SETTING SAIL

THE JOURNEY OF NEUROMORPHIC COMPUTING

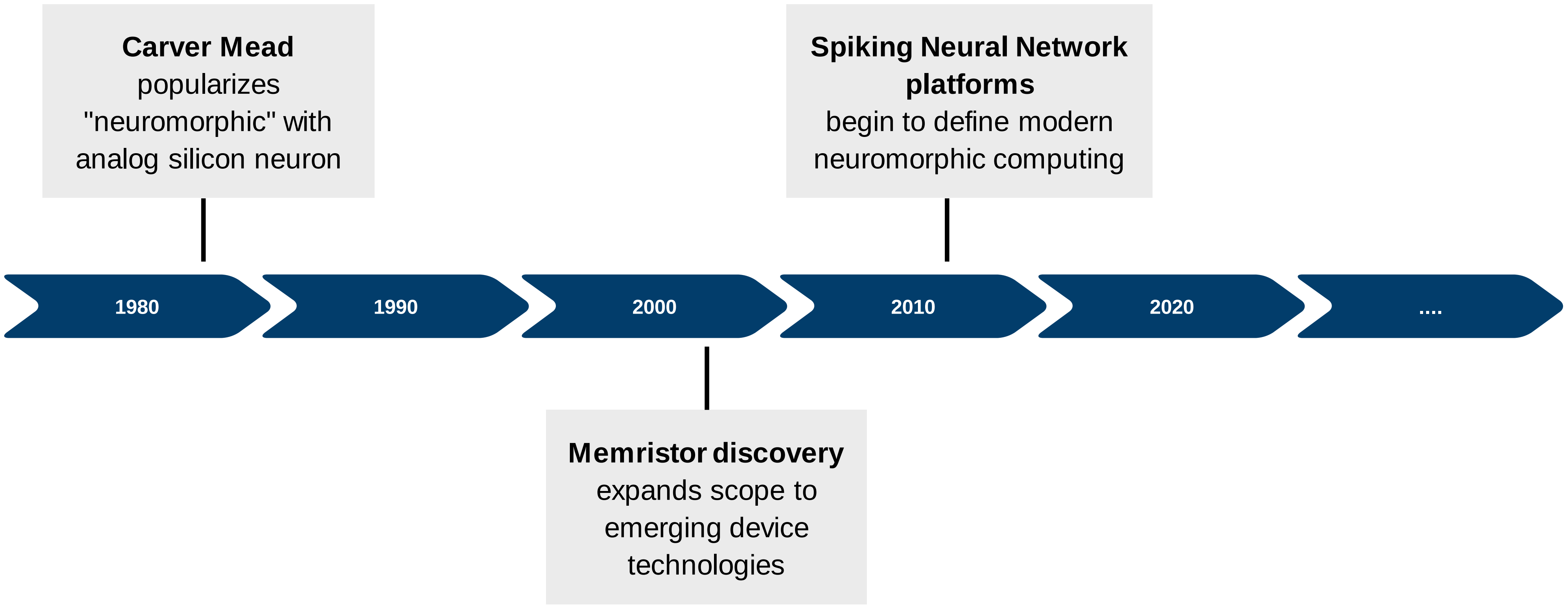
04.12.2024 I GEORGIA PSYCHOU, GUIDO TRENSCH, SANDRA DIAZ, BORIS ORTH

OUTLINE

- What is Neuromorphic Computing?
- From devices to applications: The neuromorphic landscape
- Local activities
- Outlook and future directions

WHAT IS NEUROMORPHIC COMPUTING?

The term „Neuromorphic“ in time



WHAT IS NEUROMORPHIC COMPUTING?

Why look to the brain?

