BrainScaleS via EBRAINS
“easily accessible analog”

Johannes Schemmel

Electronic Vision(s) Group
Kirchhoff Institute for Physics
Heidelberg University, Germany

BrainScaleS via EBRAINS
“easily accessible analog”

- Background
- Human Brain Project and EBRAINS
- Dimensions of neuromorphic computing
- BrainScaleS features
- BrainScaleS services in EBRAINS
- Recent example: parameter fitting
- Summary

Electronic Vision(s)

Kirchhoff Institute of Physics, Heidelberg University

Founded 1995 by Prof. Karlheinz Meier (†2018)

1995 HDR vision sensors

1996 analog image processing

2000 Perceptron based analog neural networks: EVOOPT and HAGEN

2003 First concepts for spike based analog neural networks

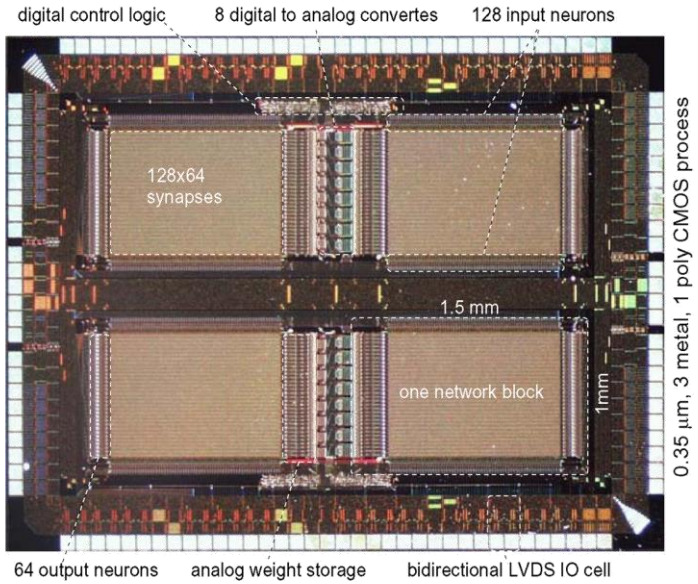
2004 First accelerated analog neural network chip with short- and long-term plasticity: Spikey

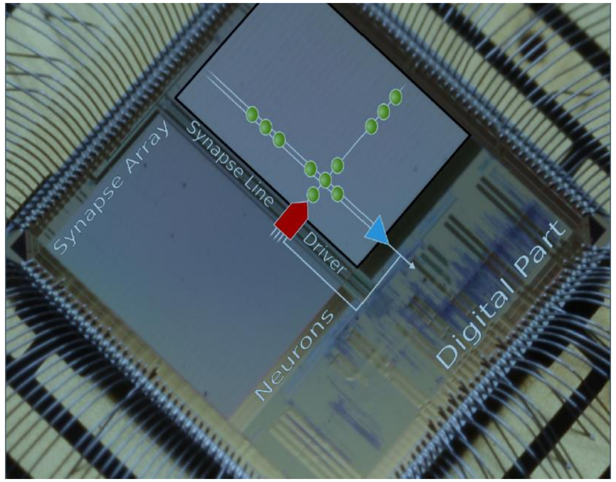
since 2010 BrainScaleS neuromorphic systems

HAGEN (2000):

Perceptron-based Neuromorphic chip introduced:

- accelerated operation
- mixed-signal Kernels





SPIKEY (2004):

spike-based Neuromorphic chip introduced:

- fully-parallel Spike-Time-Dependent-Plasticity
- analog parameter storage for calibratable physical model

FLAGSHIPS

Human Brain Project

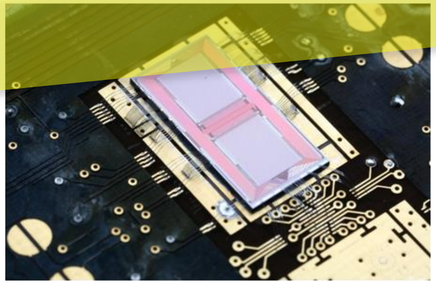
Co-funded by
the European Union

Why focus on the brain ? Three Reasons

– **Understanding the brain (Unifying Science Goal)**
  - Underpins what we are,
  - Data & knowledge are fragmented,
  - Integration is needed,
  - Large scale collaborative approach is essential.

– **Understanding brain diseases (Society)**
  - Costs Europe over €800 Billon/year,
  - Affects 1/3 people,
  - Number one cause of loss of economic productivity,
  - No fundamental treatments exist or are in sight
  - Pharma companies pulling out of the challenge.

– **Developing Future Computing (Technology)**
  - Computing underpins modern economies,
  - Traditional computing faces growing hardware, software, & energy barriers,
  - Brain can be the source of energy efficient, robust, self-adapting & compact computing technologies,
  - Knowledge driven process to derive these technologies is missing.



