SpiNNaker Applications

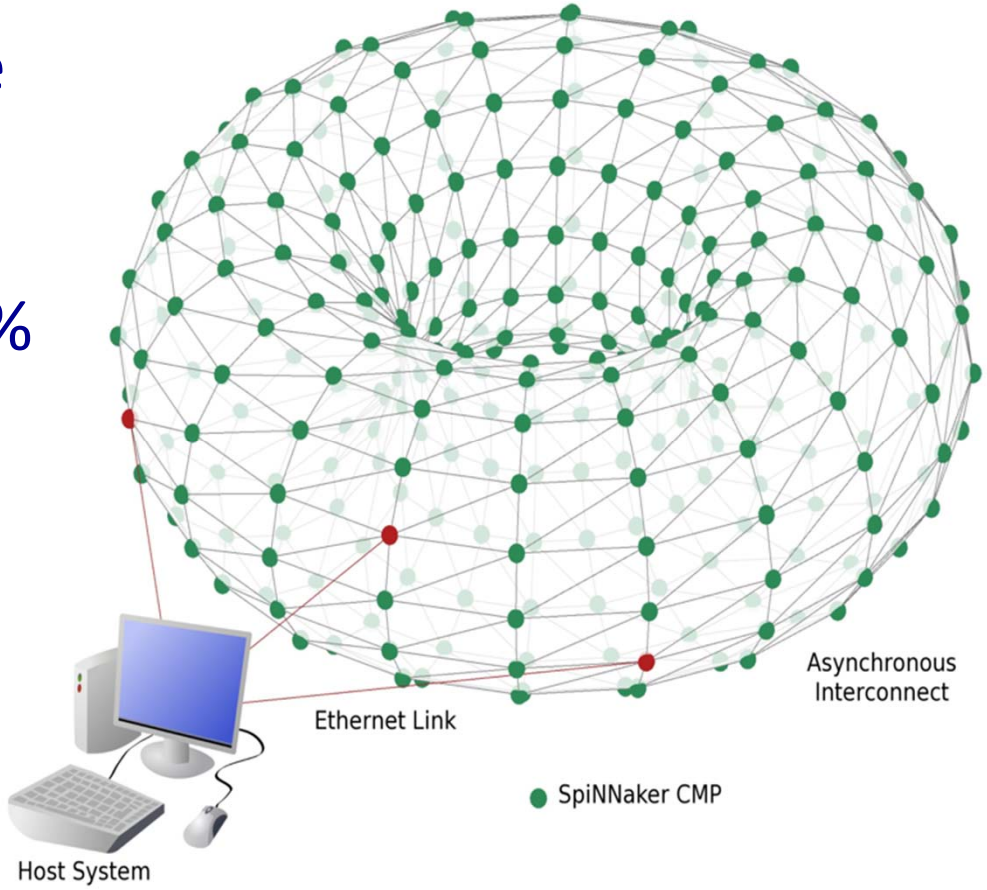
Steve Furber

ICL Professor of Computer Engineering

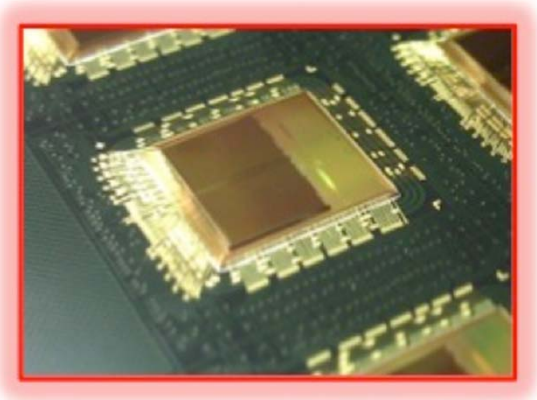
The University of Manchester

SpiNNaker project

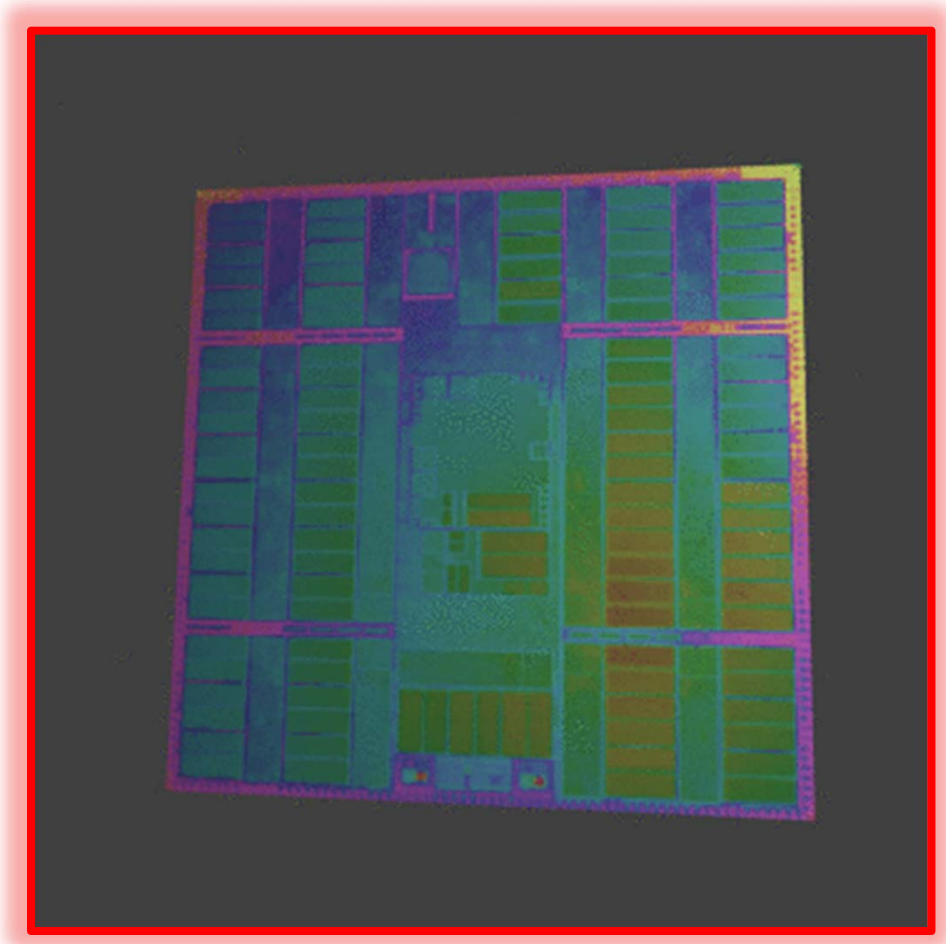
- A million mobile phone processors in one computer
- Able to model about 1% of the human brain…
- …or 10 mice!



