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ELEMENTS

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NEUROMORPHIC COMPUTING

Explaining how Projected SNN Training will Largely Impact our Interactions with Technology

WILL RIHERD

IN THE FACE OF INCREASINGLY LARGE COMPUTATIONAL DEMANDS AND THE IMPENDING HALT TO MOORE'S LAW, THE SEMICONDUCTOR INDUSTRY HAS BEEN FORCED TO RE-EVALUATE THE TRADITIONAL COMPUTING PARADIGM. CENTRAL TO THIS RE-EVALUATION HAS BEEN THE NOVEL DEVELOPMENT OF NEUROMORPHIC COMPUTING—AN APPROACH THAT, AT ITS CORE, SEEKS TO REPLICATE THE BRAIN IN SILICON. DESPITE CHALLENGES ON THE ALGORITHMIC FRONT, NEUROMORPHIC COMPUTING PROMISES A MASSIVELY PARALLEL, EFFICIENT, AND SCALABLE COMPUTATIONAL SOLUTION WITH LARGE IMPLICATIONS ON THE DAILY LIVES OF CONSUMERS. THE FUTURE OF THE TECHNOLOGY, HOWEVER, IS UNCERTAIN. WITH THE RISE OF HIGH PERFORMANCE AND QUANTUM COMPUTING AS PROMISING ALTERNATIVES, THE SEMICONDUCTOR INDUSTRY AT LARGE MUST CONSIDER THE EXTENT TO WHICH NEUROMORPHIC COMPUTING CAN EMERGE AS A VIABLE AND FEASIBLE SOLUTION IN THE COMING YEARS. IT IS VITAL, THEREFORE, TO UNDERSTAND THE THEORETICAL UNDERPINNINGS OF THE NEUROMORPHIC APPROACH AND PREDICT THE LIKELIHOOD OF ITS IMPLEMENTATION WITHIN THE NEXT DECADE.

ed on the algorithmic front. In terms of research and resources, in October of 2020, Intel announced a three-year contract with Sandia National Laboratories (a government nuclear research lab) to advance neuromorphic computing beyond edge applications to progressively complex computational problems. The result will be the development of increasingly large neuromorphic systems with the intent of integrating over one billion neurons. Creating a system with such neural capacity exhibits moderate uncertainty in the short-term. Given a) the progress Intel has made when it comes to scaling Loihi and b) the difficulty of integrating an increasingly large number of neurons, the project has an uncertainty factor of around two on the low- and high-end (i.e., the system will be developed within one half to two times the expected implementation time frame). Neuromorphic computing will also experience strong research in edge applications (particularly energy efficient robotics) as members of the INRC continue to deploy Loihi in real-time audio and video processing tests.[11]

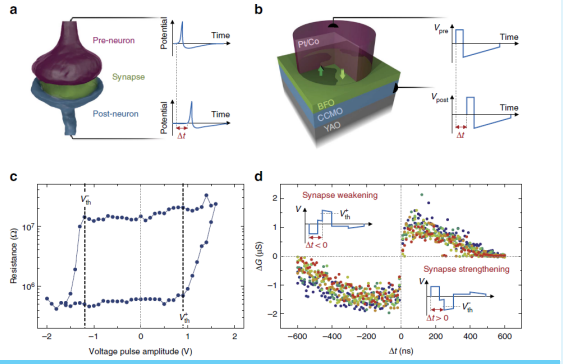
While Gartner predicts that traditional computing will hit a wall in 2025 (specifically mentioning neuromorphic computing as the leading technology for a shift in the computing paradigm), it is unlikely that a robust commercial product will be available within the next five years due to software limitations. Unlike traditional ANNs, SNNs lack a learning algorithm when it comes to parameter optimization: it is impossible to use gradient descent given the non-differentiable nature of spiking neurons (Soni).[12] Yann LeCun, the head of AI at Facebook, is a leading skeptic when it comes to neuromorphic implementation, writing that it is "premature to build a chip" when SNNs face a fundamental training challenge.[13] There is also skepticism regarding the performance of the underlying SNNs; specifically, skeptics point to the fact that SNNs do not outperform ANNs (e.g. Convolutional Neural Networks) when it comes to traditional tests of image recognition (Pfeiffer and Pfeil).[14]