Computing paradigms

Digital computing

- Excels in precise, repetitive tasks (e.g., large-scale calculations)
- Operates on predefined, rule-based processes (algorithmic steps, Turing model)
- Requires significant power (especially for tasks like AI model training, often on the order of Megawatts)

Neuromorphic computing

- Inspired by brain's biological principles: parallel processing, event-driven operations, energy-efficient adaptation
- Spiking Neural Networks (SNNs): A prominent approach within neuromorphic computing
  - Simple, parallel units (neurons)
  - Memory and processing co-located
  - Event-driven operations based on spikes
- Emulates brain-like computation: adaptability, real-time learning, energy efficiency

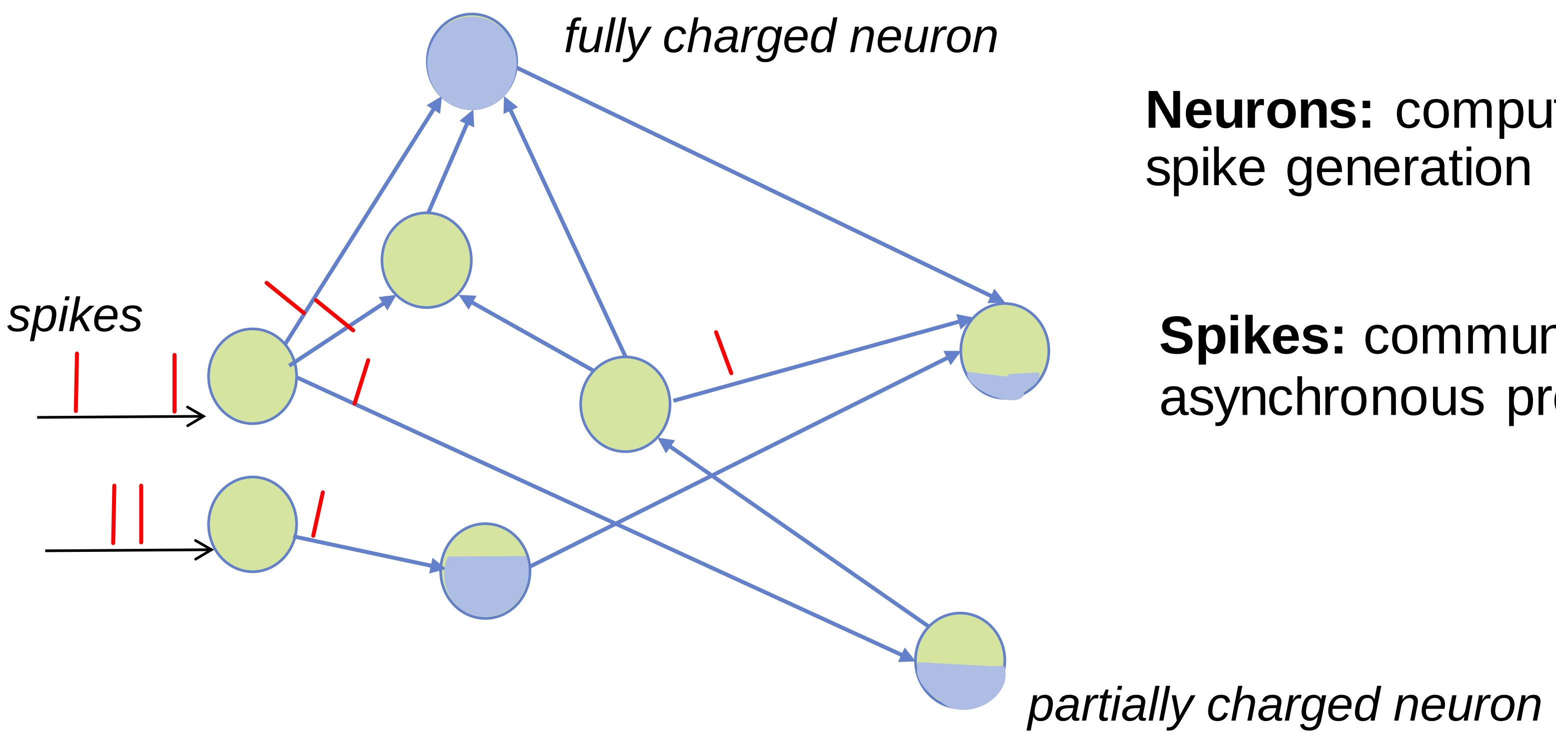
Brain computing

- Excels in pattern recognition, adaptability, and real-time decision-making
- Self-organizing neural computation, continuously interacting with and adapting to the environment
- Operates efficiently with low power (on the order of tens of Watts)

[Illustrations created using Napkin by G.Psychou]

WHAT IS NEUROMORPHIC COMPUTING?

