

Comparing Neural Accelerators & Neuromorphic Architectures – The False Idol of Operations



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#### Architectural Comparison

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- Neural accelerators & neuromorphic approaches are emerging at different scales, resource requirements, and enabling capabilities
- Beyond the similarity of executing neural network workloads, these two paradigms exhibit significant differences
- As processing, memory, and communication are the core tenets of computing, here we compare architectures of neural accelerators and neuromorphic in these terms



-CPU - GPU - FPGA - Accelerator - Neuromorphic



#### 3 Operations

There has been a trend of measuring "better" by the amount of operations



https://www.top500.org/statistics/perfdevel/

Operation counts alone can be misleading

- In neural networks do not guarantee how accurate your answer will be
- Do not measure how fast your problem will be solved

![](_page_3_Figure_4.jpeg)

![](_page_3_Figure_5.jpeg)

Emphasis on operation counts has impacted some architectural design choices

- Which furthermore impacts algorithm design choices
- Easy to follow the mindset of more

![](_page_4_Figure_4.jpeg)

![](_page_4_Figure_5.jpeg)

#### Dataflow

- Dataflow architecture executes computations as data is received
  - Ideologically similar to neural network computation flow
  - Broadly encompasses input data, intermediate computation data, as well as parameter data such as weights and biases
- A dataflow then describes how these various components are moved around in an architecture to perform computation
  - Importantly this matters because data movement from memory access requires more energy than performing computation
- Central to the analysis of how dataflows can bridge computational workflows and architectural execution through the most efficient data movement are the assumptions that data must be moved & that there are limited resources which are being scheduled

#### Stack of Input Data

![](_page_5_Figure_9.jpeg)

Neural Network Weights

![](_page_5_Figure_11.jpeg)

Hardware mapping

![](_page_5_Figure_13.jpeg)

### 7 Roofline Model

A roofline model articulates the performance of the interplay between memory and processing for a computational architecture

• Traditionally, the ridge point targets the minimum intensity needed to attain maximum performance

However, we argue alternative computing paradigms can alter the intuition and structure of the roofline model

• While the target traditionally is to optimize towards the ridgepoint, it is possible to be either computer bound or memory bound for neural network computation and still be advantageous

![](_page_6_Figure_5.jpeg)

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Quantitatively assessing aspects of computer architectures has provided an analytical means of exploring the impact of various design choices

• Comparing classes of architectures has often *relied upon optimizing a shared objective* despite pursuing different approaches

Comparing neural accelerators and neuromorphic architectures is not as straightforward

- Neural accelerators share design goals of the more traditional computational architectures but focus upon enabling the execution of neural network workloads
- Conversely, neuromorphic approaches strive to enable neural computation but do so by employing design principles of how brains function

## Computational Objectives

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Instead of assuming more operations is better, *neuromorphic event-driven computation explores what is the minimum compute needed* 

- Analogous to the minimax decision rule from game theory which strives to minimize a maximum cost
- In this context minimizing the amount of computation needed bounds the maximum cost of computation

This is a fundamentally different paradigm than the converse, maximin which aspires to maximize a minimum gain

• In this context - the objective is to maximize the amount of computation performed to advance the minimal amount of computational progress attained

> The best decision is not the same for these two paradigms as they are optimizing for different objectives

### • Conclusions

As we look to the brain for computing inspiration -

- We know from neuroscience that neuron counts alone are an insufficient measure of cognitive ability
  - For example, the human brain has approximately 86 billion neurons compared with larger brains in elephants consisting of approximately 250 billion neurons
  - Cognitive abilities in biological brains are dependent upon many factors including size, connectivity, surface area, quantity of neurons, support cells, etc.
- Understand the analytical alure to relate architectures based upon operations BUT novel approaches require understanding their unique benefits
- While the dominant motivational analogy is to compare brains with the power consumption of an ever more efficient lightbulb
  - We should also remember not every neuron fires all the time & aspire to pursue computations not operations

# Thank you

![](_page_10_Picture_1.jpeg)

Questions?