SpiNNaker chip

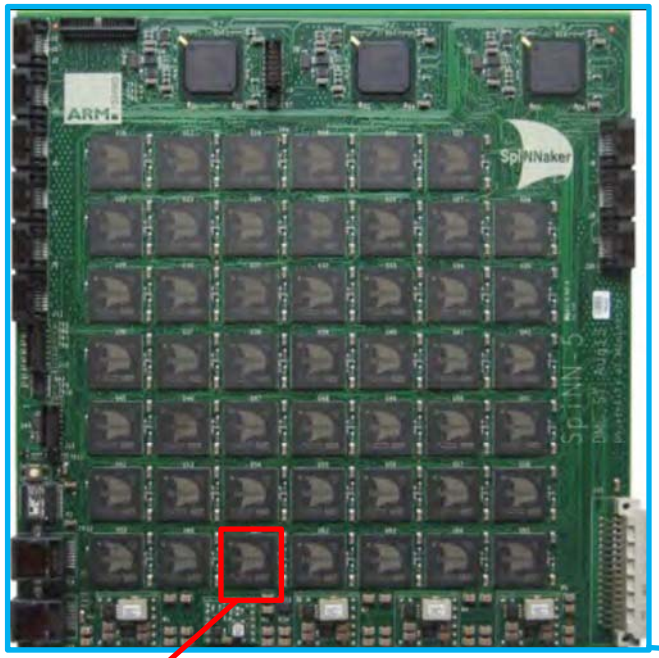


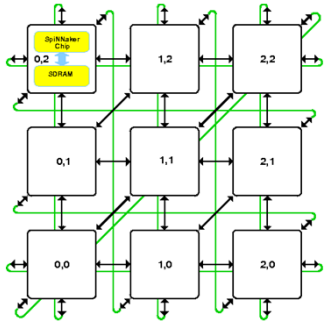
Multi-chip packaging by UNISEM Europe



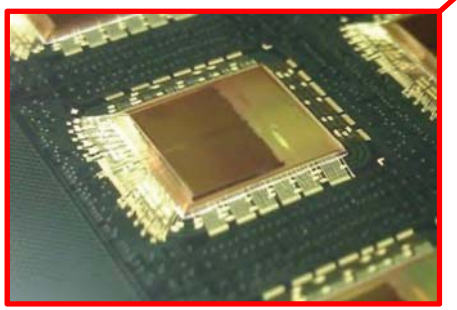
SpiNNaker machines

SpiNNaker board
(864 ARM cores)



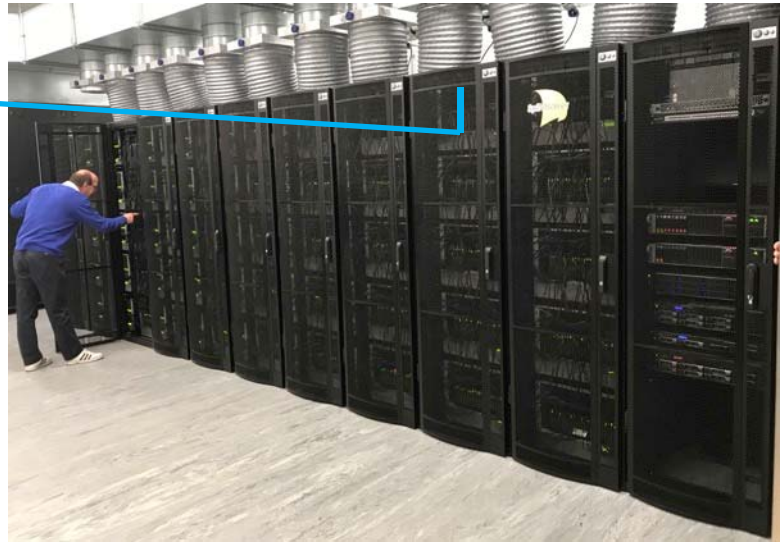


SpiNNaker chip
(18 ARM cores)



- HBP platform
  - 1M cores
  - 11 cabinets (including server)
- Launch 30 March 2016
  - then 500k cores
  - 93 remote users
  - 5,134 SpiNNaker jobs run