Spiking Neural Networks (SNNs): Constituent parts and challenges 1/2



Inspired by Schuman et. al. (2022)

Neurons: computation, spike generation

Spikes: communication, asynchronous propagation

➡ overall computation time-dependent

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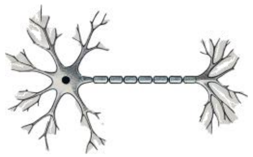
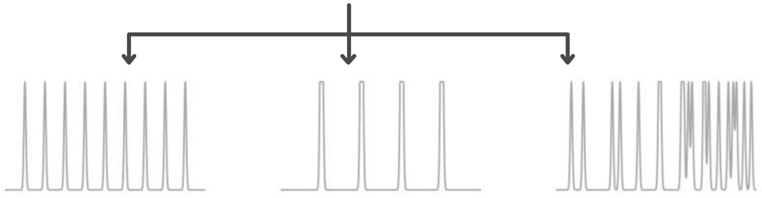
WHAT IS NEUROMORPHIC COMPUTING?

Spiking Neural Networks (SNNs): Constituent parts and challenges 2/2

Which neuron to choose?

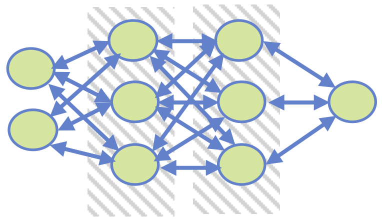


Inspiration from biological neuron

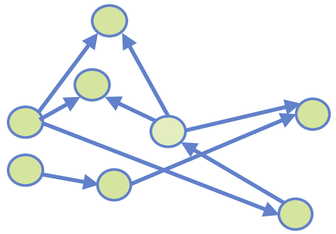


Diverse spiking behaviours

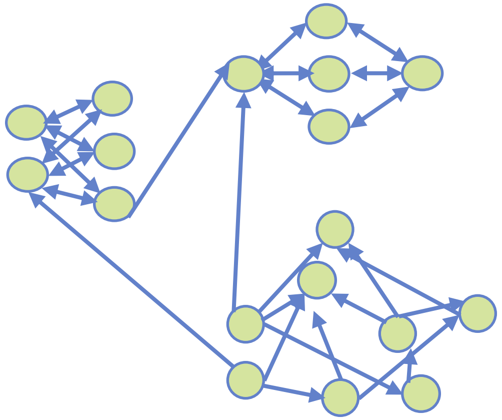
What's the ideal network structure?



Multilayer perceptron

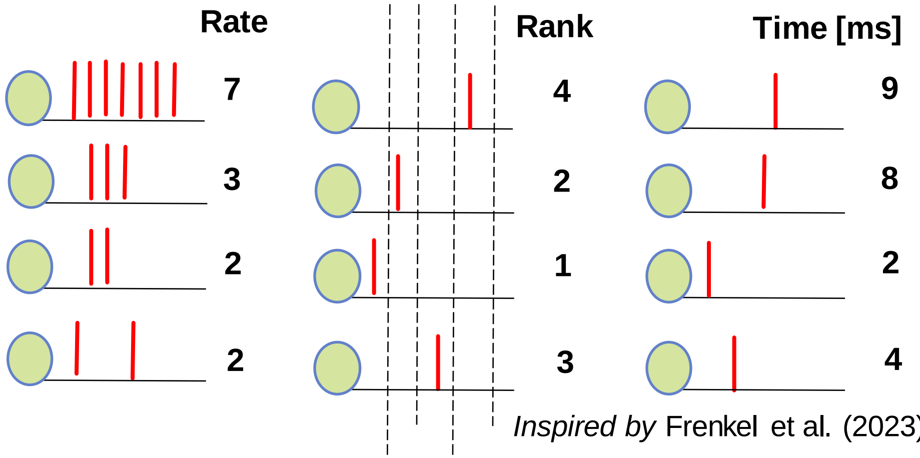


Recurrent



Dense local and sparse global connections

How to encode information?

