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Of Brains and Computers

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Of Brains and Computers

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ABSTRACT

The human brain – which we consider to be the prototypal biological computer – in its current incarnation is the result of more than a billion years of evolution. Its main functions have always been to regulate the internal milieu and to help the organism/being to survive and reproduce. With growing complexity, the brain has adopted a number of design principles that serve to maximize its efficiency in performing a broad range of tasks. The physical computer, on the other hand, has had only 200 years or so to evolve, and its perceived purpose is considerably different and far more constrained – that is, to solve a set of mathematical functions. This picture is rapidly changing however. One may argue that the functions of brains and computers are converging. This transition comes at a critical time when the roadmap for physical computing is becoming murky after a long period of exponential growth. Hence the existential questions arise if the underlaying design principles may converge or cross-breed, or if the different mechanisms (physics versus biology) will always translate into radically different solutions.

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1

Introduction

After many decades of phenomenal growth in both complexity and performance, the continuation of the pervasive Von-Neumann computing paradigm [274] is being challenged at every level – from the application and programming models all the way down to the architecture, circuit and technology layers. In fact, we are at the confluence of three simultaneous transitions. First, the exponential growth in complexity conveniently offered by technology scaling and Moore's Law, while surely continuing for another decade, is progressing at a slowing rate with a reduced return on investment, as foreseen by Gordon Moore in his ISSCC keynote address in 2003 [175]. A most significant outcome of this is that the *energy cost of doing a computation is ceasing to scale accordingly*. At the same time, the *nature of computing itself is being transformed* before our very eyes. Rather than using algorithmic approaches to tackle hard problems or to model complex systems, computers of today are being programmed by observing and absorbing large/huge data sets, adopting a machine-learning model. While instruction-based compute systems combined with massive parallelism have helped to scale machine-learning engines to impressive levels, these approaches again come at a huge energy cost, hampering their capability

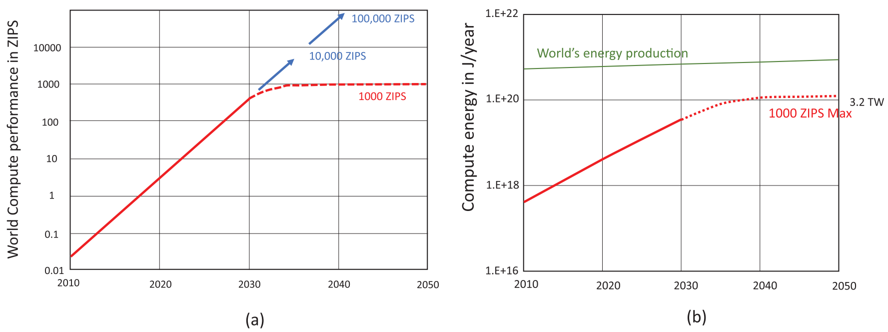

Figure 1.1: Projected growth in worldwide compute needs (in Zillions of Operations per Second) and the required energy. (Adopted from [300]).

to scale to ever larger or complex problems. A third transformation is the incredible *pervasiveness of computation*. While many computational tasks are performed in centralized compute/data facilities (the "Cloud"), computing is progressively diffusing into the physical world around us and even onto/into us or our own human body ("the Extreme Edge"), putting extraordinary demands on form factor and again energy budget [197].

The combined impact of all these factors is quite severe, as is beautifully captured by the graphs of Figure 1.1, which plot the projected growth in worldwide computation [300]. It shows how computational growth may be stunted by an emerging energy wall, that is the total energy projected to be available to humankind.

These observations force us to think about alternative computational paradigms and platforms that may help extend computational growth into the far future by providing vastly improved energy efficiency. This need equally holds for the "Cloud", the "Extreme Edge", and everything in between. A number of candidate solutions come to mind: quantum [181] and cryogenic [130] computing on one end, and organic/molecular computing [84] and synthetic biology [98] on the opposite end of the spectrum. Any one of these makes a legitimate case, but is not the focus of this monograph.

