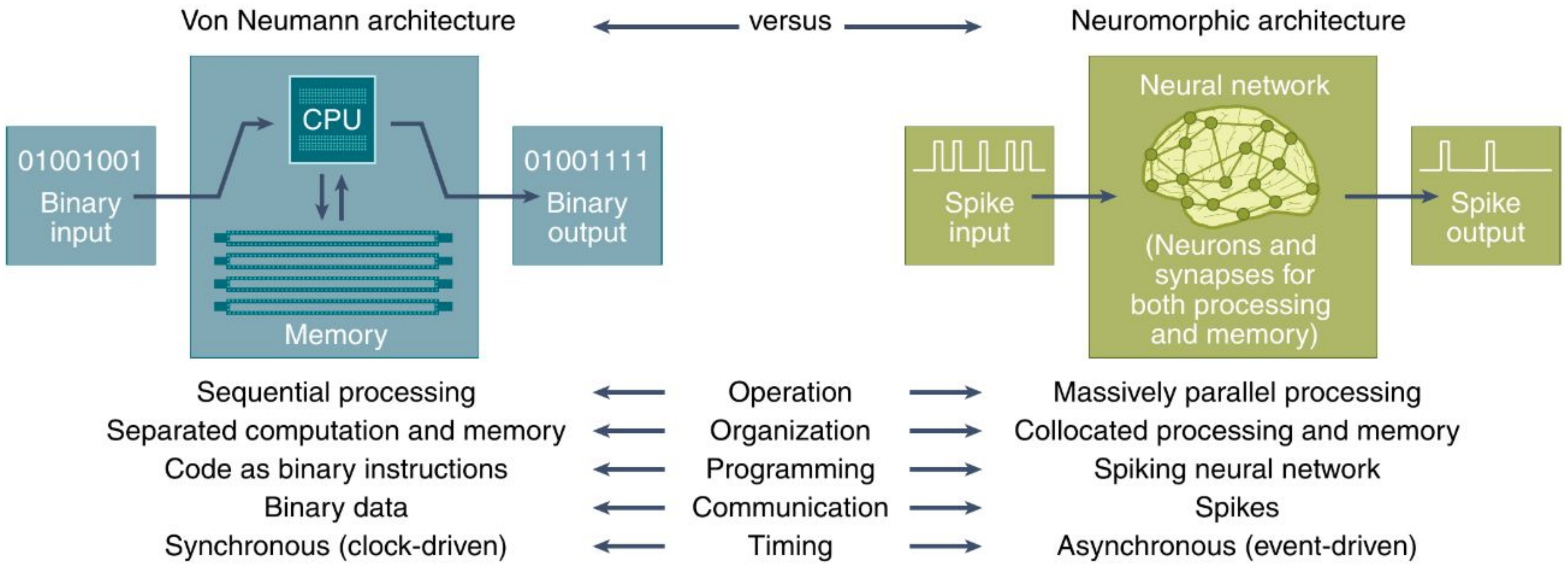
Neuromorphic Computing

Presenters:
Vishal Vijay Devadiga (CS21BTECH11061)
Shiv Tikoo (CS23BTNRK11001)

Table of Contents

Introduction

- Computing hardware has evolved from room-sized mainframes to compact, high-performance devices.
- Traditional computing architectures are nearing their limits due to the challenges of miniaturization and diminishing returns of Moore's Law.
- The current paradigm faces limitations in speed, power consumption, and scalability.
- Neuromorphic computing offers a new paradigm to keep pace with modern demands by emulating the efficiency and adaptability of the human brain.



Reference: Catherine D. Schuman, Shruti R. Kulkarni, Maryam Parsa, J. Parker Mitchell, Prasanna Date, and Bill Kay. Opportunities for neuromorphic computing algorithms and applications. Nature Computational Science, 2(1):10–19, 2022

Motivation

- **Miniaturization Limits:** Traditional computing architectures are reaching their inherent limits as feature sizes near the atomic scale.
- **Exponential Data Growth**: Coupled with the exponential growth of data generation, there is a pressing need for computing paradigms that can keep pace with modern demands.

Traditional circuits face two primary disadvantages:

❖ **Volatility**: Current digital circuits lose data when powered off, unlike biological systems that retain memory.