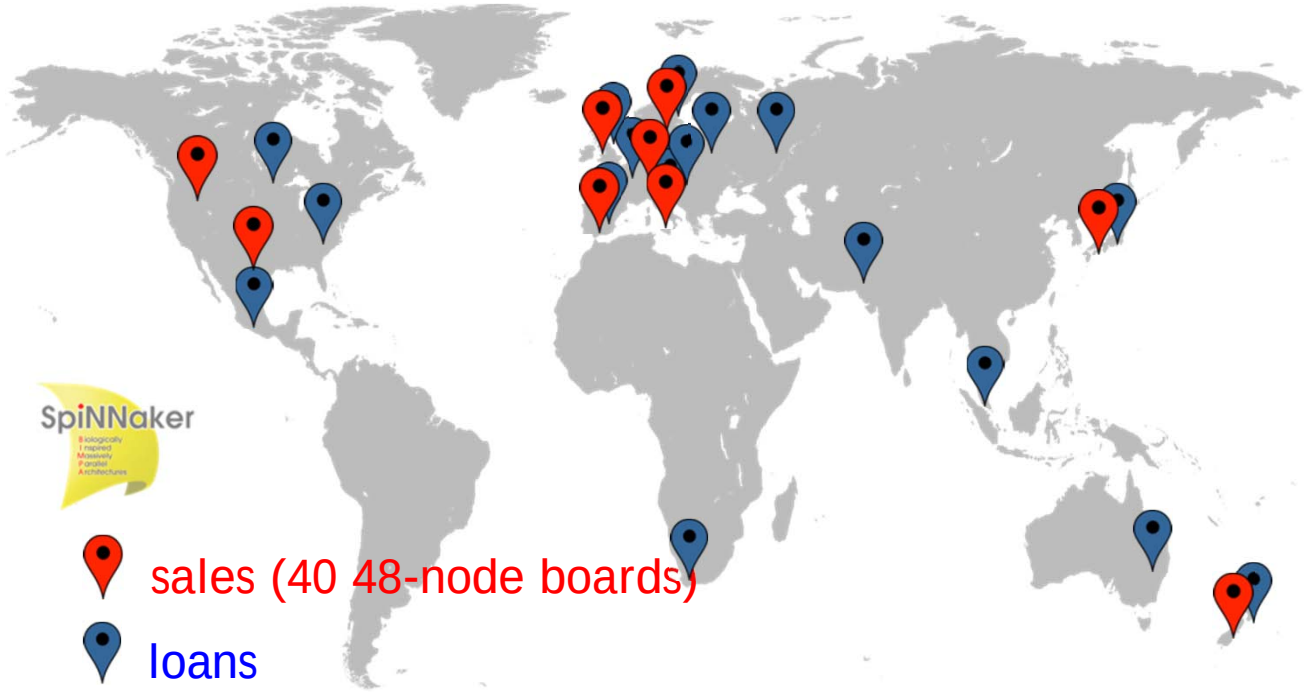
Human Brain Project



SpiNNaker racks
(1M ARM cores)

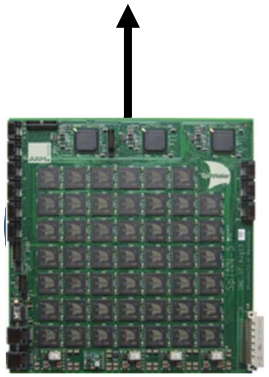
SpiNNaker machines

- 100 SpiNNaker systems in use
  - global coverage
- 4-node boards
  - training & small-scale robotics
- 48-node boards
  - insect-scale networks
- multi-board systems
- 1M-core HBP platform