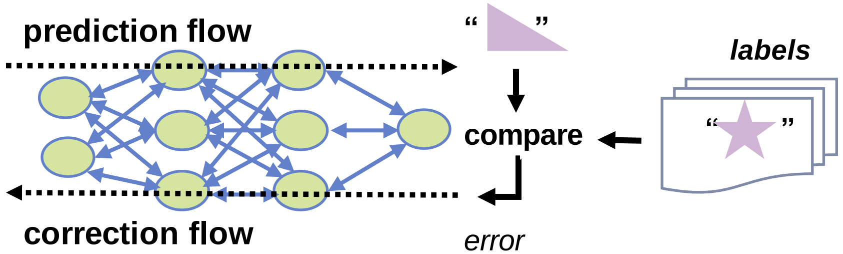


Inspired by Frenkel et al. (2023)

Learning: go local or global?

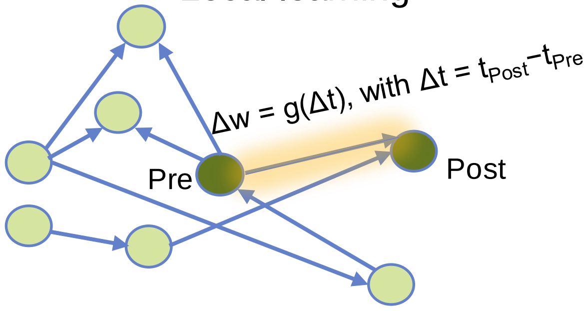
Global learning

- Backward or forward propagation?
- Differentiability of spikes



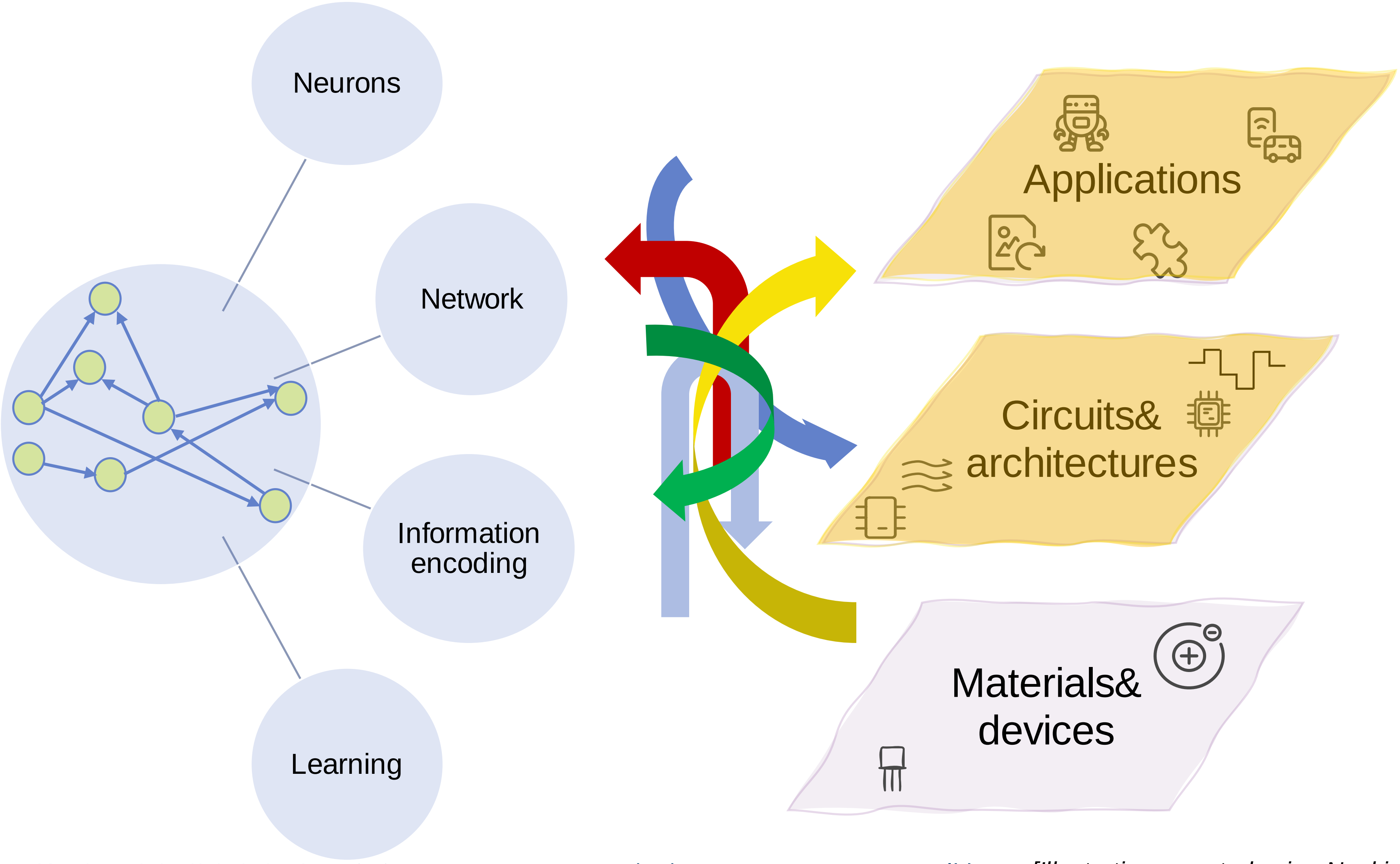
Inspired by Kurenkov (2020)