❖ **Difficulty of Repetitive Programming:** Traditional architectures struggle with tasks that are easy for the human brain, such as recognizing patterns or processing sensory data.

Background

- First introduced in the 1980s. Based on idea to use VLSI circuits with analog components to simulate behaviour of neurons in the brain.
- Inspired the development of Spiking Neural Networks(SNNs) and Hybrid Neural Networks(HNNs).
- Research on development of new types of materials / devices to be used in implementing neuromorphic systems such as phase change memory, ferroelectric materials and channel-doped biomembranes

Background

- Various Neuromorphic hardware such as Neurogrid by Stanford University, SpiNNaker by the University of Manchester, TrueNorth by IBM, and Loihi by Intel.
- Loihi, for example, is capable of simulating the behavior of 130,000 neurons across its 128 neuromorphic cores and 3 x86 cores.
- Tianjic developed by Tsinghua University in China offered a peak internal storage bandwidth of 610 GBps.

Background

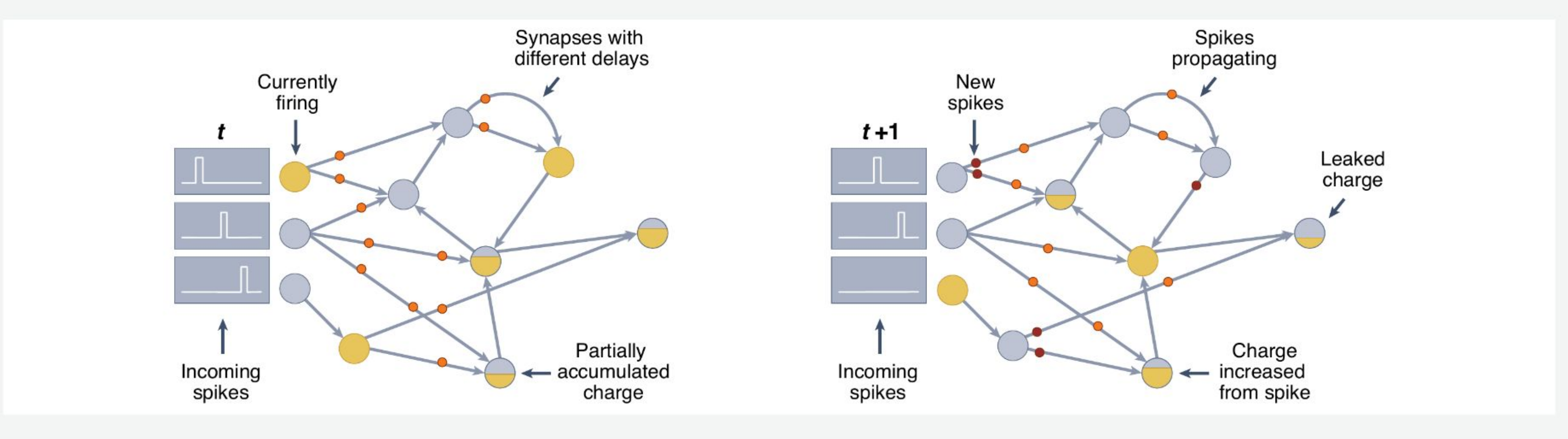
- ❖ Neuromorphic Computing can be used in a wide range of applications, including non-ML tasks such as signal processing, graph theory, and optimization.
- ❖ For example, during the pandemic in 2020, researchers used neuromorphic computing to develop a model that could predict the spread of COVID-19.

Survey

- ❖ Neuromorphic computing is still in infancy.
- ❖ Many challenges need to be addressed such as:
  - ➢ Hardware Design of Neuromorphic systems
  - ➢ Architecture and Algorithms designed for the parallel and scalable nature of neuromorphic computing
  - ➢ Developing applications that take advantage of the technology developed

SNNs

- ❖ Type of artificial neural network that takes inspiration from functioning of Human Brain.
- ❖ Unlike traditional neural networks that transmit information as continuous values, SNNs transmit information as discrete spikes, mimicking the “fire-and-forget” manner of real neurons of the brain.
- ❖ By leveraging the discrete, spike-based communication of SNNs, neuromorphic computing can potentially achieve high computational efficiency, low power consumption, and robust performance, much like the human brain.
- ❖ Traditional computing systems, with their clock-driven synchronous operations and energy-intensive processes, are reaching their physical limits. In contrast, neuromorphic computing systems with SNNs operate asynchronously, leading to potential advantages in speed, power efficiency, and real-time processing capabilities.