Neuromorphic Computing

Part of the EBRAINS initiative of the HBP

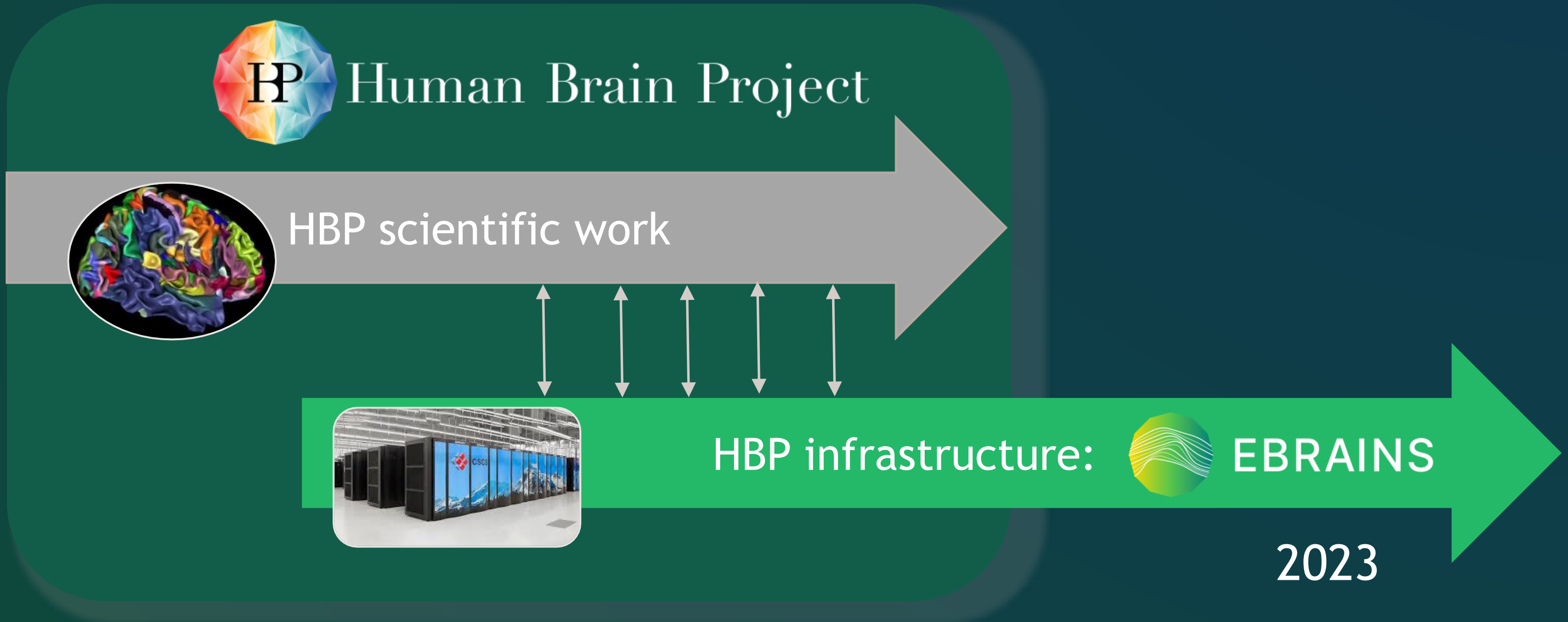
Neuromorphic computing with physical models

- Neuromorphic Machines
- Algorithms and Architectures for Neuromorphic Computing
  - Theory
  - Applications

EBRAINS’ mission: Enabling brain research advances and innovation

EBRAINS offers the neuroscience community **state-of-the-art services:**

- **Brain data and atlases**
- **Simulation and modelling tools**
- **Access to supercomputing resources**



Builds on the work of the Human Brain Project and makes it sustainable

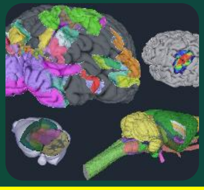
What EBRAINS brings to the scientific community

Interoperable

BrainScaleS

Data and Knowledge

- Online solutions to facilitate sharing of and access to research data, computational models and software



Atlases

- Navigate, characterise and analyse information on the basis of anatomical location

Simulation

- Solutions for brain researchers to conduct sustainable simulation studies and share their results

Brain-Inspired Technologies

- Understand and leverage the computational capabilities of spiking neural networks

Medical Data Analytics

- The Medical Data Analytics service provides two unique EBRAINS platforms, covering key areas in clinical neuroscience research

Co-developed by and with researchers

brain inspired technologies
aka brain inspired computing

compute more like the brain:

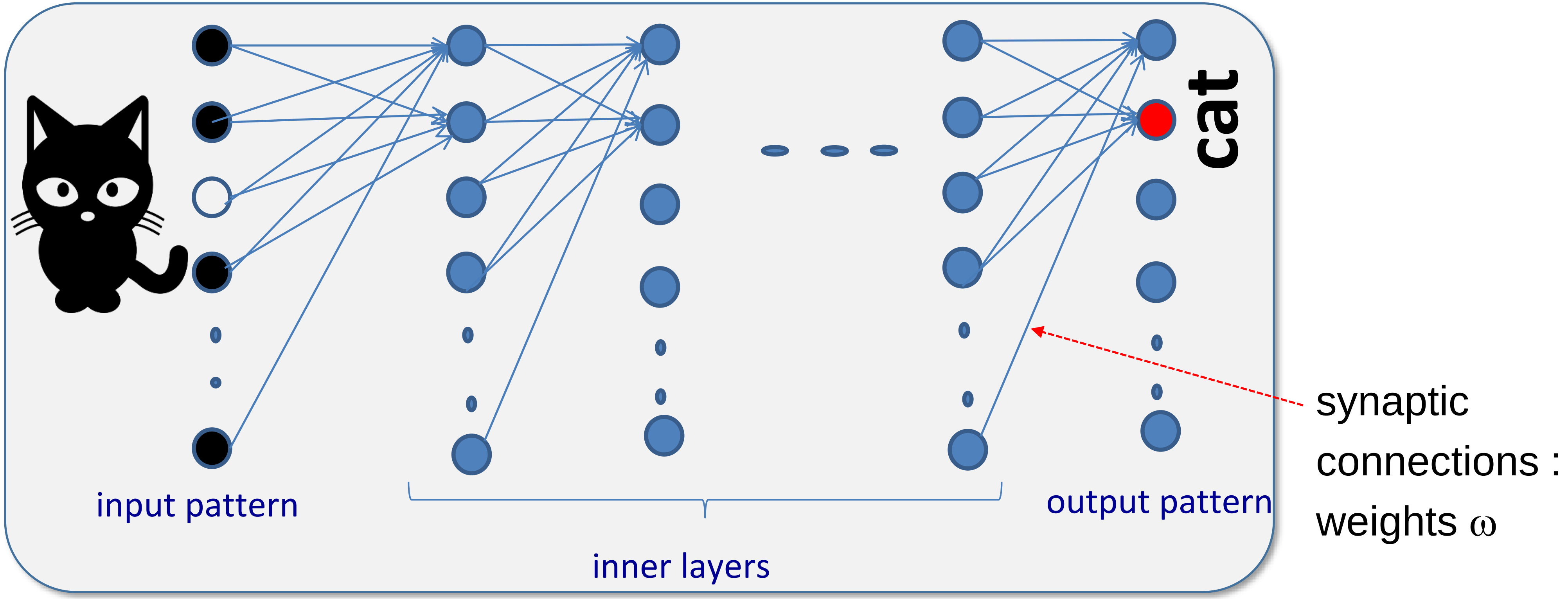
artificial neural networks

neuromorphic computing

use novel technologies:

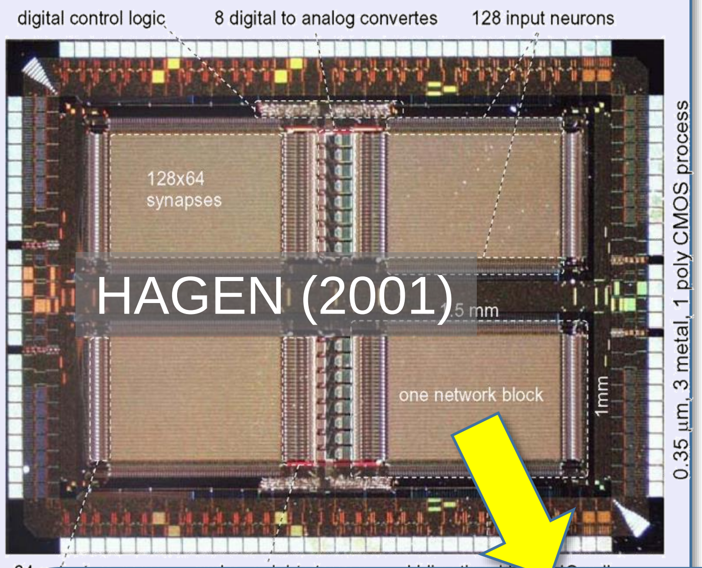
digital and analog neuromorphic hardware

high-performance neuro-simulations



Perceptron model (biology of 1950)

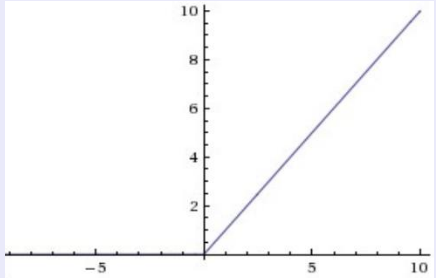
Machine Learning



- vector-matrix multiplication

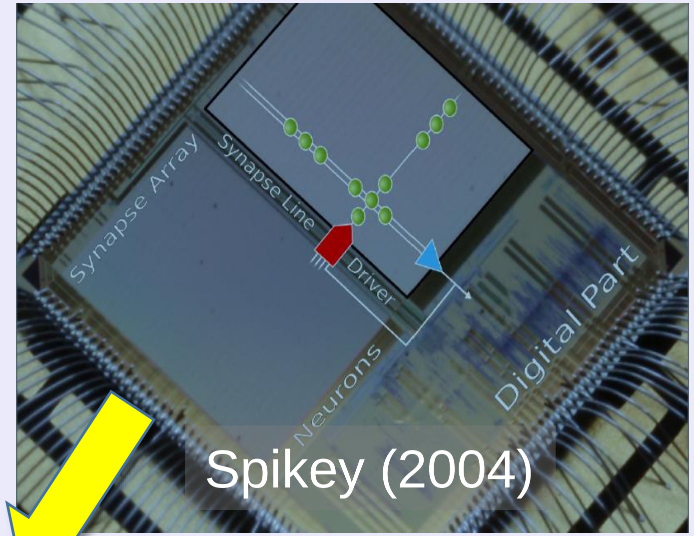
$$f\left(\sum_i w_i x_i + b\right)$$

- simple non-linear activation function f (ReLU):