Local learning



Inspired by Schuman et. al. (2022)

FROM DEVICES TO APPLICATIONS: THE NEUROMORPHIC LANDSCAPE



graph-based, optimization algorithms …

autonomous systems, robotics…

custom, programmable, digital, analog …

optical devices, memristors …

phase-change, ferroelectric …

FROM DEVICES TO APPLICATIONS

Neuromorphic experimentation platforms

Flexibility → **Specialization**

SpiNNaker 2 (2021)
SpiNNaker (2014)

- **Digital, massively parallel**
- 18 ARM cores per chip, scalable to 65,536 chips
- Up to **1 billion neurons, 1 trillion synapses**
- **Focus**: Large-scale SNN simulations with software flexibility

Loihi 2 (2021)
Loihi (2018)

- **Digital with neuromorphic cores**
- 128 cores supporting local learning rules
- Up to **130,000 neurons, 130 million synapses**
- **Focus**: On-chip learning and adaptability, suitable for real-time learning and inference tasks

NorthPole (2023)
TrueNorth (2015)

- **Digital with neurosynaptic cores**
- 4,096 cores with fixed weights
- Up to **1 million neurons, 256 million synapses**
- **Focus**: Ultra-low energy, suitable for inference with pre-trained networks

BrainScales2 (2020)
BrainScaleS (2010)

- **Analog and mixed-signal, wafer-scale**
- Scalable to 20 wafers
- Up to **4 million neurons, 800 million synapses**
- **Focus**: High biological fidelity with accelerated simulation

Other digital platforms

DynapCNN, Spiking Neural Processor T1, ODIN, Seo et al., μBrian, MorphIC and *multiple FPGA-based platforms …*

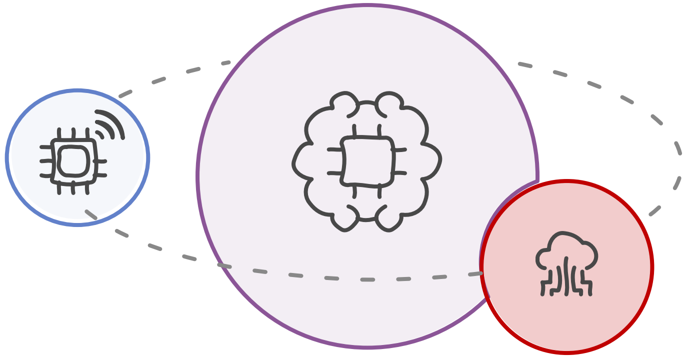
Other analog and mixed-signal platforms

ReckOn, DYNAP-SE2, Neurogrid, , ROLLS, IFAT, Mayr et al. …

- **Chips available for purchase in recent years**: *Speck* and *Xylo* by SynSense (2021), *Akida* by BrainChip (2020), and *neuromorphic cameras* (Prophesee, iniVation) (2023).

