Machine Learning With Spiking Neural Networks

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1 ~ Introduction

The quest to create intelligent machines represents a long-standing ambition, one that has gained significant momentum in recent decades with the advent of Artificial Neural Networks (ANNs). Drawing high-level inspiration from the computational principles of the mammalian brain, these models, particularly deep learning architectures like Multilayer Perceptrons (MLPs), have achieved remarkable success. They underpin many transformative technologies, exemplified by breakthroughs 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. Current state-of-the-art ANNs, while functionally powerful, require vast computational resources and energy for both training and operation. 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 performing tasks far beyond the capabilities of current AI. This profound difference in efficiency and capability suggests that contemporary ANN paradigms, often characterized by dense matrix multiplications and trained via backpropagation, might be missing or oversimplifying fundamental principles crucial for truly intelligent and scalable computation.

While one might hypothesize that further progress simply requires more computational power and incremental architectural refinements, the energy and resource costs associated with scaling current models pose significant practical limitations. This necessitates a re-evaluation of our approach. If the goal remains to create machines with brain-like capabilities and efficiency, it may be essential to draw deeper and more nuanced inspiration from neuroscience.

This essay argues that overcoming the critical limitations of scalability and energy efficiency in artificial intelligence likely requires moving beyond current mainstream ANN architectures. It will explore the potential of incorporating more sophisticated biological principles into AI design. This involves investigating alternative computational paradigms, potentially 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.

2 ~ The Current Level of Brain Inspiration

When we talk about AI today almost all models use some variation of the Multi Layer Perceptron (MLP) concept. It is a fairly old idea based on a simple model on how the brain processes information. The MLP evolved from early attempts to create computational models inspired by biological neurons. Its roots lie in the foundational work of McCulloch and Pitts (1943), who proposed a simplified binary threshold model of a neuron, and Frank Rosenblatt's Perceptron (late 1950s), which introduced a learning rule for a single computational neuron capable of classifying linearly separable patterns. However, progress stalled significantly after Minsky and Papert's 1969 book Perceptrons, which rigorously demonstrated the limitations of these single-layer models, famously highlighting their inability to solve non-linearly separable problems like the XOR function. The key insight leading 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 in the 1970s and 1980s (with key work by Werbos, Parker, LeCun, and notably Rumelhart, Hinton, and Williams in 1986). 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 units, 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.

3 ~ More advanced brain models

The perceptron, and its evolution into Multi-Layer Perceptrons (MLPs), represent foundational models in artificial intelligence inspired by early concepts of neural computation. Indeed, certain core principles resonate with biological observations: the brain comprises interconnected neurons, often organized in broadly hierarchical structures or layers[1] that process information sequentially from sensory input to higher cognitive areas. Furthermore, individual neurons integrate incoming signals—analogous to a weighted sum in MLPs—and generate an output spike or 'fire' only when a certain threshold is exceeded, a mechanism abstracted by the activation functions used in artificial neurons (McCulloch & Pitts, 1943).

[1] While 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 (Felleman & Van Essen, 1991).

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 specifics[2] , 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' (Hodgkin & Huxley, 1952). 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 (Beggs & Plenz, 2003; Chialvo, 2010). Systems like the visual cortex demonstrate this complexity, where intricate patterns of spatio-temporal spiking activity underlie feature detection, object recognition, and dynamic processing (Hubel & Wiesel, 1962; Thorpe et al., 1996). 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.

4 ~ *Challenges in Training Advanced Neural Models: The Problem of Discontinuity*

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 (Rumelhart et al., 1986). Backpropagation relies fundamentally on the network's components being differentiable; specifically, the activation functions mapping a neuron's weighted input sum to its

[2]Disentangling 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.

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.

This challenge has spurred significant research into alternative training methodologies for SNNs:

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) (Neftci et al., 2019; Zenke & Ganguli, 2018). This allows backpropagation-like algorithms (often termed “spatio-temporal backpropagation” or similar) to estimate gradients and train deep SNNs, albeit with approximations.

Bio-Inspired Local Learning Rules: Drawing inspiration from neuroscience, researchers explore learning rules based on local activity, such as Spike-Timing-Dependent Plasticity (STDP). STDP adjusts synaptic weights based on the relative timing of pre- and post-synaptic spikes (Gerstner et al., 1996; Bi & Poo, 1998). While biologically plausible and inherently suited to spike timing, purely local rules like STDP often struggle to match the performance of gradient-based methods on complex supervised learning tasks and can be harder to scale or direct towards a specific global objective. Hybrid approaches combining STDP with other mechanisms are also being investigated.

Conversion Methods: Another strategy involves training a conventional ANN (like an MLP or CNN) using standard backpropagation and then converting the trained network into an SNN (Cao et al., 2015; Diehl et al., 2015). This leverages the power of gradient-based training but may not fully exploit the unique temporal dynamics SNNs offer, and often requires careful parameter tuning during conversion.

Gradient-Free Optimization: Techniques like evolutionary algorithms or reinforcement learning can optimize SNN parameters without requiring explicit gradients, but they often suffer from lower sample efficiency and scalability issues compared to gradient descent, particularly for very large networks.

Therefore, while moving towards more biologically realistic, event-driven models like SNNs is conceptually appealing, overcoming the fundamental incompatibility with standard gradient-based optimization remains a critical area of active research and development. The success of SNNs in practice hinges significantly on the effectiveness and scalability of these alternative or adapted training techniques.

4 Bibliography