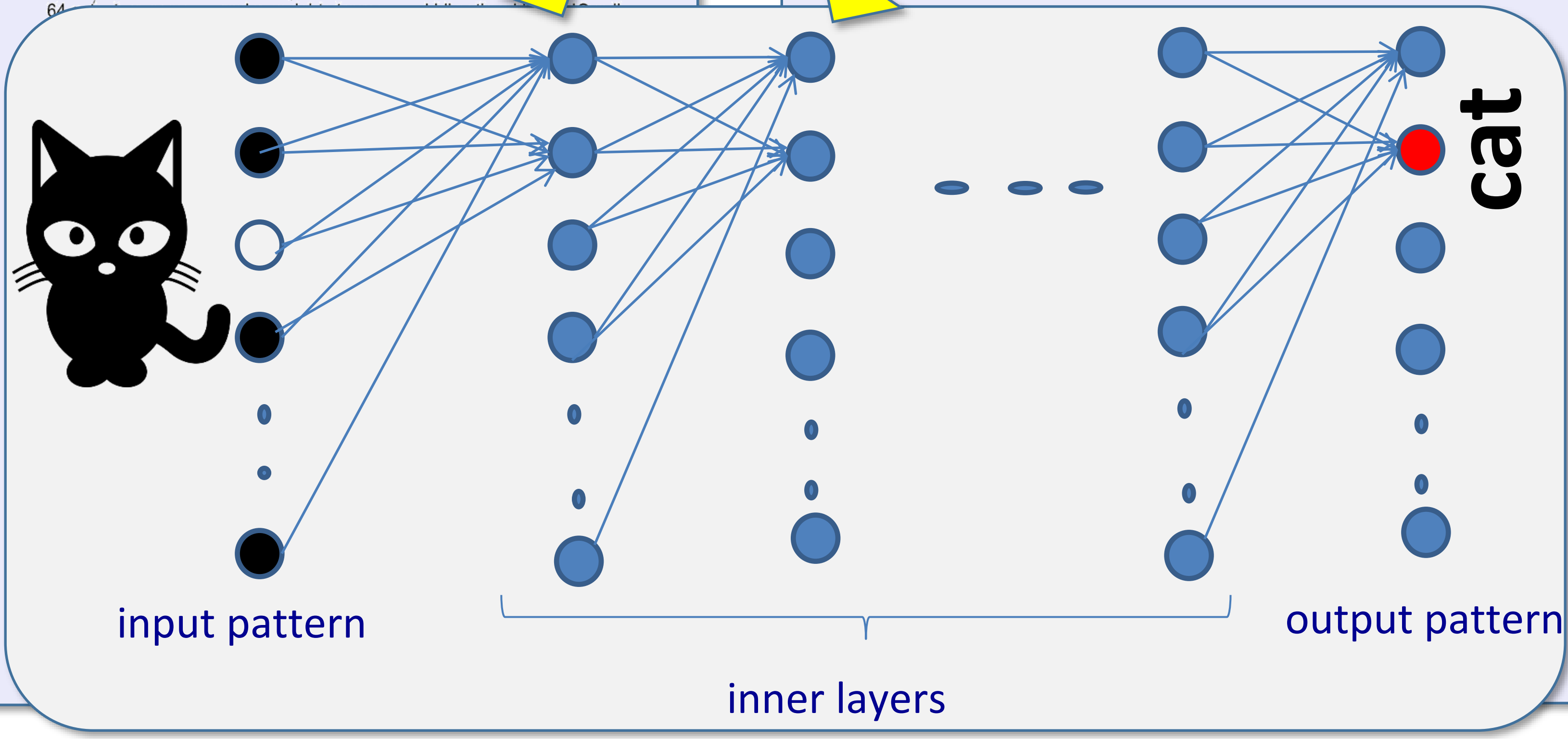
- trained with backpropagation

Spike-based model (current biology)



Brain-Inspired Computing

- time-continuous dynamical system
- vector-matrix multiplication
- complex non-linearities
- binary neuron output
- allows to model biological learning mechanisms



neuromorphic dimensions

conceptual dimensions :

rate based	←→	event based
continuous time, c. valued	←→	discrete time, d. valued
exact computations	←→	approximate, noisy, stochastic comp.
point neurons	←→	structured neurons
linear dentrides	←→	non-linear dentrides
static	←→	plastic

technological dimensions :

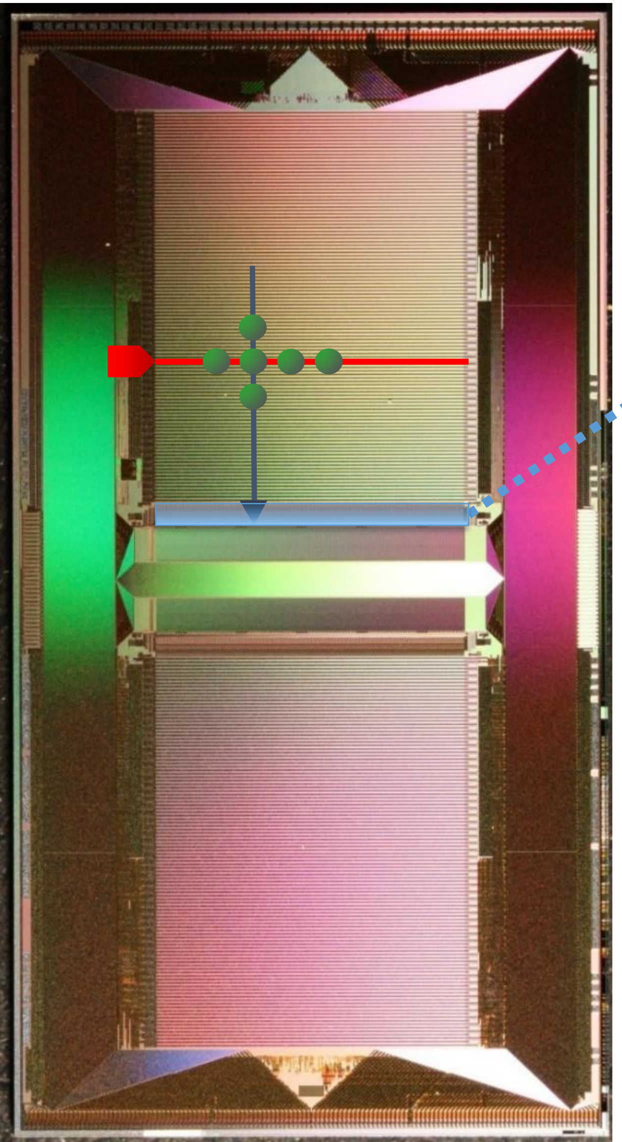
analog	←→	digital
electrical	←→	optical
standard CMOS	←→	novel devices
fully programmable	←→	fixed structure
in-memory computing	←→	von Neumann computing
constant speed	←→	variable speed
(real time or accelerated)		(best effort)

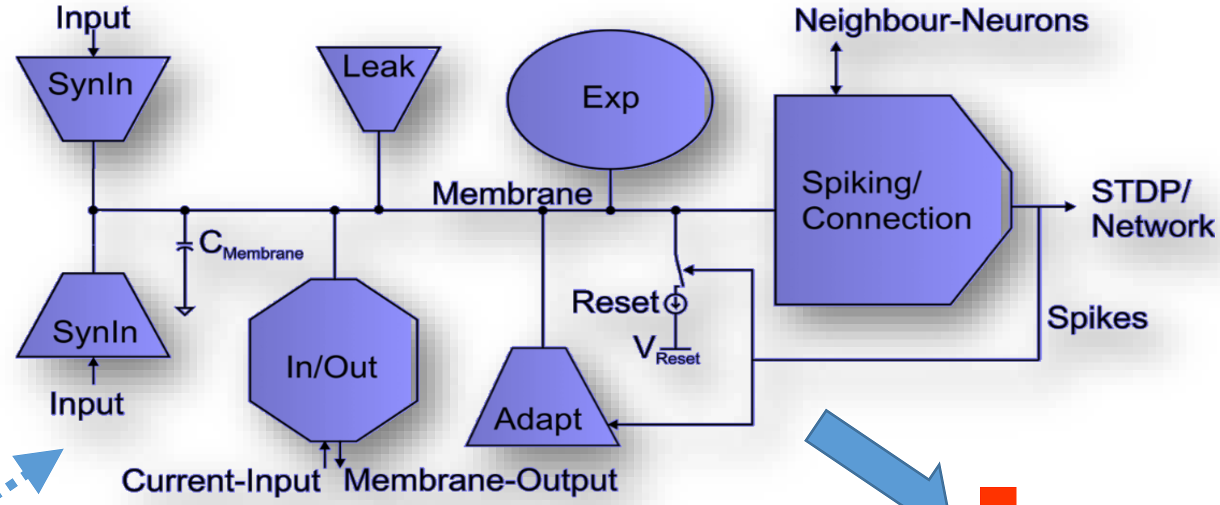
application dimensions :

research	←→	commercial
brain emulation	←→	machine learning, AI
energy, size, cost constrained	←→	energy, size, cost agnostic
fixed function	←→	needs to adapt

