

# Advances in Neuromorphic Silicon Photonics

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**Abstract:** Neuromorphic photonics is an emerging field at the nexus of photonics and neuroscience, which combines the advantages of optics and electronics. We will look at challenges of photonic information processing, describe photonic neural-network approaches, and offer a glimpse at this field's future.

AI has always captured our imagination and it has the potential to change almost every aspect of our lives through new medical treatments, new assistive robots, intelligent modes of transportation, and more. Inspired by the human brain and spurred by the advances in deep learning, the past six years has seen a renaissance in AI. IBM, HP, Intel, Google, Apple, and Microsoft have all shifted their core technological strategies from “mobile first” to “AI first”. Deep learning with artificial neural networks has expanded from image recognition to translating languages, generating realistic speech indistinguishable from that of a human, and beating humans at highly complex strategy games like Go. At present, AI algorithms are executed on traditional CPUs, GPUs and neuromorphic (brain-inspired) electronics (IBM TrueNorth and Google TPU). However, electronic architectures face fundamental limits as Moore's law is slowing down and moving data electronically on metal wires is intrinsically bandwidth-limited and energy inefficient—critical challenges facing AI hardware. For instance, Google's AlphaGo AI requires weeks to train and uses 1920 CPUs and 280 GPUs, which translates into massive power consumption, reaching around \$3000 in electric bill per game.

Neuromorphic photonics [1] has experienced a recent surge of interest over the last few years, promising orders of magnitude improvements in both speed and energy efficiency over digital electronics using: artificial neural networks [2-5], spiking neural networks [6-8], and reservoir computing [9]. By combining the high bandwidth and efficiency of photonic devices with the adaptive, parallelism and complexity attained by methods similar to those seen in the brain, photonic processors have the potential to be at least ten thousand times faster than state-of-the-art electronic processors while consuming less energy/computation [10].

We will look at some of the traditional challenges of photonic information processing, describe the photonic neural-network approaches being developed by our lab and others, discuss their applications in neuromorphic computing and machine learning, talk about the scalability of these platforms, and conclude with a future outlook of neuro-inspired photonic processing. This talk is intended for a wide audience and hopes to teach how theory, research, and device concepts from neuromorphic photonics could be applied in practical machine learning systems.

## References

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