FROM DEVICES TO APPLICATIONS

Exploring neuromorphic applications



Real time, adaptive tasks

- Decentralized, resource-constrained, real-time tasks
- Event-driven processing with online learning for real-time adaptation
- Ideal for robotics, wearables, IoT devices, and autonomous systems

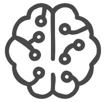
Computationally intensive tasks

- Large-scale, resource-demanding tasks
- Significant computational demands combined with energy-efficient processing
- Neuromorphic efficiency to address problems that are resource-intensive for traditional systems

Neural network–based

- AI inference, e.g. drug discovery

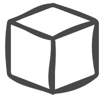
- Neuroscience simulations



Non-neural network-based, emerging

- Graph-based problems, optimization problems

- Quantum emulation to assist algorithm development



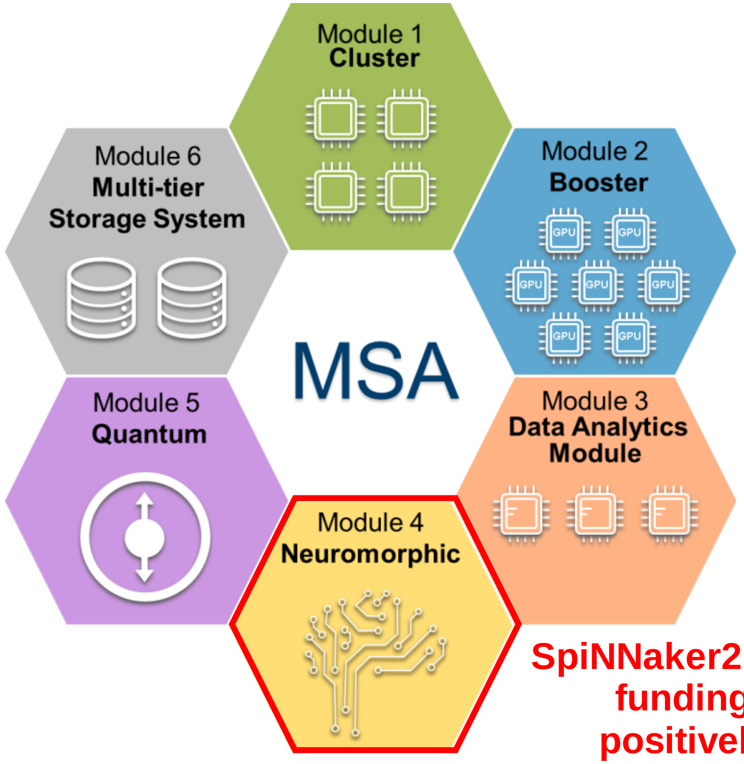
[Illustrations created using Napkin by G.Psychou]

LOCAL ACTIVITIES: NEUROMORPHIC COMPUTING AT JSC

Modular Supercomputing Architecture (MSA) workflows

Integrating transformative technologies (Quantum Computing [QC] and Neuromorphic Computing [NC]) into HPC workflows using MSA. Examples :

- **Emulating quantum**: Perform QC emulation on NC module, validate on QC hardware.
- **Brain simulations**: Run neuroscience simulations on NC module with pre- and post-processing on cluster module.
- **Synthetic brain data generation**: NC module produces structural and functional brain data for training foundation models on booster module.
- **AI workflows**: Cluster and booster modules handle data-intensive training; NC module provides energy-efficient inference.



SpiNNaker2-based module funding proposal positively reviewed

- **Suarez** et al. *"Modular Supercomputing Architecture – A Success Story of European R&D"*, ETP4HPC White Paper. (2022) Available at https://www.etp4hpc.eu/white-papers.html#msa.
- **Suarez** et al., "*Modular Supercomputing Architecture: from idea to production*", Chapter 9 in Contemporary High Performance Computing: from Petascale toward Exascale, Volume 3, p 223-251, CRC Press. (2019)

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LOCAL ACTIVITIES: NEUROMORPHIC COMPUTING AT FZJ

Jülich Neuromorphic Computing Alliance (JUNCA)

