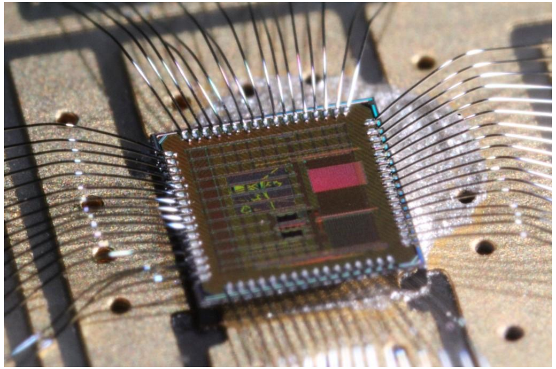
BrainScaleS Hands-On Tutorial
—Overview—



S. Schmitt
E. Müller
Heidelberg University

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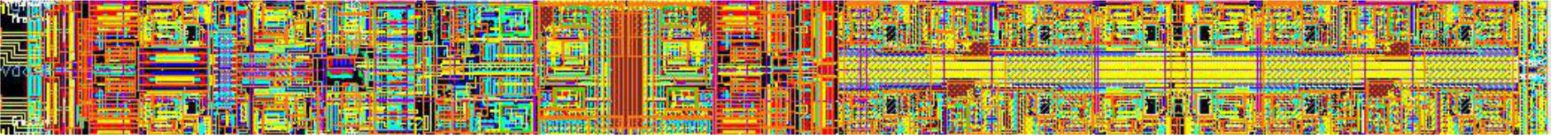
Albany CNSE Campus
Albany, NY

BrainScaleS-2 Prototype

BrainScaleS-1 Wafer Module

Electronic Vision(s)

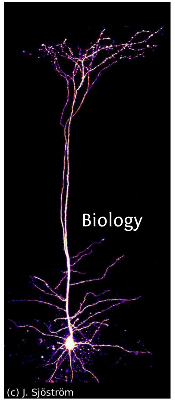


BrainScaleS Architectures

$$C\frac{dV}{dt} = -g_L(V - E_L) + I + g_L\Delta_T \exp(\frac{V - V_T}{\Delta T}) - w$$

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

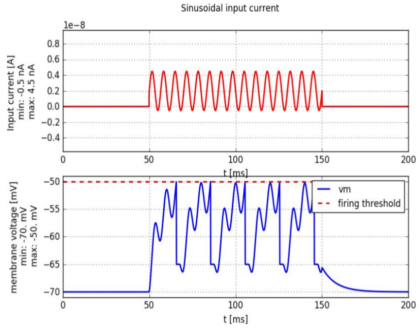
(Adaptive Exponential Integrate-and-Fire)

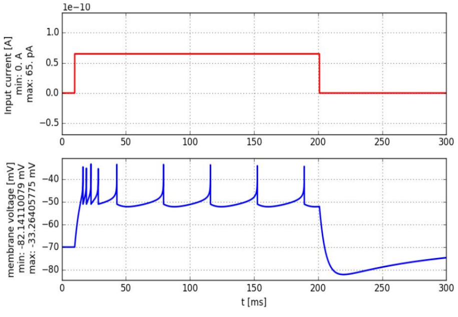


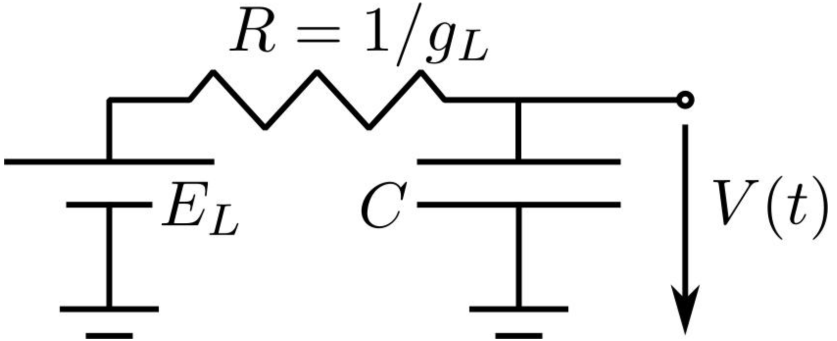
- Physical Model:
  - an electronic circuit for each neuron and synapse
  - Time models itself
- Accelerated dynamics: 1000 - 10000 faster wrt. biology

$$C\frac{dV}{dt} = -g_L(V - E_L) + I$$

(Integrate-and-Fire)