BrainScaleS overview : accelerated, analog NMC with hybrid plasticity

photograph of the BrainScaleS 1 neuromorphic chip

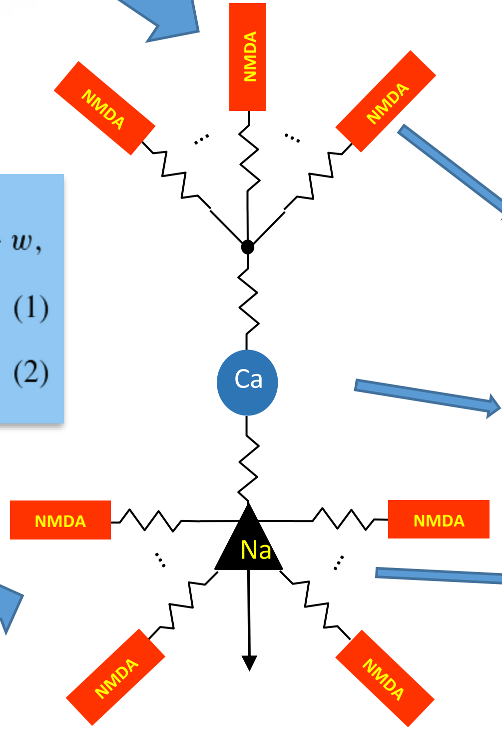


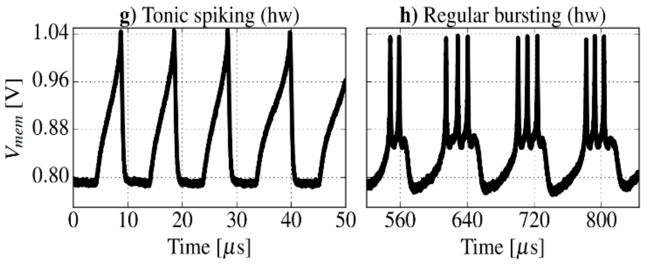


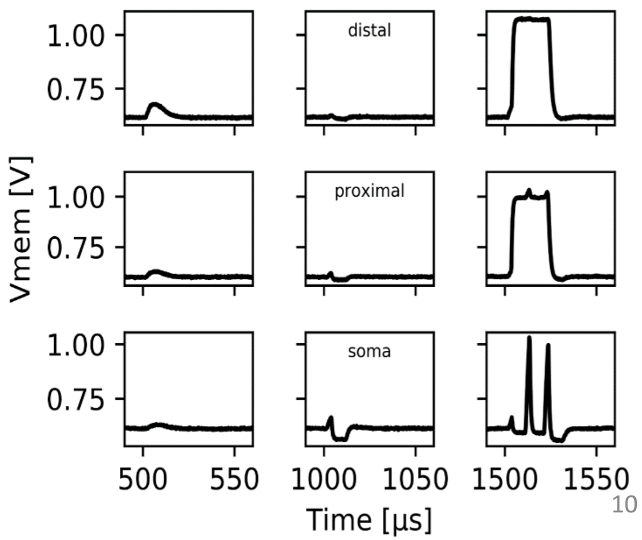
- modular neuron structure
- Adaptive Exponential I&F model
- full set of ion-channel circuits for each compartment
- 24 calibration parameters per compartment
- full on-chip plasticity supported by embedded SIMD CPUs

$$C\frac{dV}{dt} = -g_L(V - E_L) + g_L \Delta_T \exp\left(\frac{V - V_T}{\Delta_T}\right) + I - w, \quad (1)$$

$$\tau_w \frac{dw}{dt} = a(V - E_L) - w. \quad (2)$$







complex neurons can be build by connecting individual compartments

neuromorphic dimensions covered by BrainScaleS

conceptual dimensions :	rate based	←→	event based
	continuous time, valued	←→	discrete time, valued
	exact computations	←→	approximate, noisy, stochastic comp.
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BrainScaleS service sub-categories within EBRAINS

- accelerated emulation of networks of structured neurons with non-linear dendrites
  (Emulating dendritic computing paradigms on analog neuromorphic hardware, Jakob Kaiser et.al., Neuroscience, 2021)
- large parameter sweeps for network operation tuning
  (Autocorrelations in homeostatic spiking neural networks as a result of emergent bistable activity, J Zierenberg et. al., Bulletin of the American Physical Society, 2022/3/14,
  Control of criticality and computation in spiking neuromorphic networks with plasticity, B Cramer et.al., Nature communications, 2020/6/5)
- biology inspired learning experiments with programmed local plasticity
  (Structural plasticity on an accelerated analog neuromorphic hardware system, S Billaudelle et. al., Neural Networks, 2021/1/1)
- learning-to-learn sweeps of meta-parameters (Neuromorphic Hardware Learns to Learn, T Bohnstingl et.al., Front Neurosci.,2019)
- inference experiments for solving tasks using optimized network parameters generated by hardware-in-the-loop gradient-based training
  (Surrogate gradients for analog neuromorphic computing, B Cramer et.al., pnas.2109194119, 2022;
  Fast and energy-efficient neuromorphic deep learning with first-spike times, J Göltz et.al, Nature machine intelligence, 2021/9)
- applications of spiking neural networks for approximate computing
  (Spiking neuromorphic chip learns entangled quantum states, S Czischek, et. al. , SciPost Physics 12 (1), 039, 2022)
- parameter fitting to match experimental observations
- direct real-time coupling between in-vitro preparations in wet-labs and the BrainScaleS system
  → initially with HeiCINN in Heidelberg, but open for others
- repeated execution of a network and/or long operation to gather statistical information or for sampling from stochastic models
- interactive execution of small models with immediate visualization for educational purposes
  → girls’ day, advanced lab course
- experimental platform for analogue computing research
  (Towards Addressing Noise and Static Variations of Analog Computations Using Efficient Retraining, B Klein et.al., ECML PKDD, 2021/9/13)
  → first industry collaboration shows promising results in the area of optical communication
  (submitted to Signal Processing in Photonic Communications 22)

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A subset of these can be already accessed through the current HBP NMC online access and will be part of the hands-on demo!