Theory and modeling to understand dynamics and **computation in the brain**

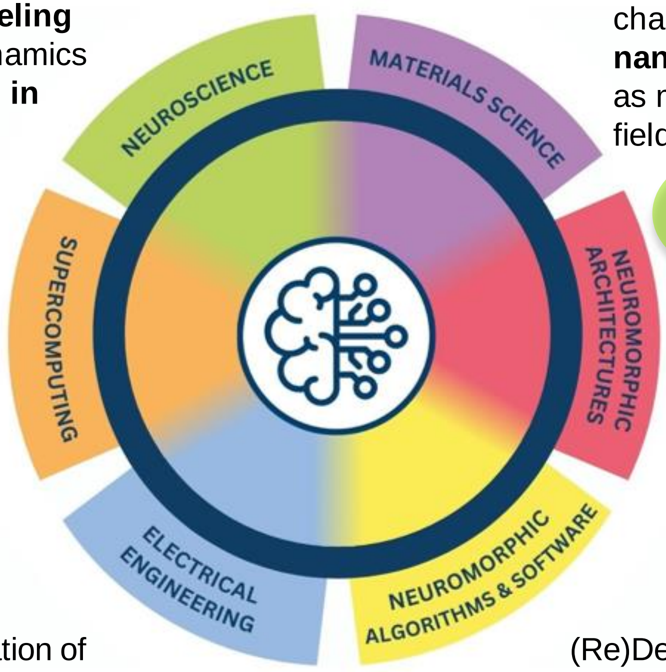
IAS-6

Development and integration of **High-performance computing architectures** and tools for **brain research** and **AI**

JSC

Conception and implementation of physical-mathematical neuromorphic principles in special **integrated circuits and prototypes**

ZEA-2



Design, fabrication and characterization of **nanoelectronic elements** such as memristors and nanowire field-effect transistors

PGI-7 PGI-9 PGI-10

Co-design and engineering of **brain-inspired hardware** for challenging computational problems

PGI-14

(Re)Design of **computing algorithms** and computer **architectures** from the perspective of neuroscience

PGI-15

FACTS AND FIGURES

Resources:
> 13 institute divisions
contribute to the field

Budget:
59 million €
(institutional: 19 million €, third-party funds: 40 mio. € in 2023)

PhD students:
63
(directly supervised by scientists of the institute divisions in 2023)

Publications:
more than **80**
in 2023

Employees:
192
(third-party funded: 60 in 2023)

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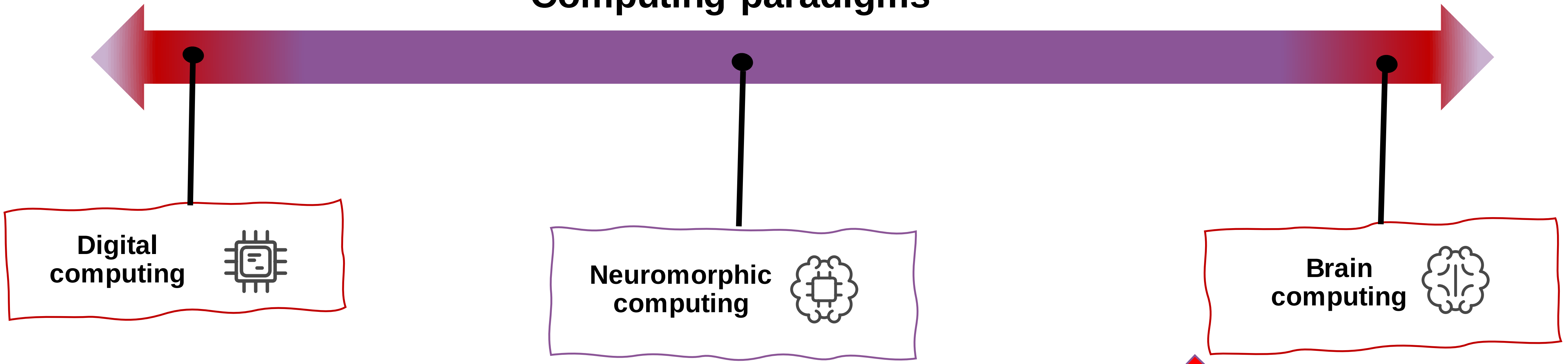
SAILING INTO THE FUTURE

Computing paradigms



Mid-term goals

- **Algorithmic advancements**: Broaden application scope
- **Standardization frameworks**
  - Benchmarks and metrics
  - Software stack
- **Moving beyond disciplines**
  - Software-hardware codesign
  - Neuroscientific insights (cell types, motifs, plasticity)
- **Theoretical foundations**: Unified framework for neuromorphic concepts

Long-term goals

- **Information representation**: Novel encoding methods
- **Temporal dynamics**: Multiscale biological time models
- **Embodied intelligence**: Active sensing and sensory-motor loops
- **3D integration**: Advanced architectures for connectivity
- **New computational paradigms**: Inspired by neuroscience and non-linear dynamics

[Illustrations created using Napkin by G.Psychou]

THANK YOU!

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