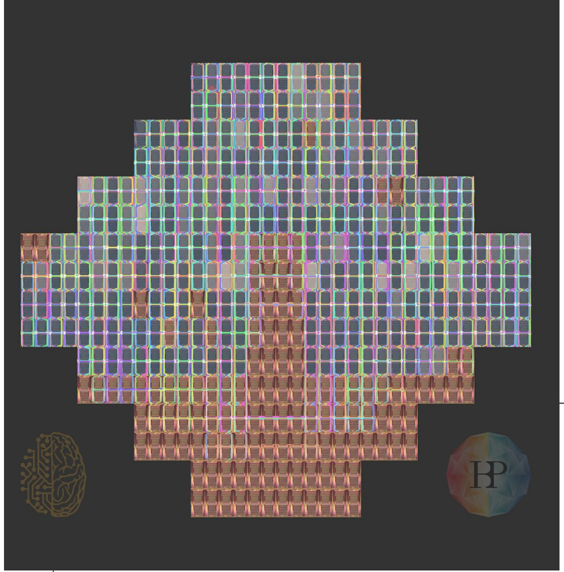
BrainScaleS-1

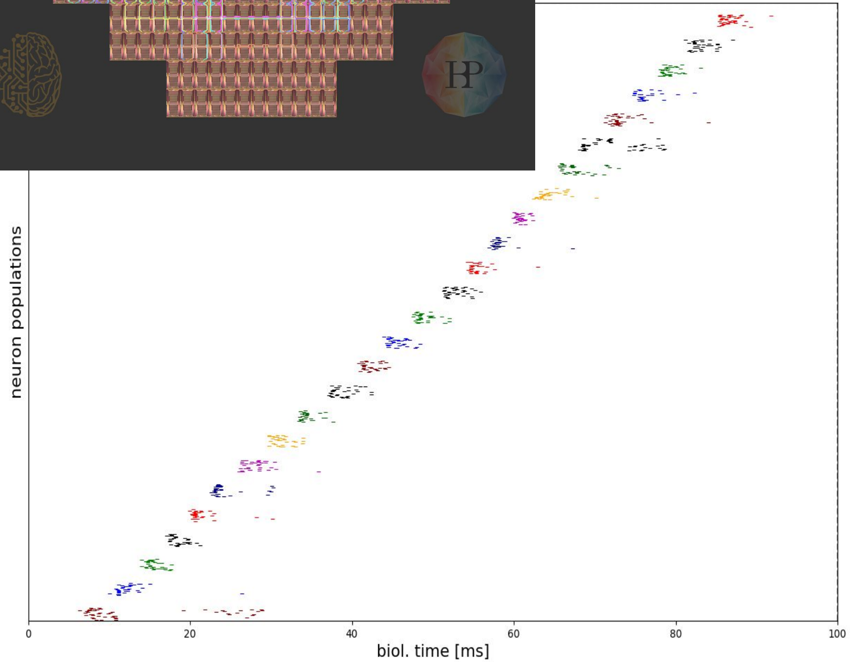
- Wafer scale neuromorphic experiments can be conducted via PyNN
- Networks described in terms of populations of neurons and their connections
- Low-level access to hardware parameters possible

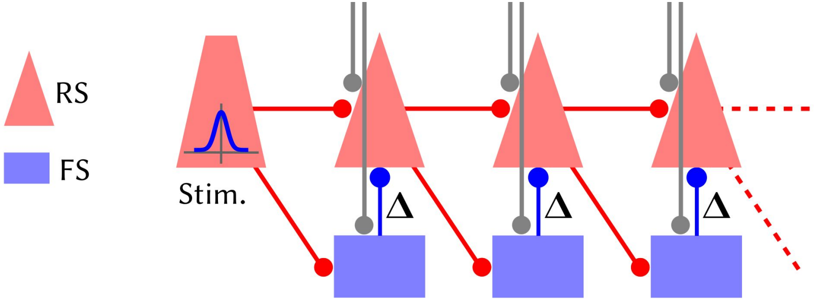
Wafer-scale Synfire Chain

- Hardware Implementation similar to “Characterization and Compensation of Network-Level Anomalies in Mixed-Signal Neuromorphic Modeling Platforms” (Petrovici 2014)