SpiNNaker applications

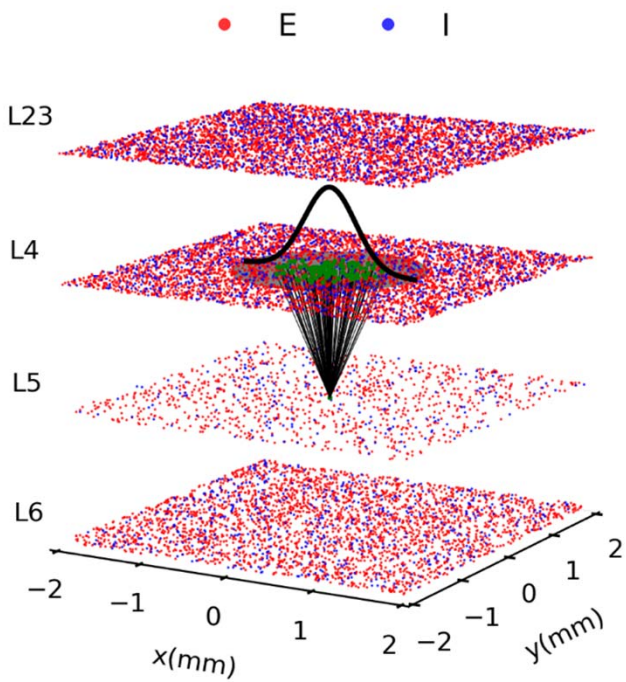
Computational Neuroscience

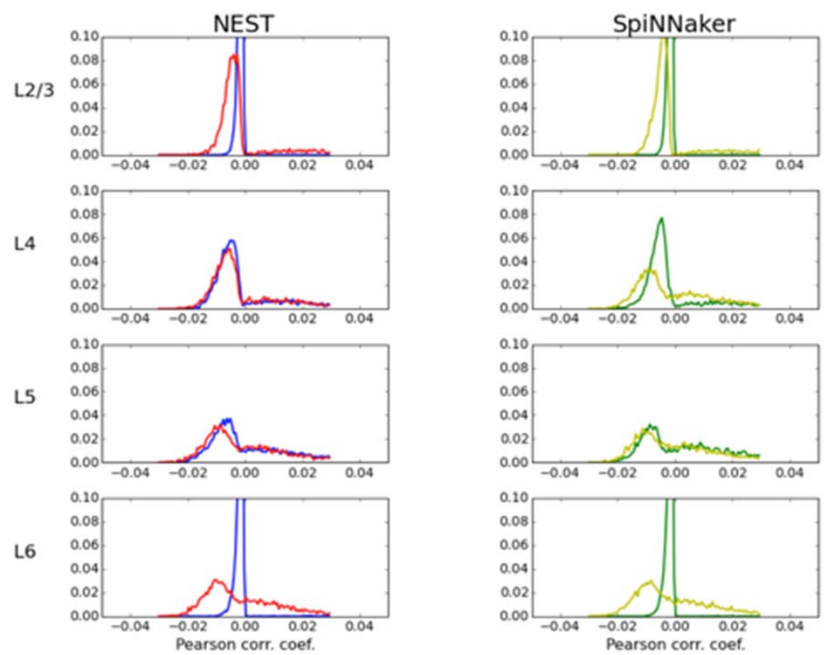


Cortical microcolumn

1st full-scale simulation of 1mm^2 cortex on neuromorphic & HPC systems

- 77,169 neurons, 285M synapses, 2,901 cores
- using as benchmark example:
  - since improved run-time by x80: 10 hours → 7.5 minutes
  - work in progress to improve efficiency by x60: real time, cores/3

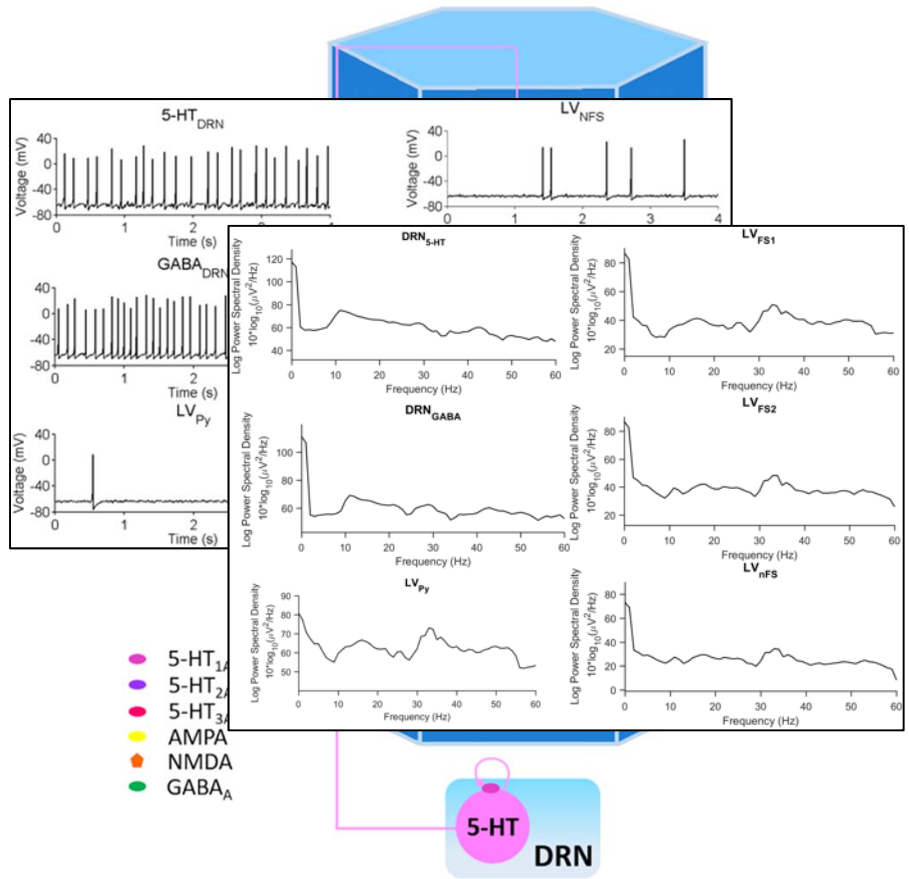




S.J. van Albada, A.G. Rowley, A. Stokes, J. Senk, M. Hopkins, M. Schmidt, D.R. Lester, M. Diesmann, S.B. Furber, *Performance comparison of the digital neuromorphic hardware SpiNNaker and the Neural network simulation software NEST for a full-scale cortical microcircuit model*. Frontiers 2018.

Computational Neuroscience

- Serotonin modulates Pre Frontal Cortex
  - neurons express range of serotonin receptors
  - respond at different timescales
- Dorsal Raphe Nucleus stimulation modulates brain rhythms
  - releases serotonin
- Computational model to simulate serotonergic modulation
  - monitor local effects – firing rates
  - understand global effect on connected brain regions – oscillation in local field potential