Reference: Catherine D. Schuman, Shruti R. Kulkarni, Maryam Parsa, J. Parker Mitchell, Prasanna Date, and Bill Kay. Opportunities for neuromorphic computing algorithms and applications. Nature Computational Science, 2(1):10–19, 2022

SNNs

Multi-stack Optimization:

- ❖ The paper advocates for a paradigm shift in computational design by proposing multi-stack optimization, integrating devices, circuits, and algorithms for efficient information processing.
- ❖ This approach aims to emulate the brain's natural prowess in information processing, striving for unparalleled efficiency.

Data Representation and Encoding:

- ❖ Proposes encoding data as sequences of discrete spikes, mirroring the asynchronous communication observed in biological neurons.
- ❖ This innovative approach holds promise for enhancing the efficiency and scalability of neuromorphic systems.

SNNs

Novel Neuron Models:

- ❖ Introduces novel neuron models tailored to capture the nuanced temporal dynamics of biological neurons.
- ❖ These models enable SNNs to more faithfully emulate the brain’s intricate information processing mechanisms, unlocking new frontiers in cognitive computing.

Learning Algorithms:

- ❖ Addresses the challenge of designing learning algorithms optimized for event-driven dynamical systems.
- ❖ These algorithms adapt dynamically to environmental stimuli, paving the way for robust and adaptive neuromorphic systems.

SNNs

Synergy between SNNs and Neuromorphic Architectures:

- ❖ Highlights the complementarity between SNNs and neuromorphic architectures, echoing biological neuron firing patterns.
- ❖ SNNs transmit discrete spikes of information, aligning well with the architecture's design.

System Software Frameworks:

- ❖ Discusses the importance of system software frameworks in deploying machine learning applications on neuromorphic hardware.
- ❖ These frameworks facilitate the intricate interplay between algorithms and hardware components, streamlining design, training, and deployment.

Challenges in Integration:

- ❖ Navigates through the challenges related to performance optimization, energy efficiency, and reliability in integrating SNNs with neuromorphic architectures.

