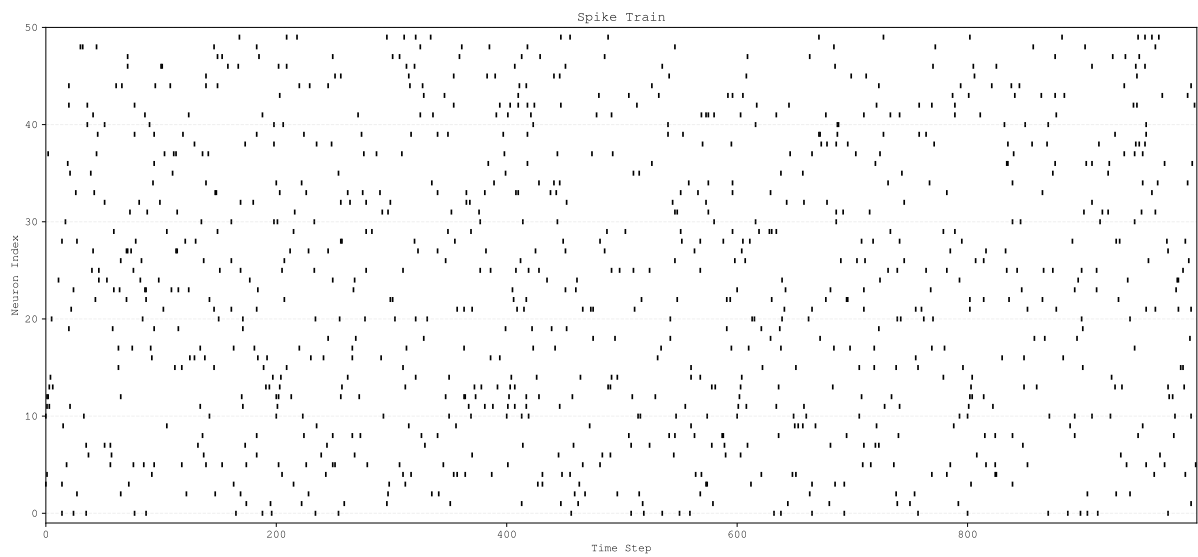


Figure 2: spike train

2.1 ~ NEURON MODELS

2.2 ~ LEARNING

2.3 ~ NETWORK

3 ~ RESULTS

4 ~ DISCUSSION

BIBLIOGRAPHY