Rather we are exploring how insights in the operation of the human brain, the prototypal biological computer, can help foster a new generation of physical computational engines with vastly improved efficiency. Over a span of hundreds of thousands of years, the brain has emerged, evolved and adapted to deal with evermore complex tasks. To do so, it has embraced a number of design principles that serve to maximize its efficiency while performing a broad range of tasks. And extremely successfully so, to say the least. Consuming only 20 W on average, the brain performs tasks that either require orders of magnitude more power, or are simply not possible on the computers of today.

Of course, this has not gone unnoticed. As early as the mid-1940s, researchers including McCullough and Pitts, inspired by biological neural nets that constitute animal brains, started to explore how to build "artificial neural networks" (ANNs or NNs in short) [163], ultimately leading to the following understanding:

> An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron receives a signal then processes it and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called edges. Neurons and edges typically have a weight that adjusts as learning proceeds. [20]

While this model in itself is simple enough, it took decades to turn it into useful paradigm, and it required contributions from a great many researchers to bring the field to where it is today. These include the structure, topology and dimension of the networks, the numbers of layers, and the mechanisms for learning (that is, programming the weights). While the initial results were exciting as harbingers of a new paradigm, they were mediocre in scale and complexity at best. It was not until the advent of CMOS technology and VLSI (Very Large Scale Integration) [165] in the mid 1980s, with its exponential growth in complexity, that artificial neural networks gave a semblance of becoming practical. Today's networks, buoyed by the availability of specialized high-performance processors such as the nVidia GPU [93] and the Google TPU [264], have risen to unprecedented levels of complexity solving really hard problems that had escaped traditional (algorithmic) computers so far. This is best illustrated by the chart of Figure 1.2. It shows how the computational complexity of the leading ANN flavor of the day increased by a factor of 300,000 between 2012 and 2018, an impressive growth factor of 8.2/year! The state-of-the-art game-playing AlphaZero network [240] consists of many tens of layers, contains hundreds of thousands of nodes, and hundreds of millions of weights. This amazing performance comes at a severe energy/power cost: During inference (playing), it uses only 4 TPUS and consumes around 1 kW. However, for training (learning), it employs 5000 TPUs for about 40 days, which translates into a total energy cost of around 4.5 TJ ($= 10^{12}$ J) [168]. This is equivalent to powering 1400 houses for one month (assuming a power consumption of 900 kWh/month for an average home).

Clearly, further scaling of this approach is problematic unless ways are found to make computation more energy-efficient. As we observed earlier, technology scaling on itself may yield relatively little over the long term. An alternative approach is to delve deeper into the operation of the brain, identifying and exploiting the mechanisms that make it so efficient.

As an example, consider the way how data is represented. All ANN engines mentioned in the previous section represent data in a digital format. This is in contrast with the brain, where data is represented as spiking events and processing in the neuron is mostly analog. This observation inspired Carver Mead at CalTech (among others) to explore the realization of neurons using analog CMOS circuits, an approach he called "neuromorphic" [164]. In recent times, the term *neuromorphic* has been used to describe analog, digital, mixed-mode analog/digital VLSI, and software systems that implement models of neural systems for perception, motor control, or multisensory integration [183]. The original target of these neuromorphic systems was to mimic human sensory capabilities such as auditory or vision processing, but the focus has expanded considerably since. Applications now include navigation