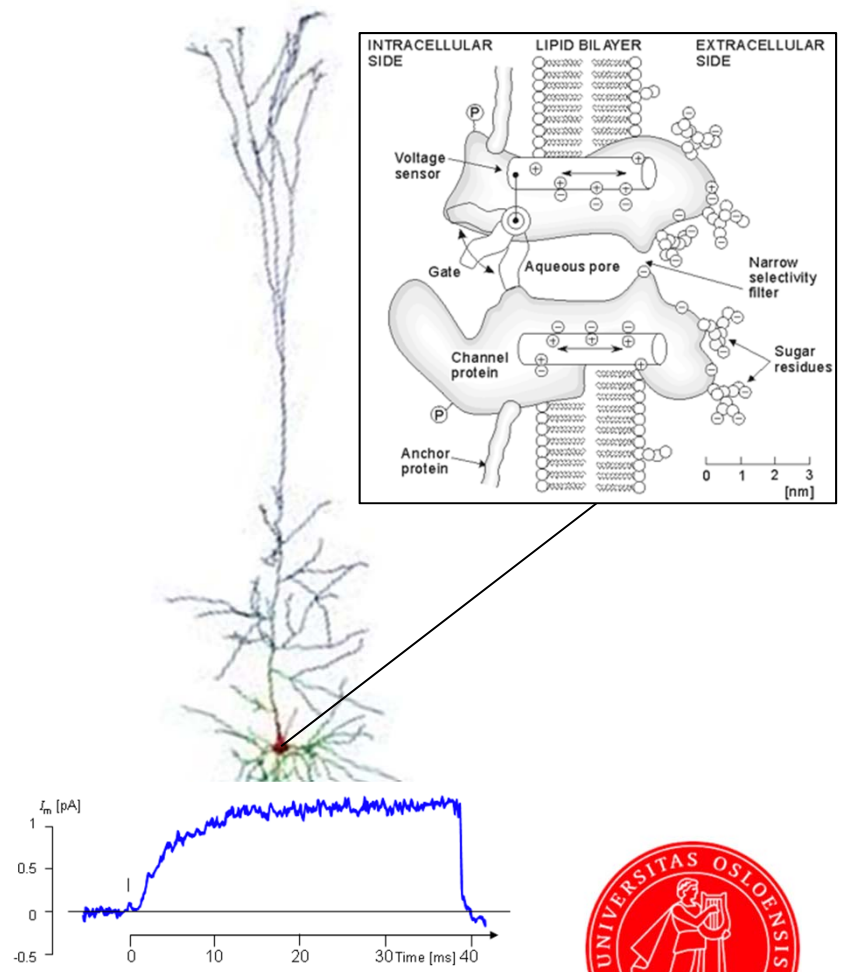


Celada, P., et al. *Serotonin modulation of cortical neurons and networks*. Frontiers in Neuroscience. 2013

Joshi, A., & Rhodes, O,. et al. *Serotonergic modulation of cortical columnar dynamics: A large-scale neuronal network simulation study using SpiNNaker*. In prep.

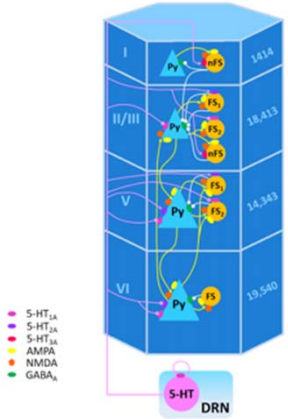
Computational Neuroscience

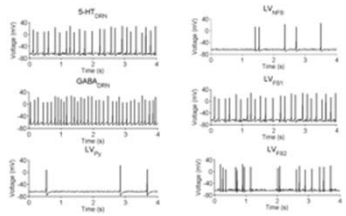
- Explore chemistry modulating neuron behaviour
  - intracellular dynamics (ion channels)
- Simulate patch-clamp experiments from biology
- Incorporate findings at larger scales
  - study effect on consciousness
  - multiple brain regions

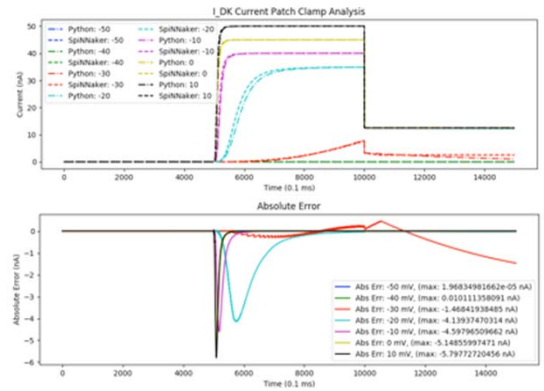


Jaakko Malmivuo and Robert Plonsey, 1995

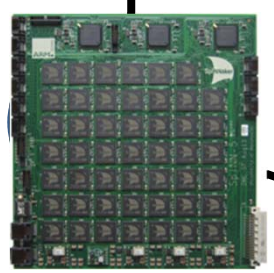
SpiNNaker applications







Computational Neuroscience



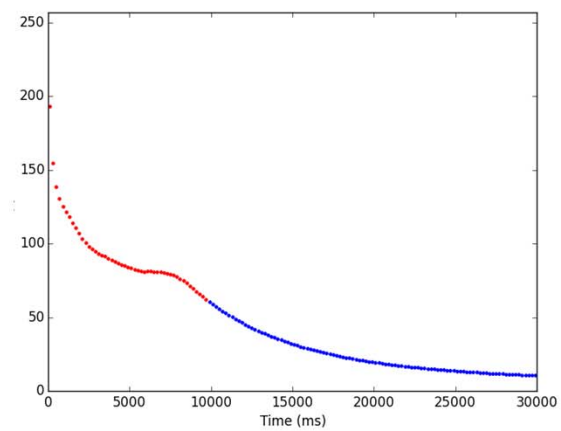
Theoretical Neuroscience

Constraint satisfaction problems

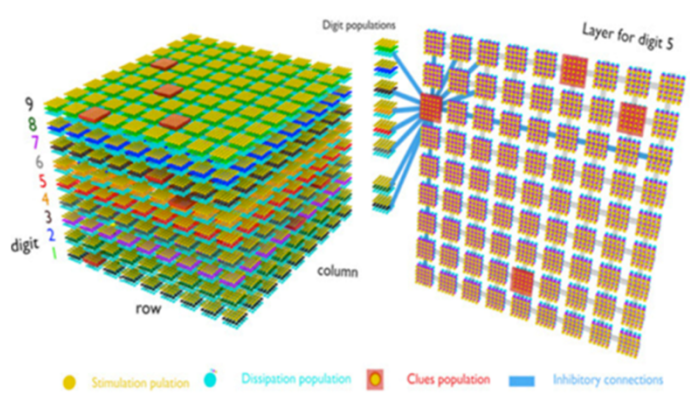
Stochastic spiking neural network:

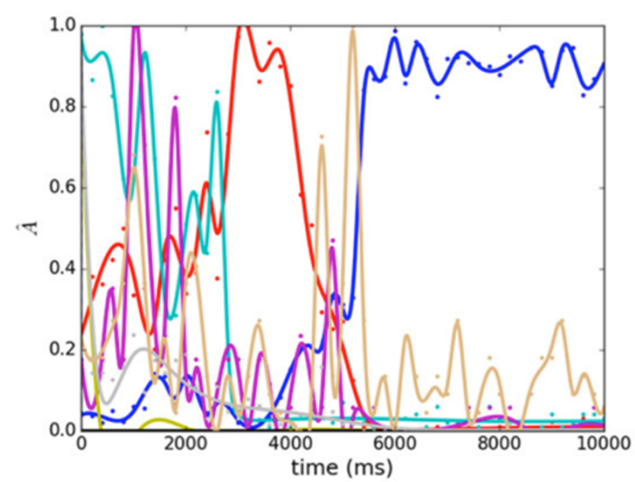
- solves CSPs, e.g. Sudoku
  - 37k neurons
  - 86M synapses
- also
  - map colouring
  - Ising spin systems

4	6	1	9	5	8	6	7	3
3	8	5	6	7	7	4	9	1
7	8	9	3	3	1	6	8	5
6	9	6	8	1	3	5	5	7
5	3	8	7	9	2	1	4	6
1	2	4	7	6	5	8	3	9
3	5	3	1	8	6	9	9	4
8	1	6	4	4	9	3	6	2
9	4	2	5	3	6	7	1	8



work by: Gabriel Fonseca Guerra (PhD student)



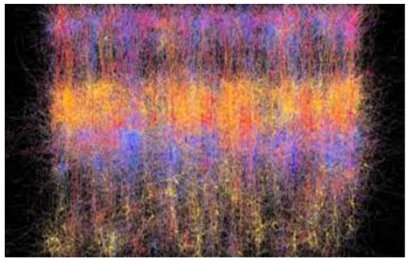


G. A. Fonseca Guerra and S. B. Furber, *Using Stochastic Spiking Neural Networks on SpiNNaker to Solve Constraint Satisfaction Problems*, Frontiers 2018.

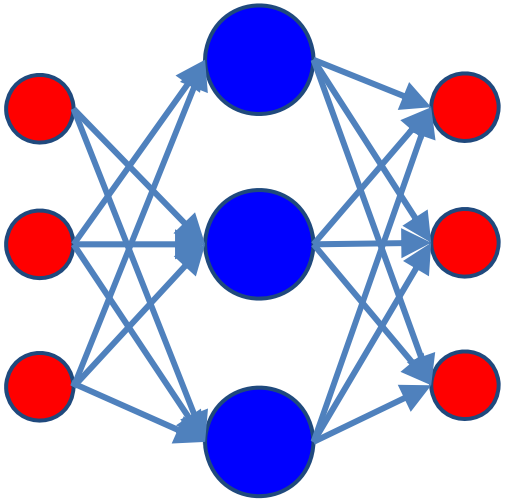
S. Habenschuss, Z. Jonke, and W. Maass, *Stochastic computations in cortical microcircuit models*, PLOS Computational Biology, 9(11):e1003311, 2013.

Theoretical Neuroscience

- Network plasticity for learning and memory
  - adjust synaptic connections
  - add/remove connections



- HBP Co-Design Project 5
  - functional plasticity for learning on neuromorphic hardware



- Bridge the gap from neuroplasticity to machine learning?

Rhodes, O., et al. *How On-Chip Learning Impacts SpiNNaker Realtime Performance*. In prep.

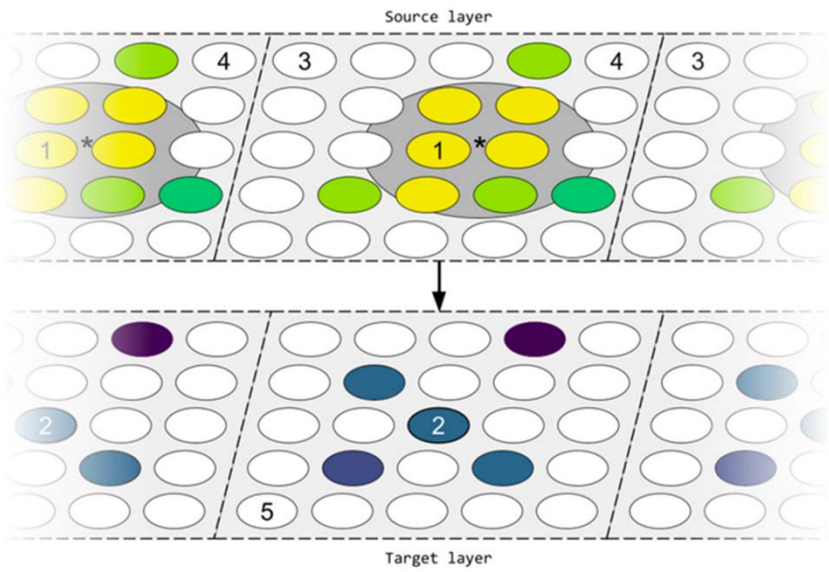
Human Brain Project

Theoretical Neuroscience

Structural plasticity

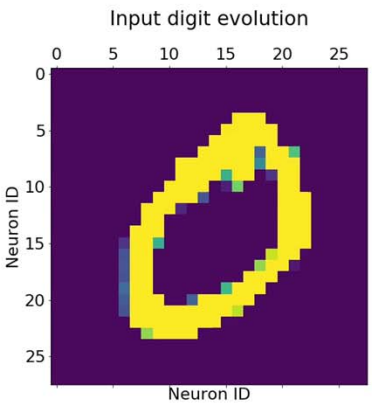
- Create/remove connections to facilitate learning/consolidation
  - feedforward and recurrent
  - distance-dependent receptive field
  - pruning of weak connections