Medium Term (5-10 Years)

While SNNs currently face learning challenges, it is expected that within the next five to ten years, researchers will develop novel and efficient approaches to SNN training. Current advancements have largely been focused on implementing a form of transfer learning (i.e., a process by which parameters are optimized in one "place" and transferred to a new "place"). In March of 2019, Terry Sejnowski of The Salk Institute of La Jolla and his team were able to train a standard recurrent neural network (RNN) via gradient descent methods and transfer the learned parameters to an SNN (Tiernan, "Neuromorphic computing finds new life"). While parameter transferring is a step in the right direction, Sejnowski admits that the next step—learning the SNN itself—is still "in the early days," but that there is "going to be another big shift, which will probably occur within the next five to ten years." Given both the difficulty and current progress of SNN training, there is moderate uncertainty regarding how quickly development will occur on the algorithmic front, with a general uncertainty factor of one and one-half to two times on the high-end. If an efficient learning rule is established, it is possible we will begin to see commercially viable neuromorphic chips within the decade, allowing for complex, energy efficient tasks on the "edge" (e.g., smartphones). Such commercial implementation, however, is highly dependent on the economic feasibility of widespread production, an aspect of neuromorphic chip development that is still in its infancy.

Long Term (10+ Years)

Although the future of SNN training and the economic practicality of neuromorphic hardware is uncertain in the near-term, it is possible that beyond 2030 we begin to witness a shift in the current computing paradigm. Such a shift would be characterized by the wide-spread use of neuromorphic chips in energy-constrained edge devices (e.g., mobile devices, computers, robotics, etc.). Sejnowski predicts that once the software is developed and the hardware is "sufficiently cheap," the implementation of such chips will be "ubiquitous...like sensors in phones." Abu Sebastian, Principal Research Staff Member at IBM Zurich, predicts that neuromorphic computing will play a vital role in the future feasibility of autonomous vehicles, making the point that you cannot "collect a frame, pass it



ARTIFICIAL SYNAPSES BASED ON FERRO-ELECTRIC TUNNEL JUNCTIONS *(COURTESY OF WIKIMEDIA COMMONS)*

through to a deep neural net, and wait for the response when you're traveling down a freeway at 70 miles an hour" (Greengard). The long-term draw of neuromorphic computing, is energy-efficient, on-board processing that is applicable to a wide range of technologies, from autonomous vehicles to independently operating interstellar spacecraft. Neuromorphic chips are also poised to play a large role in future medical devices and artificial body parts that can benefit from increasingly fast, on-site processing.

While neuromorphic architecture could become ubiquitous beyond 2030, it is important to note the false dichotomy between standard computer architecture and neuromorphic hardware.[15] The promise of neuromorphic chips lies in the creation of an adaptive system capable of the efficient processing of highly noisy, increasingly complex, spatio-temporal data, *not* the high-speed processing of predictable, deterministic processes (Greengard). It is shortsighted, therefore, to view neuromorphic computing as a fundamental alternative to traditional computing: the two technologies are complementary to each other, excelling in tasks suited to their specific design. It is also important to note the uncertainty surrounding the long-term ubiquity of neuromorphic computing, namely, that there is a three-way race between neuromorphic computing, high performance computing, and quantum computing (Vorhies).[16] Given the advancements of competing fields, it is possible the technology is outperformed before it is commercially viable (either by existing competitors or a novel approach yet to be developed). The future of computing, then, is largely undecided, with the only certainty being that our current computing paradigm will shift in response to the impending halt to Gordon Moore's 1965 prediction.