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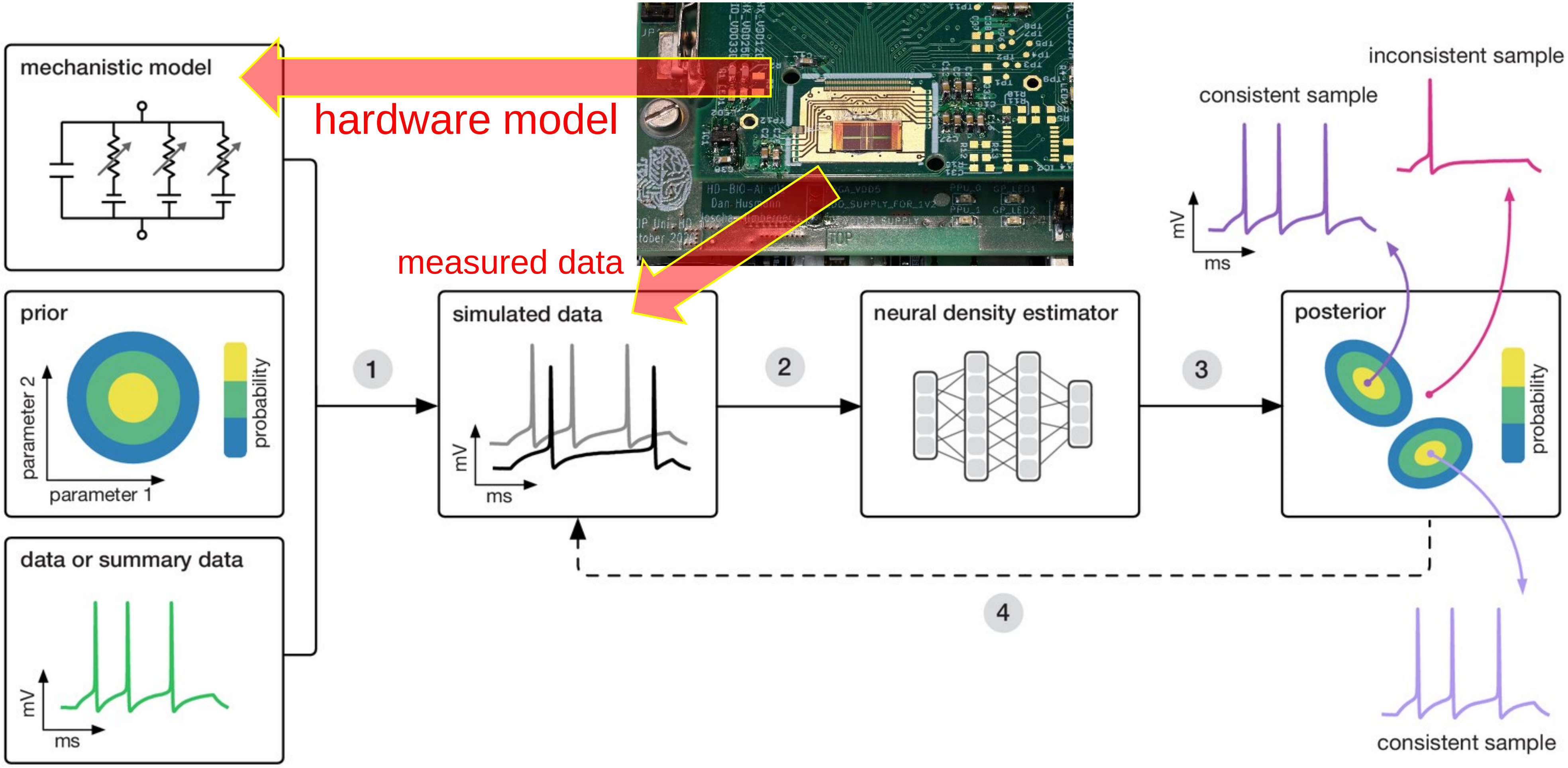
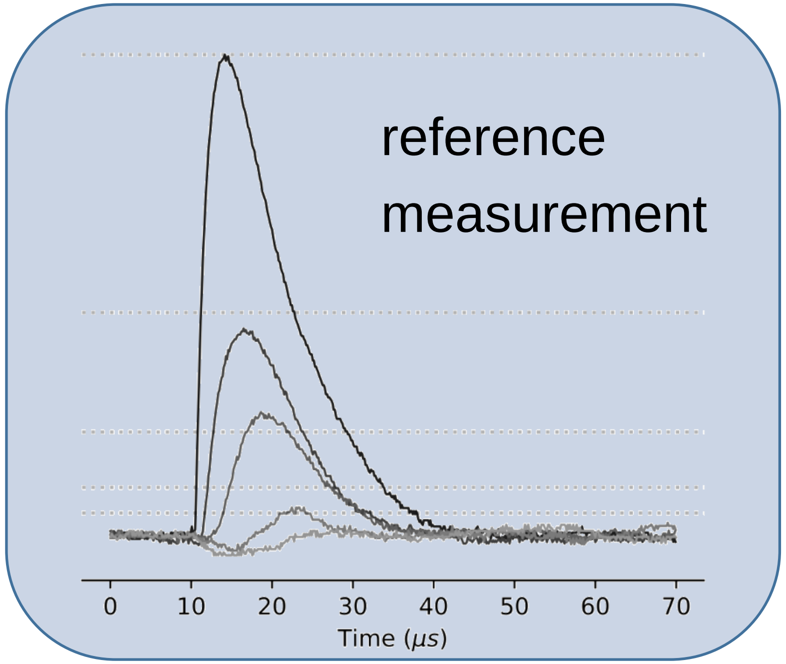
example:
fitting BrainScaleS neurons to experimental data