- > 13k neurons and ~200k synapses

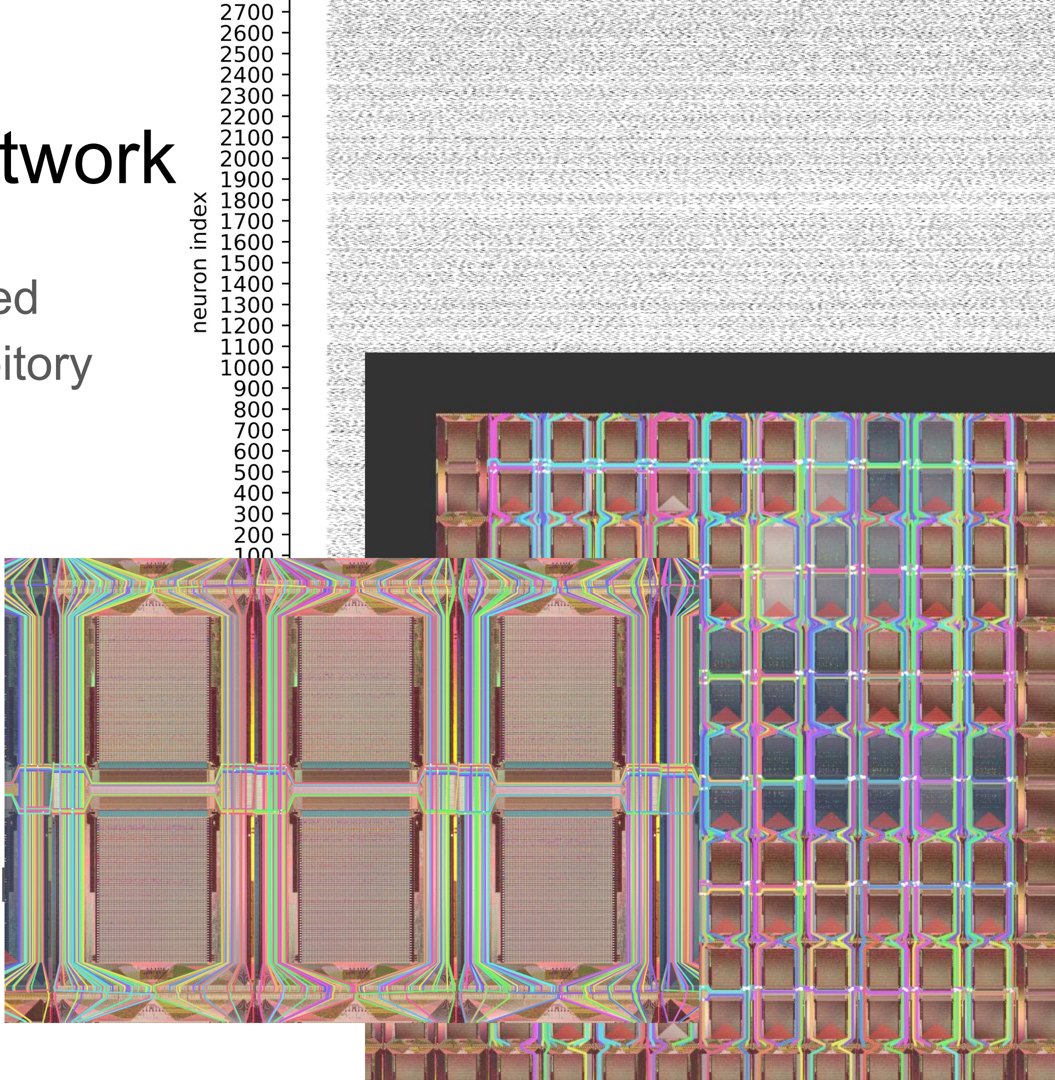






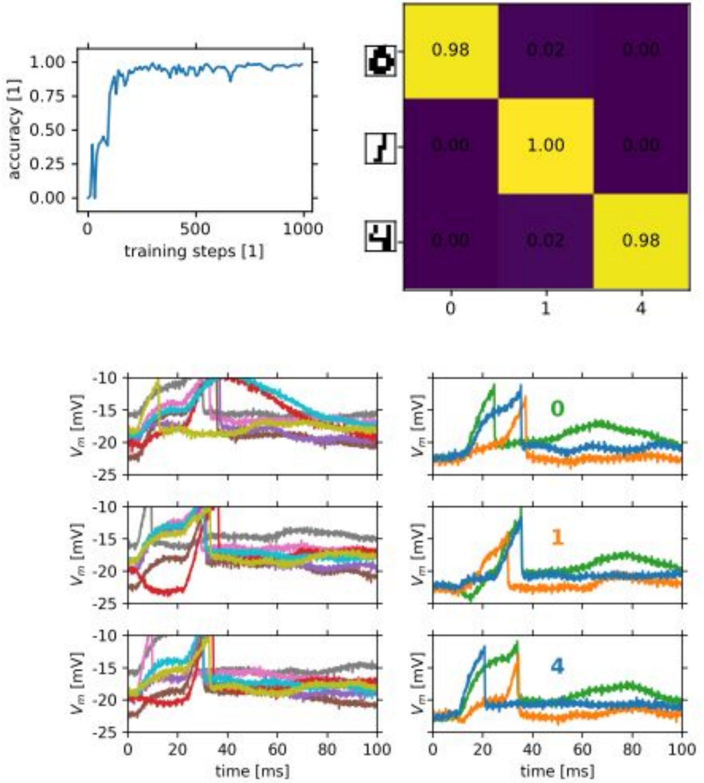
(Balanced) Random Network

- “Dynamics of Sparsely Connected Networks of Excitatory and Inhibitory Spiking Neurons” (Brunel 2000)
- 3000 neurons
- ~700k synapses
- 138 HICANN chips
- 800 individual external poisson sources with 50 Hz each -> 40 k (bio) (400 MHz wall clock rate)



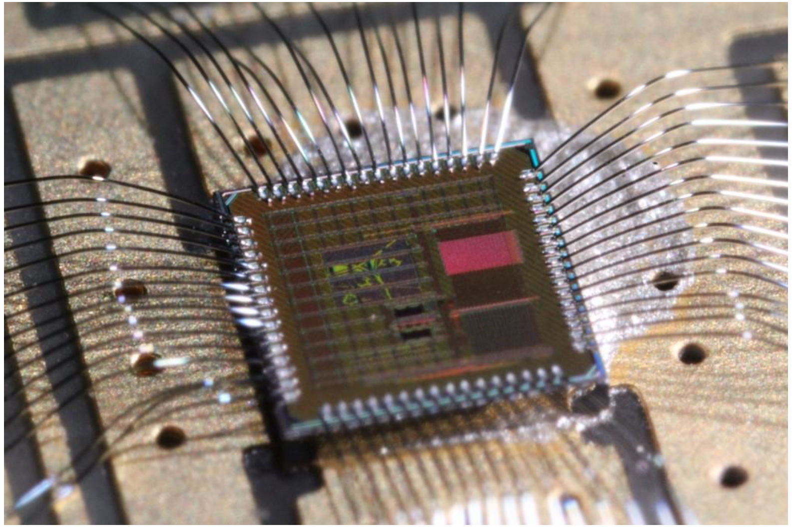
Training deep networks with time-to-first-spike coding on the BrainScaleS wafer-scale system

- Hardware Implementation of “Supervised Learning Based on Temporal Coding in Spiking Neural Networks” (Mostafa 2018)
- Proof-of-concept implementation that learns to recognize patterns on the BrainScaleS using **time-to-first-spike** coding
- Single spikes promise to be an energy efficient and fast (~µs) approach to feature detection on neuromorphic hardware