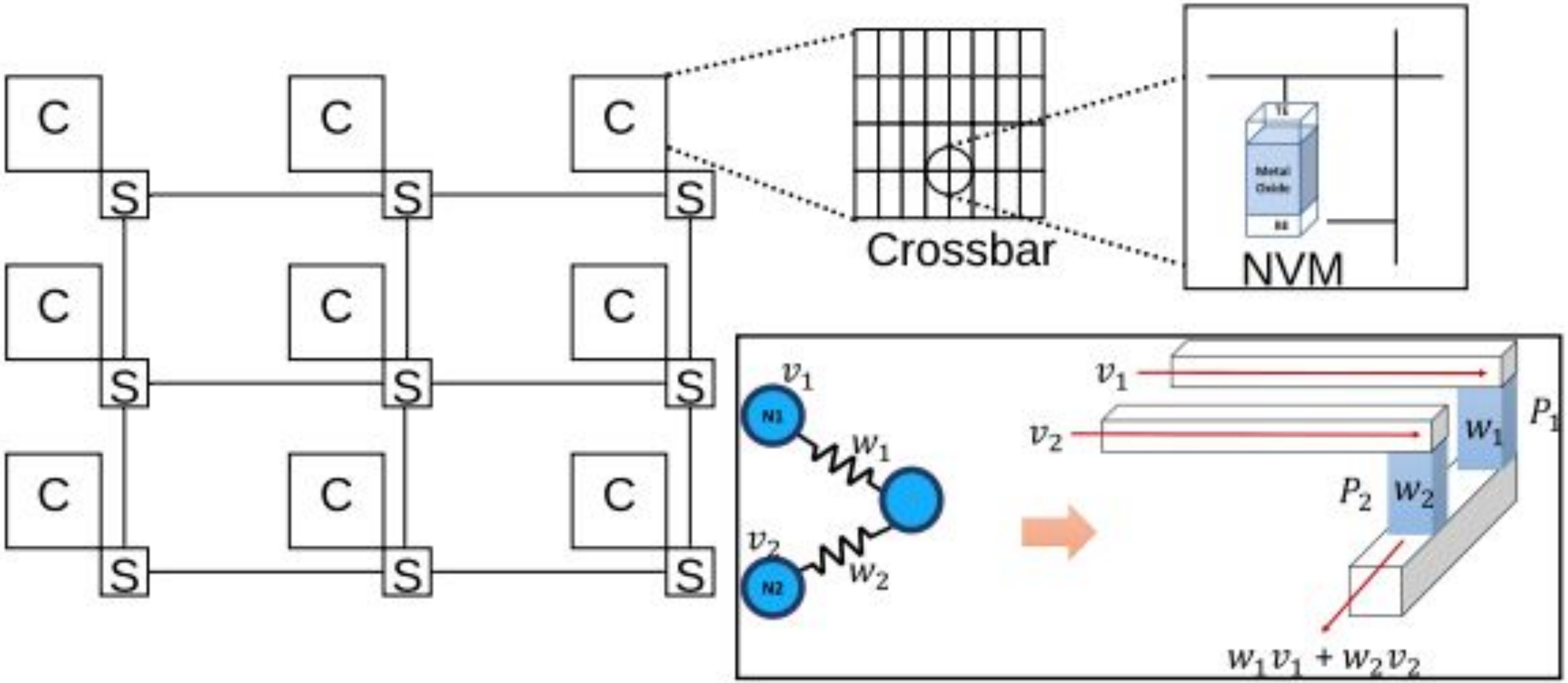


Figure 2: A representative tile-based neuromorphic hardware [47].

Reference: Phu Khanh Huynh, M. Lakshmi Varshika, Ankita Paul, Murat Isik, Adarsha Balaji, and Anup Das. Implementing spiking neural networks on neuromorphic architectures: A review, 2022

SNNs

Vulnerabilities of Neuromorphic Systems:

- ❖ Discusses the susceptibility of neuromorphic systems to faults, compromising system reliability.
- ❖ Explores various side-channel information that can be exploited by attackers, posing security risks.

Resilience of SNNs:

- ❖ Highlights the resilience of spike-based computation in SNNs against transient faults.
- ❖ Addresses the impact of permanent and intermittent faults on module functionality within neuromorphic systems.

SNNs

Development of Fault-Tolerant Mechanisms:

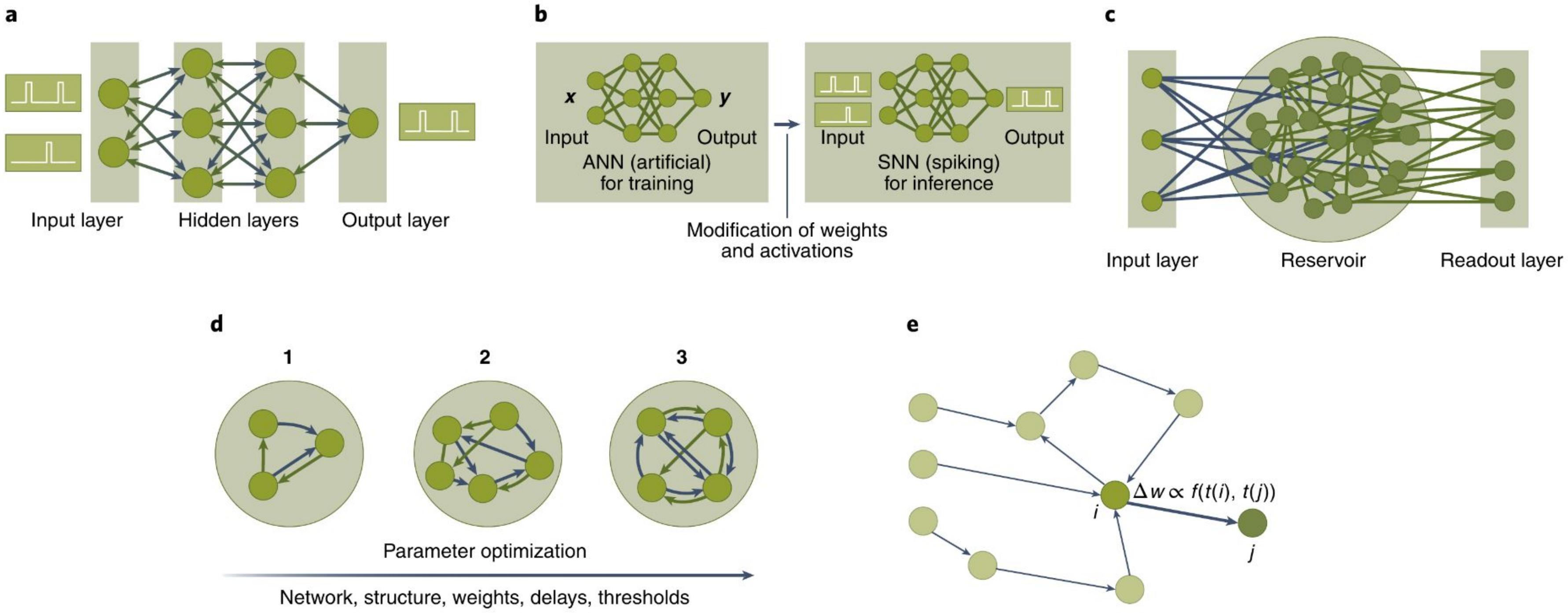
❖ Advocates for the development of robust fault-tolerant mechanisms to ensure the practical implementation and reliability of neuromorphic systems.
❖ Emphasizes the importance of addressing growing concerns surrounding system reliability and security.