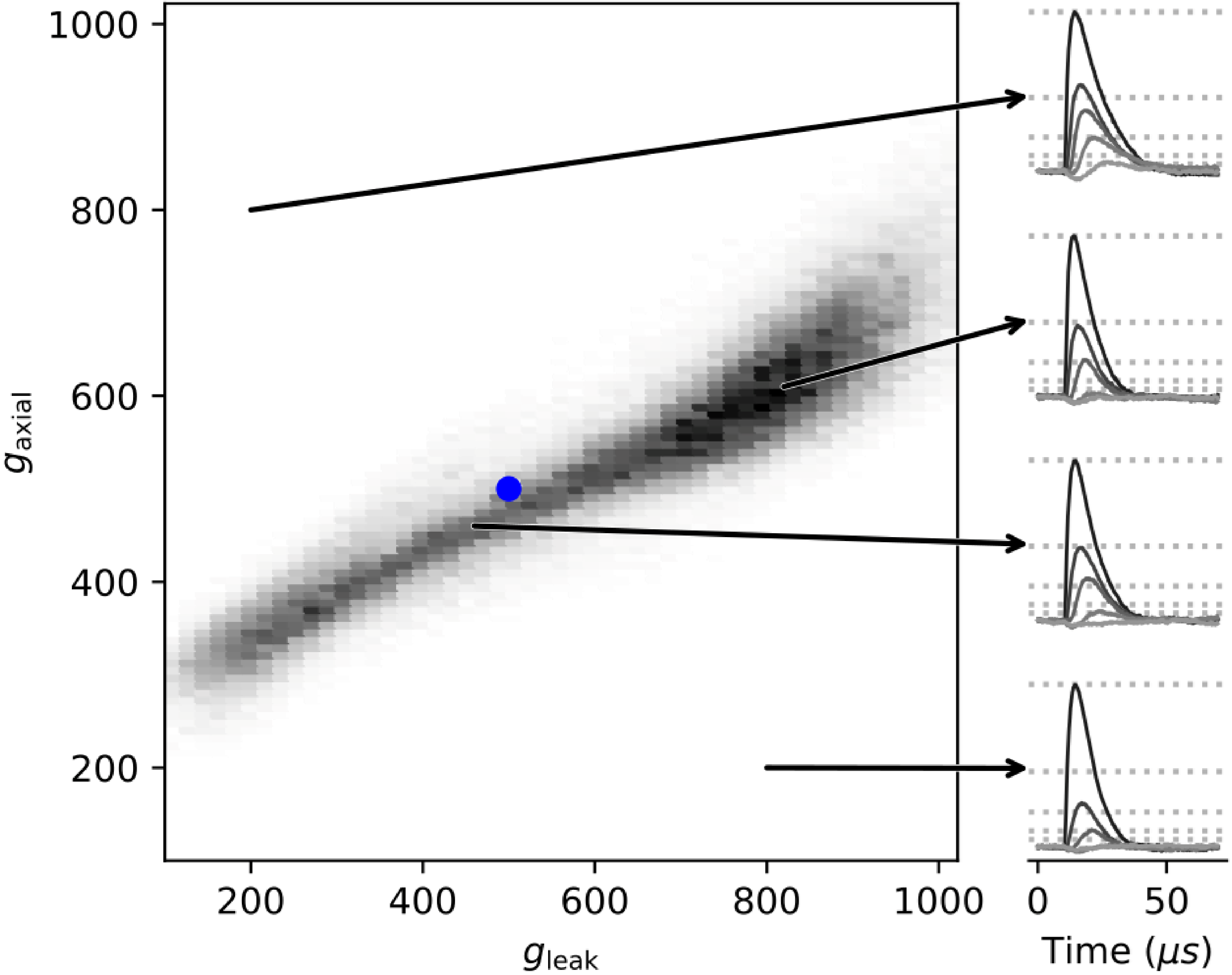
"Training deep neural density estimators to identify mechanistic models of neural dynamics", Pedro J Gonçalves et. al., eLife 2020;9:e56261 DOI: 10.7554/ELIFE.56261

early results from BSS-2 hardware

- chain of five dendritic compartments
- finding the correct parameter for leakage and inter-compartmental conductance