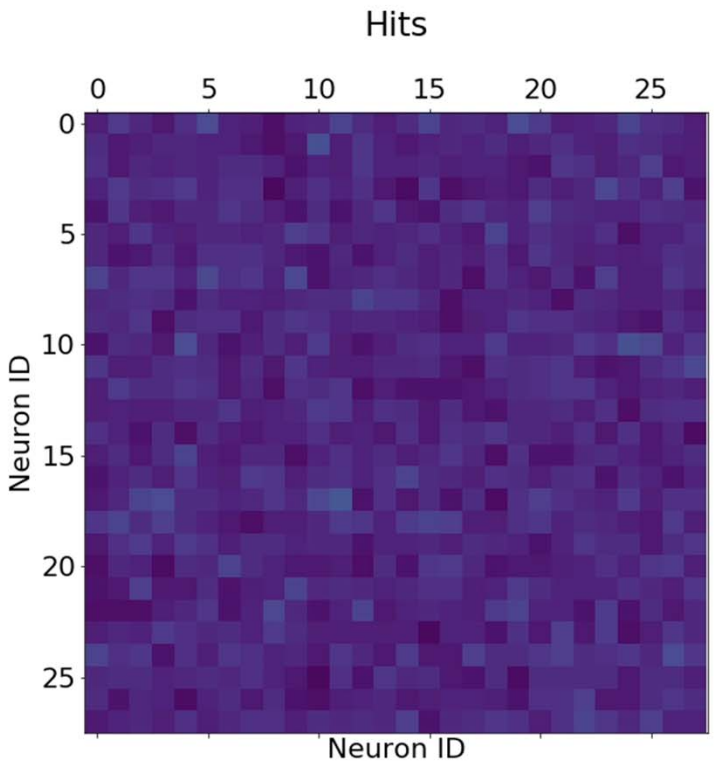
- Computational challenge
  - update connection matrices on-the-fly
  - maintain network dynamics and computational performance

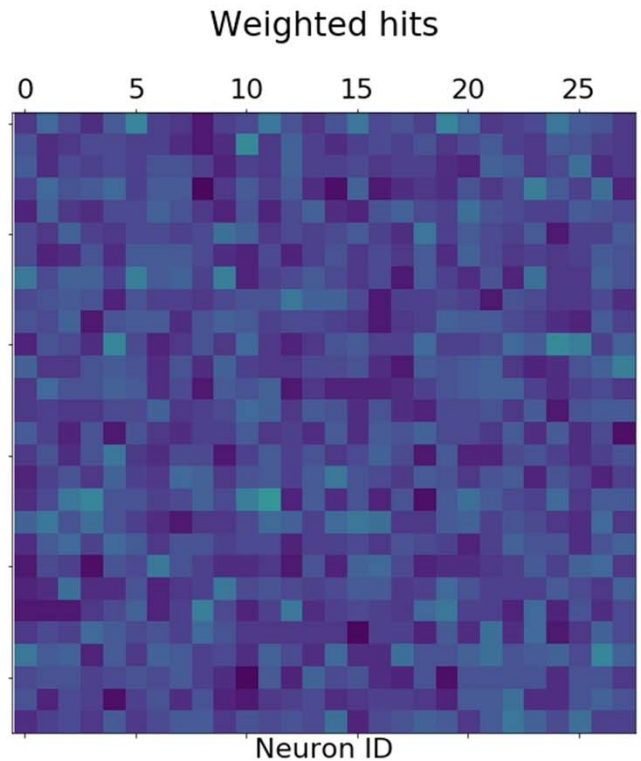


Bogdan, P., et al. *Structural Plasticity on the SpiNNaker Many-Core Neuromorphic System*. Frontiers in Neuroscience. 2018

Theoretical Neuroscience



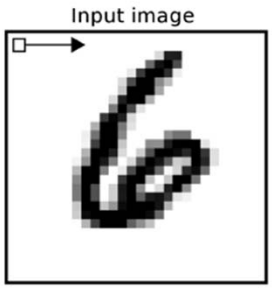


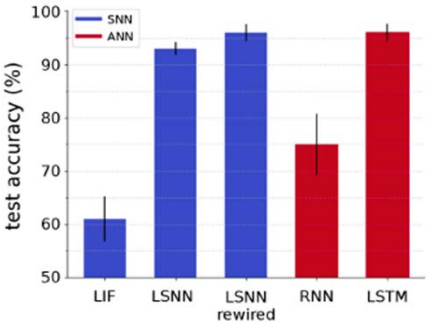


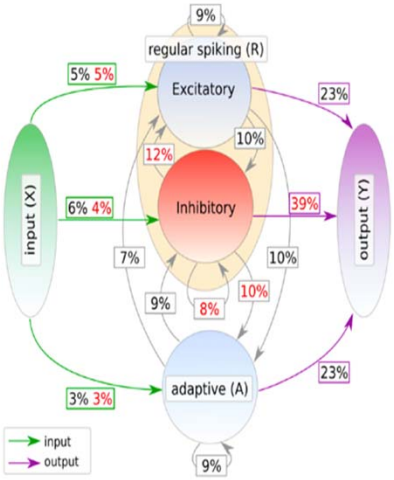
Hopkins, M., et al. *Spiking Neural Networks for Computer Vision*. Royal Society Interface Focus, 2018.