Scalable Neuro-morphic Fault-Tolerant Context-Dependent Learning (FCL) Framework:

❖ Introduces a groundbreaking scalable FCL hardware framework addressing fault-tolerance in context-dependent tasks.
❖ Provides insights into maintaining robust learning capabilities despite hardware faults, opening new possibilities for resilient neuromorphic systems.

Algorithms for Neuromorphic Computing

- ❖ Neuromorphic Architecture is highly parallelizable and inherently scalable.
- ❖ However there are only a few algorithms that take advantage of it.
- ❖ Traditional algorithms used in Artificial Neural Networks may not be suited for neuromorphic systems.



Reference: Catherine D. Schuman, Shruti R. Kulkarni, Maryam Parsa, J. Parker Mitchell, Prasanna Date, and Bill Kay. Opportunities for neuromorphic computing algorithms and applications. Nature Computational Science, 2(1):10–19, 2022

Algorithms for Neuromorphic Computing

- ❖ Backpropagation may not be well suited for neuromorphic systems due to its high computational complexity and memory requirements. Also the fact that SNNs are inherently stochastic and non-deterministic, makes it difficult to train them using traditional backpropagation algorithms.
- ❖ Spike-based quasi-backpropagation adapt the backpropagation algorithm to work with SNNs by using surrogate gradients and smoothed activation functions to compute the gradients while maintaining the spiking behavior of the neurons.

Algorithms for Neuromorphic Computing

- ANNs have a long history of research, there are many algorithms and optimizations that have been developed for them.
- Performing a mapping process from ANNs to SNNs is a challenging task, but inherently leads to better performance with respect to energy efficiency and speed.
- However this mapping process can lead to loss of accuracy due to the conversion of continuous values to spikes

Algorithms for Neuromorphic Computing

- ❖ Reservoir Computing is a popular algorithm used in neuromorphic systems that is based on the idea of using a large network of recurrently connected neurons to perform computations.
- ❖ The network does not involve any training of the SNN components. It uses sparse connectivity and random weights to cast inputs to a higher dimensionality space. The output is then read out from the network using a linear classifier.
- ❖ Reservoir computing has been shown to be highly efficient and scalable and has been used in a wide range of applications.