BrainScaleS-2

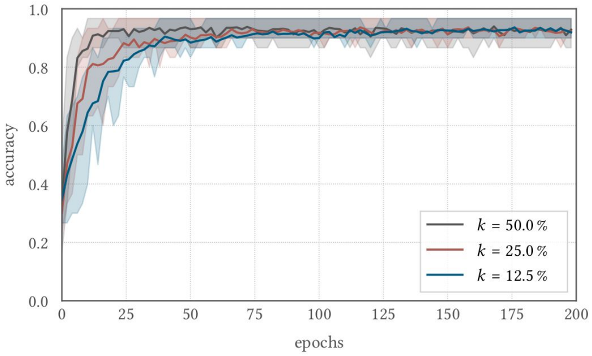
- Essentially all of BSS-1 (however: small prototype chip)
- Embedded processor for programmable plasticity
  - observe: accumulated correlation, neuron spike counts, (individual spikes)
  - control: weights, neuron parameters, …
  - → two-factor + reward-modulated STDP, structural plasticity, homeostasis, …
- Embedded processor for other tasks:
  - virtual environments; closed-loop sensor/motor modeling
  - self-calibration

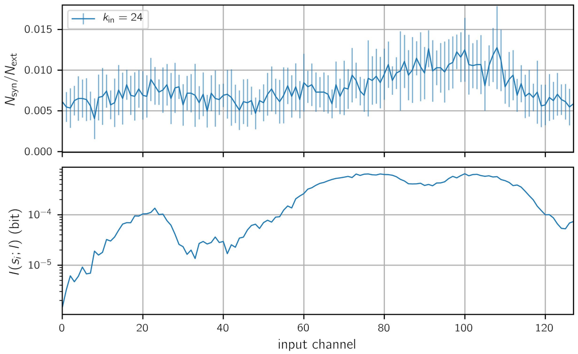


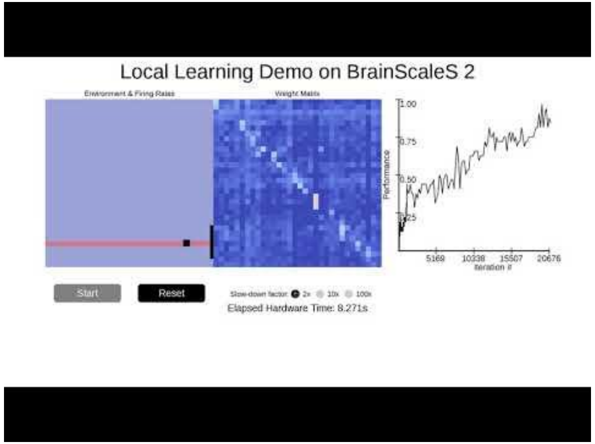
BrainScaleS-2 Experiments

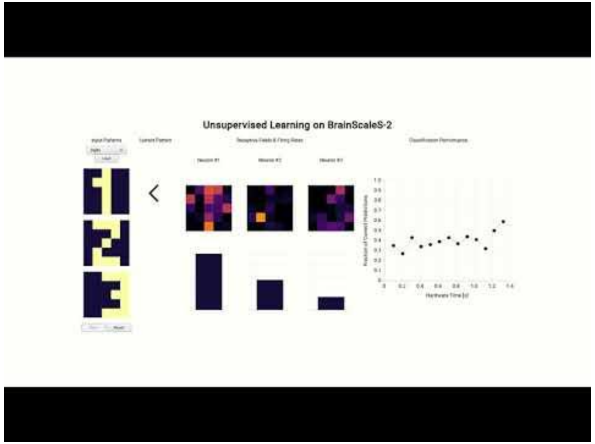
Examples:

- Structural Plasticity
  - e.g. auditory feature selection
- Closed-Loop Reinforcement Learning
  (https://doi.org/10.3389/fnins.2019.00260)
- Unsupervised learning, e.g., using Spike-based Expectation Maximization









BrainScaleS-1: Hands-On

- You will remote access BrainScaleS-1 via a jupyter notebook
- You will define spiking neural networks using the Python-based PyNN API
- You will visualization the generated hardware configuration
- You will run experiments and analyse the results

BrainScaleS-2: Hands-On

- You will access one local "HICANN-DLS v2 Prototype"
  - (we can also use some more setups remotely)
- You will work with the lowest configuration API level (exposing all bits and pieces)
- You will use the embedded processor