IMPLICATIONS

Consumers and AI Integration

Despite uncertainties regarding the path of computing, a future characterized by the widespread adoption of neuromorphic technology would have significant implications on the way consumers interact with digital devices. Peter Suma, co-CEO of Applied Brain Research, imagines a world in which neuromorphic technology enables an extreme integration of artificial intelligence into our daily lives (Ferry). Suma describes a future in which a technology like Siri transcends basic voice commands (i.e., a Siri that listens and sees all of your conversations and interactions). If you were to ask Siri what idea your friend Melissa came up with regarding your wife's birthday gift, the efficient, continuous, on-board processing of data made possible by neuromorphic computing would enable Siri to recall the conversation with your friend the week prior, bringing up both the idea and a variety of similar, personalized ideas. The salient point in Suma's eyes is that the efficiency of neuromorphic chips would enable the local storage of information, resolving widespread privacy concerns regarding consumer data. From autonomous vehicles to smart homes and edge devices, Suma's point is clear: the promise of neuromorphic technology is a future characterized by the extreme integration of artificial intelligence into our daily lives.

Semiconductor Industry

Research scientist at Hewlett Packard Enterprise, Suhas Kumar, summarizes the state of computing as a "huge rush to find something" that can continue the improvement in computer science that we have witnessed the past half century. Semiconductor manufacturers, therefore, are faced with a critical choice of whether to invest in risky chip research to compete in a future characterized by advanced computing technologies. While IBM has seen success with its TrueNorth system, Intel has exhibited the strongest commitment to neuromorphic research, evidenced by its continued progress in creating increasingly scalable neuromorphic systems. Intel's competitors are also faced with the challenge of determining the *type* of research they wish to undertake (i.e., whether they believe high performance or quantum computing will ultimately outperform the neuromorphic approach). Regardless, the challenge is clear: the computing industry will witness a shift in the coming decades, and the companies that lead this shift will capitalize on the widespread adoption of their novel technology.

"The promise of neuromorphic chips lies in the cration of an adaptive system capable of the efficient processing of highly noisy, increasingly complex, spatio-temporal data"

Large Technology Firms

Beyond the semiconductor industry, large technology companies (e.g., Google, Facebook, Amazon, etc.) are faced with the decision to embark upon internal research regarding computing hardware. As deep learning processes continue to surpass the capabilities of existing technology, companies with large workloads and available capital are faced with the decision of whether to invest internally in chip development. In February of 2019, Facebook's Yann LeCun briefly described "internal activities" the firm was taking to address the growing computational divide, referencing Google's Tensor Processing Unit as another example of the type of internal efforts large technology firms are capable of taking (Tiernan, "Facebook's Yann LeCun"). While the future is uncertain, it is clear there is a demand for change, and the feasibility of neuromorphic hardware should figure prominently in the minds of firm leaders who are considering undertaking or continuing internal development activities.

CONCLUSION

From computer science and biology to mathematics, physics, and electrical engineering, neuromorphic computing is a cross-disciplinary challenge that requires a fundamental rethinking of the way computers operate. Neuromorphic research, however, is progressing: firms like Intel are leading the charge in chip development, and the success of their efforts will have large-scale implications on consumers, the semiconductor industry, and technology firms alike. It is vital, therefore, that business leaders consider the possibilities and threats of this novel technology, understanding that the future computing paradigm will be decided by innovative firms who are rethinking current processes.

ENDNOTES

1. The term neuromorphic means "taking the form of the brain" (Fulton III). Intel (a leader in neuromorphic research) summarizes neuromorphic technology as "chips that function less like traditional computers and more like the human brain" ("Intel Newsroom–Neuromorphic Computing").

2. It can be argued that the original notion of neuromorphic computing was first proposed in Alan Turing's 1948 paper, Intelligent Machinery. However, the concept is typically attributed to Carver Mead's 1989 Analog VLSI and Neural Systems, a paper in which Mead argued that chips with an increasingly dense collection of transistors could best communicate via a replication of the brain's neural wiring.