Algorithms for Neuromorphic Computing

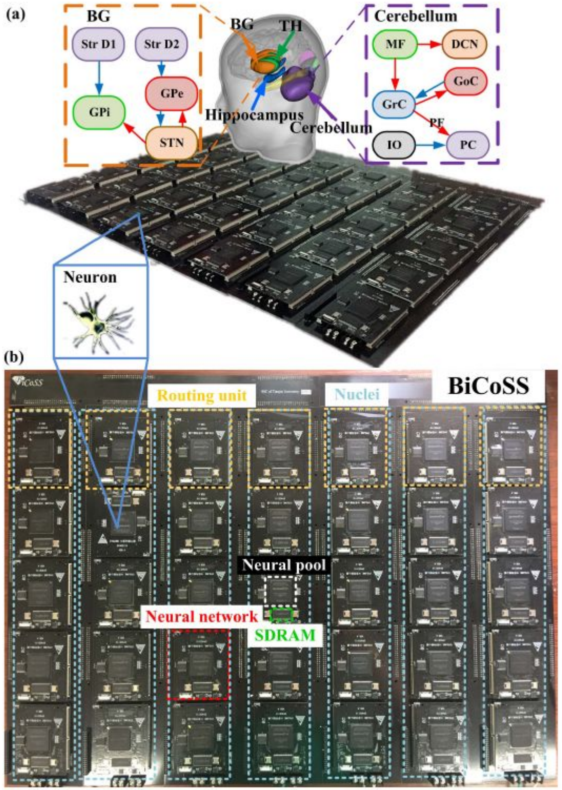
- ❖ Evolutionary Approaches is another popular algorithm used in neuromorphic systems that is based on the idea of using multiple generations of populations and selecting the best individuals to evolve the population.
- ❖ This approach can be used to optimize the parameters of the SNNs and is highly efficient and scalable as it does not require any differentiability in activation functions nor rely on any particular network structure

Algorithms for Neuromorphic Computing

- ❖ However there are still many challenges to be overcome in terms of developing algorithms that are efficient and scalable for neuromorphic systems.
- ❖ There is not yet a ML algorithm that substantially outperforms traditional ML algorithms in terms of accuracy, speed, and energy efficiency. This leads to the argument that neuromorphic computing is useful for its low power computing abilities.
- ❖ Another key challenge is the lack of a standard benchmark for evaluating neuromorphic algorithms. There are many different neuromorphic systems available, each with its own architecture and capabilities.
- ❖ This makes it difficult to compare the performance of different algorithms across different systems. There is a need for a standard benchmark that can be used to evaluate the performance of neuromorphic algorithms and systems.

BiCoSS and CerebelluMorphic

- Two neuromorphic systems published by same group around the same time in 2022 and thus share a lot of design principles.
- Intends to mimic the human brain by executing neural models for multiple cognitive organs such as the cerebellum, hippocampus and basal ganglia.



Reference: Shuangming Yang, Jiang Wang, Xinyu Hao, Huiyan Li, Xile Wei, Bin Deng, and Kenneth A. Loparo. Bicoss: Toward large-scale cognition brain with multigranular neuromorphic architecture. IEEE Transactions on Neural Networks and Learning Systems, 33(7):2801–2815, 2022.

BiCoSS and CerebelluMorphic

- 3 main design principles:
  - Independent Reconfigurable Population Process: Uses FPGAs to reconfigure system to perform tasks of different complexity.
  - Stochastic Neural Hierarchy: Response of Neurons can be tuned with respect to intensity of the impulse received.
  - Routing Scheme: Different synapses have different spiking activities, and synaptic dynamics, allowing to mimic behaviour of various organs of the brain.
- A key challenge in neuromorphic computing is achieving further brain complexity. These two architecture are just the beginning of realizing large-scale brain models and lay the groundwork for further research in the field of neuromorphic computing.

Memristor

- ❖ Transistors technology is reaching its physical limits in terms of size and power consumption.
- ❖ Memristors are materials that are:
  - ➢ Capable of changing its resistance in response to amount of voltage applied to it and the time length during which voltage is applied.
  - ➢ Proposed in 1971, but first developed in 2008 by HP Labs.
  - ➢ Can mimic biological synapses.