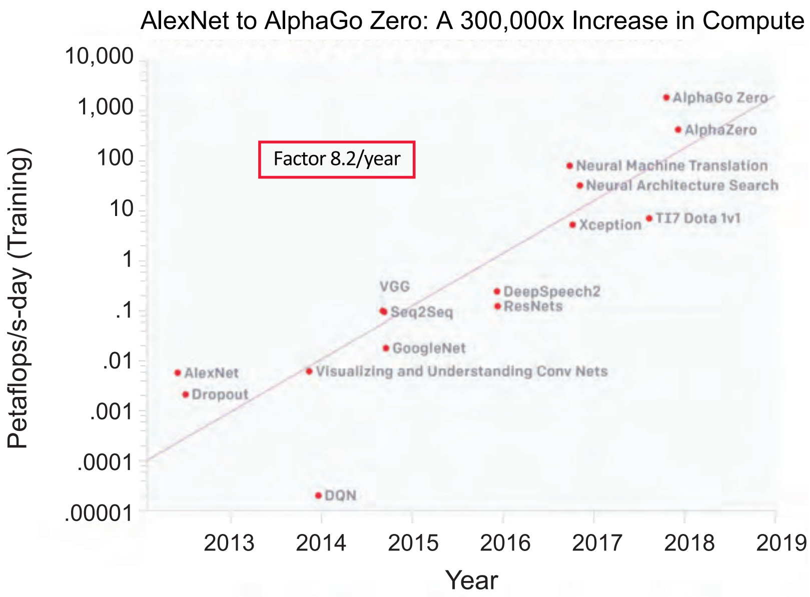

Figure 1.2: Advances in ANNs and their computational requirements (Adopted from [6]). A petaflop/s-day (pfs-day) consists of performing 10^{15} neural net operations per second for one day, or a total of about 10^{20} operations. This compute-time product serves as a mental convenience, similar to kWh for energy.

and robot control. On an even larger scale, neuromorphic systems have been conceived leading to systems that encompass many millions of neurons. The allure of the neuromorphic approach is that it opens the door for realizations that are potentially a lot more efficient by using innovative architecture, circuit and device concepts. At the same time, formidable hurdles towards scalability, programmability and robustness need be overcome.

Neuromorphic systems are just one possible form of cross-fertilization between biological and physical computing. Other neural concepts at different levels of abstraction can help inspire us to rethink how to efficiently perform a number of meaningful tasks and functions. This leads to the topic of this monograph. Our goal is to review some of the insights arising from both computational neuroscience and computer engineering, and evaluate how these could combine to help us build a next generation of "computing" systems – *systems that are evolutionary;*

adapt to the task at hand and changes in the environment; are close to optimally efficient; and inherently robust and resilient. To create insights and identify opportunities, we first put organic (neural) and physical computing face-to-face, and compare how they arose (Section 2), how they differ right now with respect to a number of metrics such as computational and power density (Section 3), and how these metrics may change over the future decades (Section 4). A similar analysis is performed at the architectural/computational model level (Section 5). While doing so, we establish some ground truths in terms of obtainable performance, bandwidth and power/energy efficiency. Moving forward, a number of neural design principles that may translate into design guidelines for future computers are identified (Section 6). On close examination of these and other observations, it becomes apparent that cross-fertilization between the domains is already happening at multiple levels, albeit in an incremental way (Section 7). The monograph completes with perspectives on where brain-inspired computing may lead us (Section 8), some speculative bets (Section 9), and a number of forward-looking reflections (Section 9.1).

Before diving into the details, it is important to outline what this monograph does not attempt to address. Throughout the discourse or organic versus digital computing, one compelling question keeps resurfacing: *if and when will it be possible to build a computer with the same computational density as the human brain at a power density that is equivalent or smaller.* Many attempts have been and are being made to address this question. Kurt Kurzweil in his blockbuster book titled "The Singularity is Near: When Humans Transcend Technology" estimates the time it will take for computational capacity, on an exponential growth path, to rival the raw computing power of the brain [142]. Based on an estimation of the computational capacity of the brain, he estimated that $1000 will buy computer power equal to a single brain "by around 2020" (!). As we show in this monograph, we are not at that point just yet. Even so, Kurzweil identified a number of important metrics and establishes clear roadmaps on how to potentially get there. He rightly points out that creating true artificial intelligence (AI) requires more than raw computational capacity, and requires us to first understand human intelligence. Without a question, neuroscience is making steady progress towards that understanding. A broad variety of imaging techniques (such as fMRI, PET, optogenetics, etc.) have emerged that allow us to peer into the brain, reverse engineer the circuitry and the network, map functionality, and study its dynamics with increasing space and time resolution. [160] presents a great overview of the different mechanism currently in use, under development or under consideration.

Notwithstanding all this progress, a full understanding of the computational principles and models of the brain is far from within reach, and making educated statements of brain-computer equivalence is premature. *Hence, we restrict ourselves in this text to a face-to-face study of the underlaying fabrics (devices, circuits, architectures and models) of physical and biological computers in our quest to derive universal principles and concepts for a future generation of energy-efficient computers.*

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