3. The downside of traditional computer architecture is typically referred to as the von Neumann bottleneck—the notion that despite increases in processing speed, processors are forced to remain idle while data is transferred to and from the memory of a chip, resulting in increased latency.

4. Neuromorphic chips employ analog circuitry to transfer electrical signals between "neurons." The idea is that the system will be able to modulate the amount of electricity flowing between nodes, mimicking the fact that brain signals naturally have varying degrees of strength.

5. A key emphasis of neuromorphic computing is the selective mapping of neural connections. In order to operate at maximum efficiency, the brain uses only the specific neurons and synapses necessary to perform a given task. Neuromorphic systems, therefore, seek to emulate this efficiency by strategically and selectively forming connections between neighboring neurons.

6. Each "spike" in an SNN is a single-bit impulse that is analogous to an action potential in a naturally occurring neuron. A given node in the network is capable of spiking only if a state variable exceeds a given threshold.

7. In fully-connected ANNs, all nodes compute and send their output to the next layer at each time step, even if nothing has significantly changed, making the overall network computationally expensive. Conversely, SNNs employ neurons that process input separately and are only connected to local neighbors, implying that the entire layer does not need to be calculated for information to proceed to the next layer.

8. In 1965 Intel's co-founder Gordon Moore predicted that the number of transistors that could be placed on an integrated circuit would double every two years while costs remain constant / decline.

9. Loihi comprises 128 neuromorphic cores, 131,000 "neurons", and 130 million "synapses" (connections). The chip is named after an active submarine volcano off the coast of Hawaii that is set to emerge one day. The idea is that neuromorphic computing is analogously "emerging" and will eventually break the "surface" of the current computing environment.

10. In December 2018 Intel announced the creation of Kapoho Bay, Intel's smallest neuromorphic system consisting of two Loihi chips. In July of 2019 Intel was able to scale Loihi into their 64-chip Pohoiki Beach, representing the neural capacity of 8 million neurons. Most recently, Intel debuted its 768-chip Pohoiki Springs with a collective neural capacity of 100 million neurons. The chips reside in a chassis the size of five standard servers and is provided to members of the Intel Neuromorphic Research Community via a cloud-based system. Intel hopes it will emerge as a "tool for researchers to develop and characterize new neuro-inspired algorithms for real-time processing, problem solving, adaptation and learning" ("Intel Newsroom–Pohoiki Springs").

11. In July of 2020 the National University of Singapore ran an event-driven, visual-tactile perception test on Intel's Loihi chip

as well as various GPU systems to compare power consumption (Russel). The Loihi test chip slightly outperformed the GPU systems (in inferences per second) at significantly lower power consumption.

TABLE III
INFERENCE SPEED AND POWER UTILIZATION

	GPU	Loihi
Num. Inferences per second	616.63	749.23
Average Power (W)	60.24	1.34

It is important to note that Loihi's strong performance is largely the result of the entire system (in this case, robotic sensors, data formats, algorithms, and the Loihi architecture) being "re-engineered in an event-based paradigm" (Mike Davies, Director of Neuromorphic Research at Intel. See Russel). Put simply, when the system is consistent with Loihi's event-based architecture, neuromorphic hardware outperforms traditional GPU's when it comes to energy efficiency.

12. Existing deep learning algorithms depend on stochastic gradient descent and error backpropagation to efficiently "learn" a given ANN. Since SNNs operate in discontinuous, non-differentiable spikes, it is impossible to apply existing learning rules directly to SNN training (Pfeiffer and Pfeil).