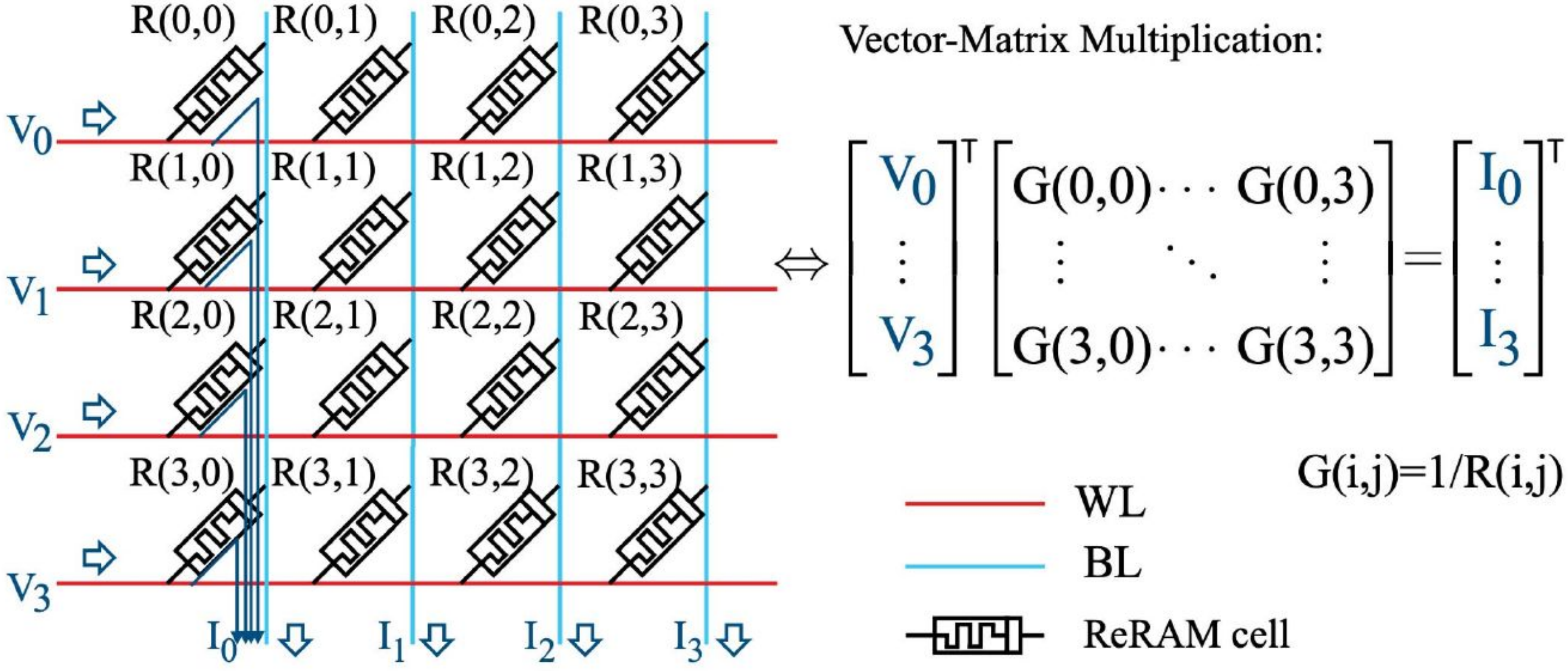
Disadvantages:

- Reliability Issues: Prone to errors in conductance leading to data corruption.
- Still in early stages of development: Issues with fabrication and integration with existing technologies

Memristor

Advantages:

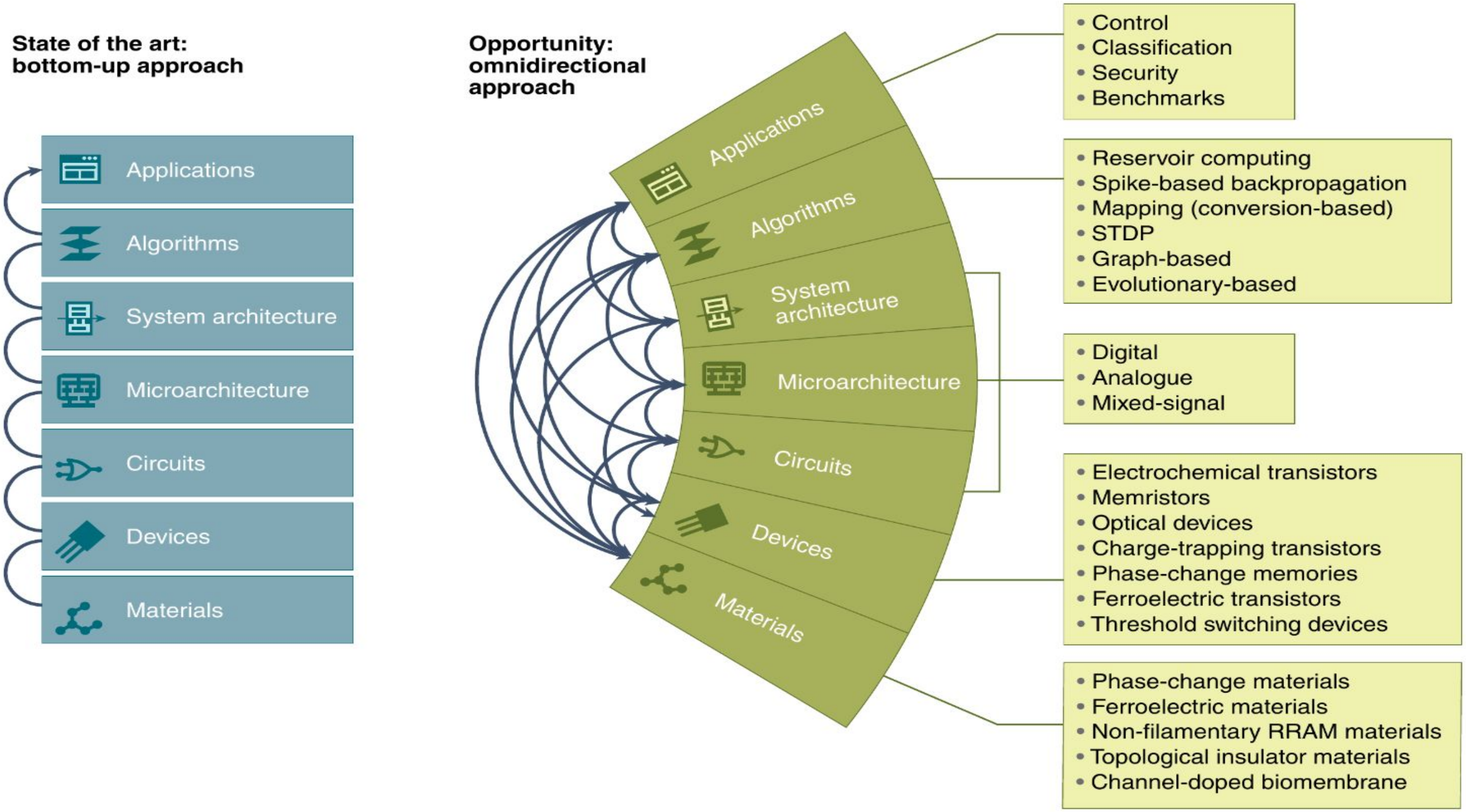
- Retain information even after powered off, ideal for memory storage.
- Consume less power than traditional transistors.
- Can be packed more densely
- Can stored multiple bits of data per cell
- Memristors are be arranged in structures such as Cubes of memristors for 3D Integration, Memristor Array for higher density
- Memristor Crossbars are of relevance for neural networks
  - Can be used to implement vector matrix multiplication
  - Voltage applied changes the resistance of memristors, such that output(resistance) is the dot product of input and weight vectors.
  - Allows for parallel processing of multiple weights and inputs.



Reference: Xiaoxuan Yang, Brady Taylor, Ailong Wu, Yiran Chen, and Leon O. Chua. Research progress on memristor: From synapses to computing systems. IEEE Transactions on Circuits and Systems I: Regular Papers, 69(5):1845–1857, 2022.

Conclusion

- ❖ Neuromorphic computing is a promising new computing paradigm that has the potential to revolutionize the way we think about computing.
- ❖ Over the years, researchers have developed several different types of neuromorphic hardware, architecture, and algorithms. Several large-scale neuromorphic systems have been developed and are available for research and development.
- ❖ There are still many challenges faced:
  - ➢ Various Functions of brain are still not fully understood
  - ➢ Software-Hardware Codesign. Need more research in integration of individual aspects of neuromorphic system. Integration of such systems is quite difficult because they encompass a wide range of technologies and disciplines.



Reference: Catherine D. Schuman, Shruti R. Kulkarni, Maryam Parsa, J. Parker Mitchell, Prasanna Date, and Bill Kay. Opportunities for neuromorphic computing algorithms and applications. Nature Computational Science, 2(1):10–19, 2022

Thank you