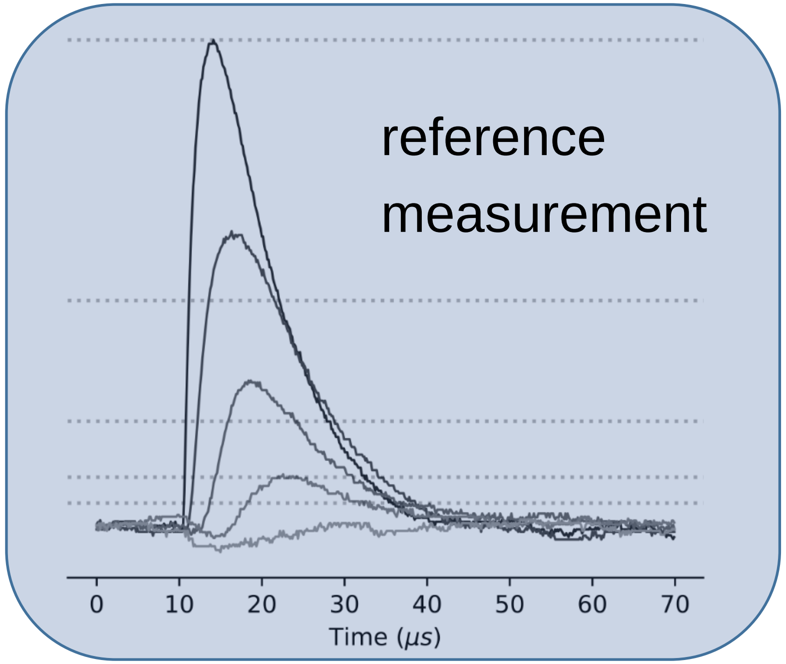


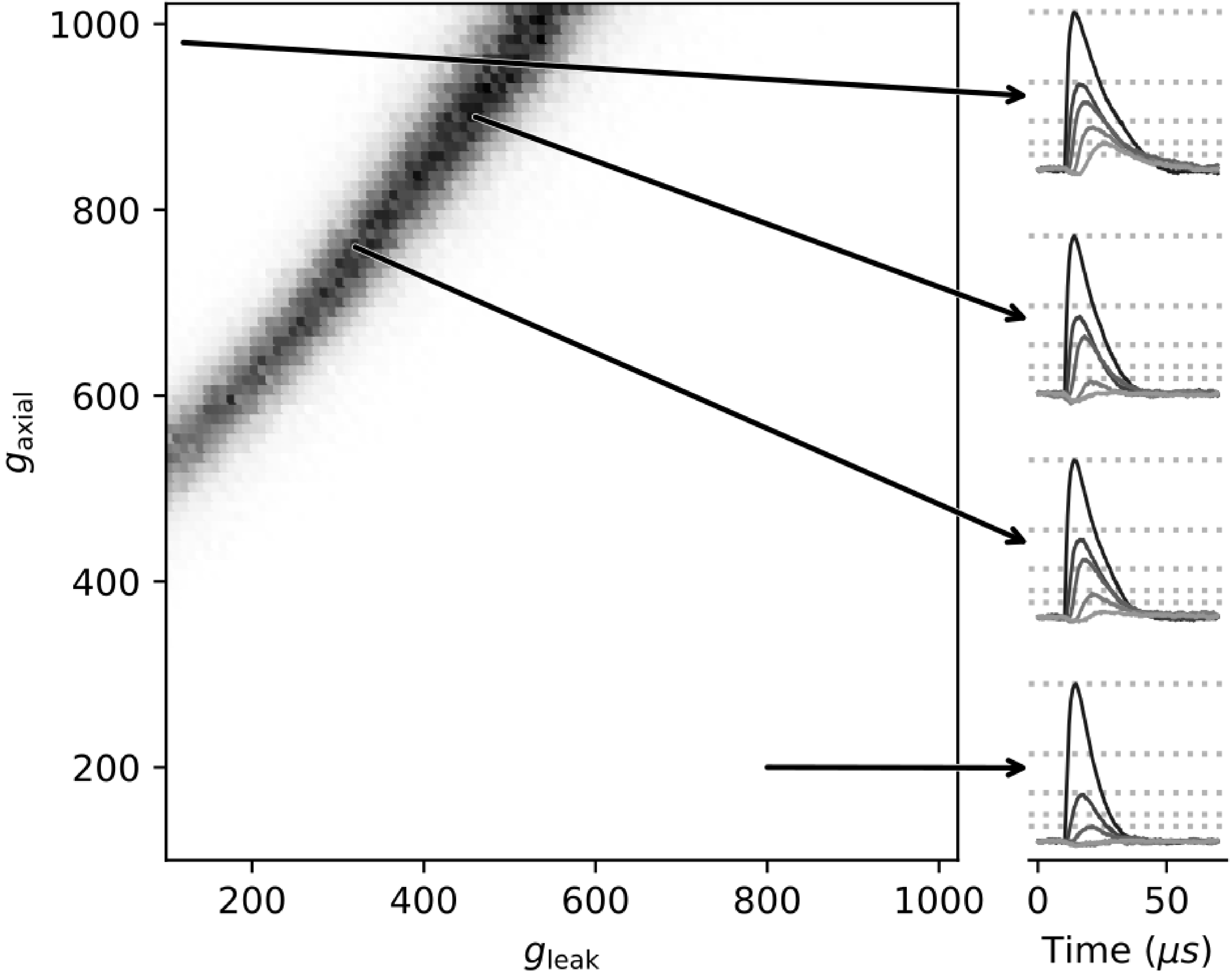
ongoing PhD thesis from Jakob Kaiser, in collaboration with Sebastian Schmitt, Tetzlaff lab, University Göttingen



fitting to a different chip

- reference is measured on a different chip
- no 100% fit of the data using only two parameters possible





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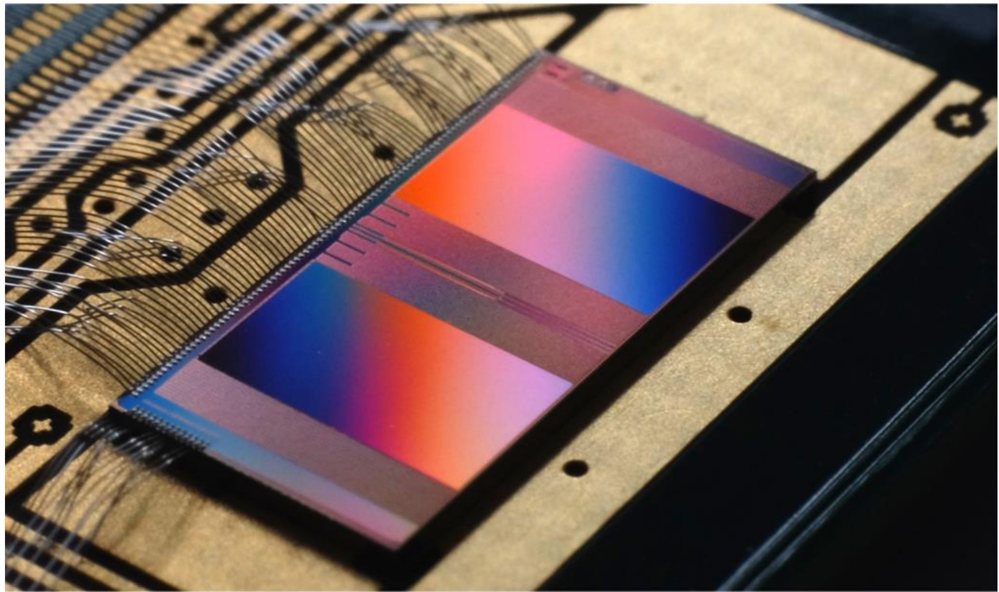
easily accessible analog computing: EBRAINS neuromorphic service BrainScaleS

- make *conceptual neuromorphic dimensions* of BrainScaleS remote accessible
- encapsulate its *technological neuromorphic dimensions* into the EBRAINS remote user framework
- support all *application dimensions*
- by implementing all EBRAINS dimensions :
  - software
  - user interface
  - documentation
  - tutorials
  - support
  - hardware operation and maintenance



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…

2010 BrainScaleS-1 analog neuromorphic computing wafer scale system

2018 BrainScaleS-2 invents hybrid plasticity

2020 BrainScaleS-2 part of EBRAINS