13. At the 2019 International Solid State Circuits Conference in San Francisco, LeCun heavily criticized neuromorphic computing in his opening keynote address. While Intel's Mike Davies agrees that there is a lot of progress to be made on the algorithmic front, which he claims is "holding back the field," Yann's criticism resulted in a fireback from Davies citing the efficacy of neuromorphic chips in a December report produced by Applied Brain Research of Waterloo, Ontario. Davies's fireback was met with a detailed Facebook post by LeCun outlining the issues he sees with neuromorphic hardware, specifically citing the lack of an efficient training algorithm.

14. It is important to point out that SNNs are not optimized for performance on existing AI Benchmarks (e.g., ImageNet). Just how the brain is not optimized (but capable of) classifying an image that is quickly flashed on the retina, SNNs struggle with the typical frame-based test of software accuracy. The evaluation of SNNs, therefore, requires benchmark testing that emphasizes the functionality of spiking networks—i.e., "making decisions based on continuous input streams while moving in the real world" (Pfeiffer and Pfeil).

15. Dan Hutcheson, CEO of VLSI Research (an independent market analysis and consulting firm that tracks the semiconductor industry), describes the false dichotomy as follows: "Today's computers are very good at what they do. They will continue to outperform neuromorphic computing systems for conventional processing tasks. The technologies are complementary and so they will coexist." Adam Stieg, associate director of the California NanoSystems Institute at the University of California at Los Angeles, further describes how "conventional von Neumann-based computing systems" perform very well with "high-speed, predictable, deterministic processes," but struggle with increasing complexity. The promise of neuromorphic computing, therefore, is the opening up of "an entirely new and unexplored area of computing"—one that allows us to "do things with computers that we couldn't have imagined in the past" (See Greengard).

16. High-performance computing (HPC) can be generalized as a process of optimizing chip architecture for existing deep learning algorithms (Vorhies). The majority of attention is currently placed on HPC, with large technology firms beginning to enter the chip manufacturing field by developing their own proprietary chips (e.g., Google's Tensor Processing Unit) (Tiernan, "Facebook's Yann LeCun"). Conversely, quantum computing is analogous to neuromorphic computing in that it represents a rethinking of existing computer architecture. Rather than operating in bits (0 or 1), quantum computing employs quantum bits (qubits) that can be set to 0, 1, or both simultaneously (Cho).

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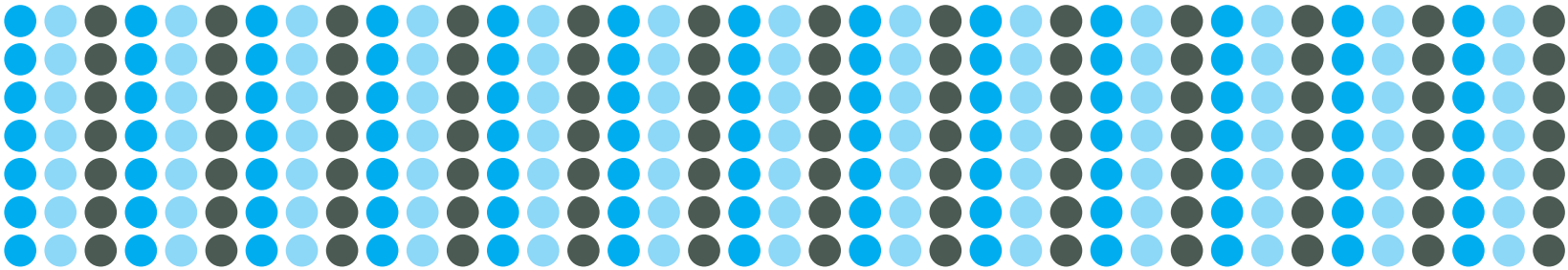

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82 **AMERICA GLOBAL TRADE DEFICIT**
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98 **CHARLES COUGHLIN, LEADER OF THE CHRISTIAN FRONT**

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100 **GERMAN AMERICAN BUND RALLY, NEW YORK, MADISON SQUARE GAREN, FEB 1939**

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