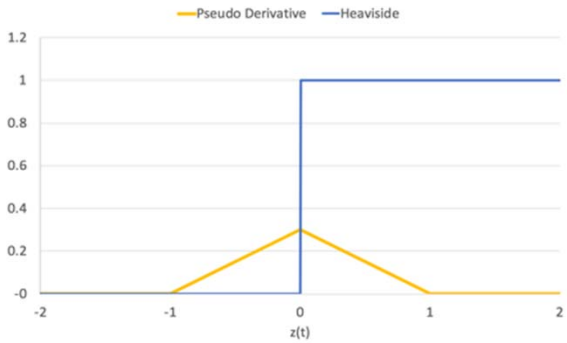
Theoretical Neuroscience

- Transfer machine learning concepts to brain-like spiking neurons
  - Long Short Term Memory (LSTM) units
  - BPTT & SGD
- Train SNNs via error back-propagation
  - recurrent spiking neural networks
  - pseudo differential to overcome discontinuity of gradient at spike
- First deployment on neuromorphic hardware
  - unlock scale and explore performance







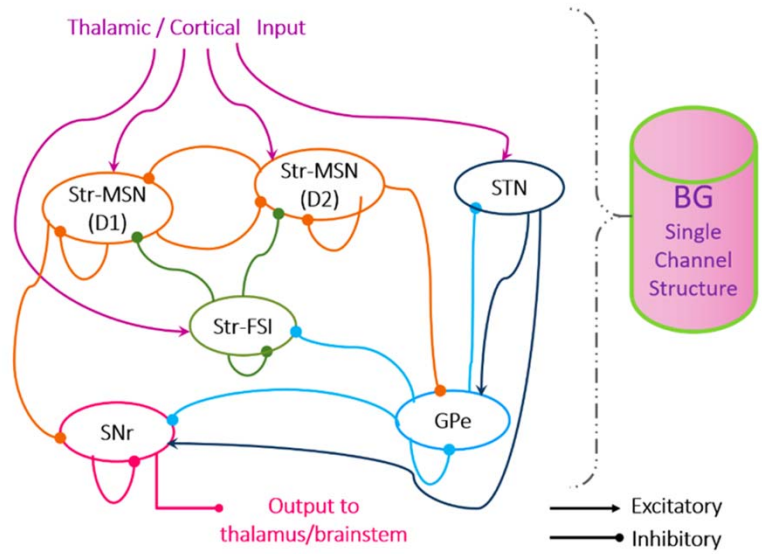


Bellec, G., et al. *Long short-term memory and learning-to-learn in networks of spiking neurons*. NIPS 2018.

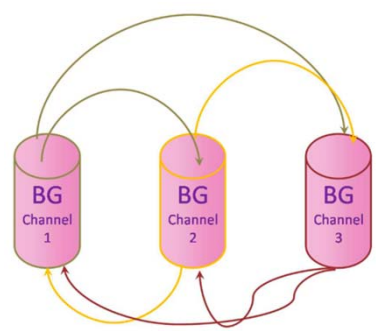
Rhodes, O., et al. *Gradient-based training of LSNNs on neuromorphic hardware*. In prep.

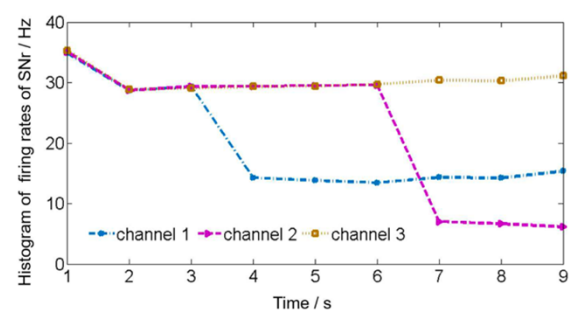
Theoretical Neuroscience

- Basal Ganglia – biological decision making and action selection
  - Single channel model inspired by biology: neuron dynamics; numbers; and topology



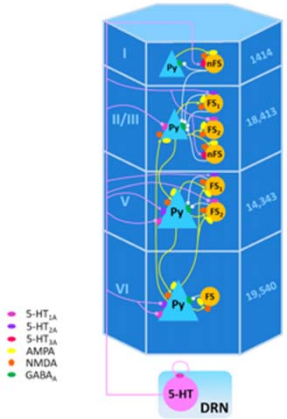
- Dopamine is central to network function
  - Expressed via two receptor types
  - Explore how modulation relates to scale and disease

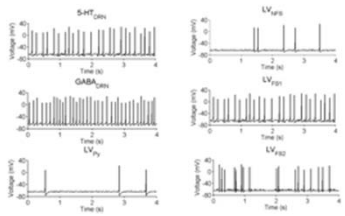


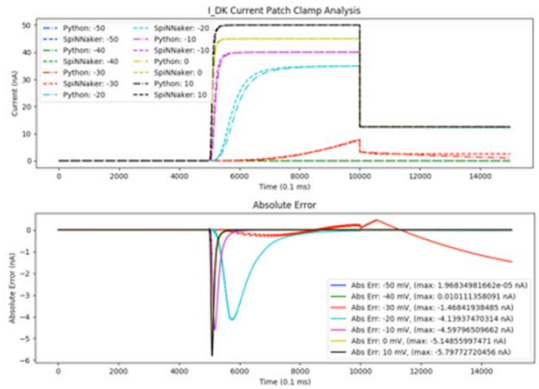


Sen-Bhattacharya, B., et al. *Building a Spiking Neural Network Model of the Basal Ganglia on SpiNNaker.* IEEE Transaction on Cognitive and Developmental Systems. 2018

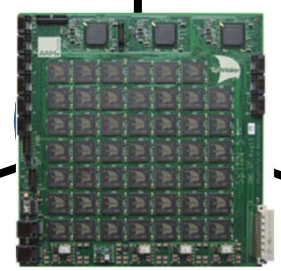
SpiNNaker applications





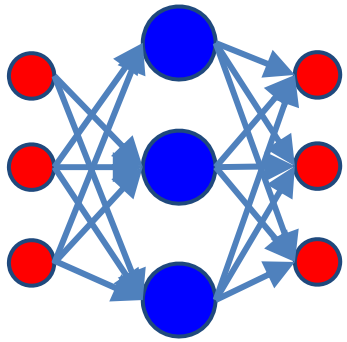


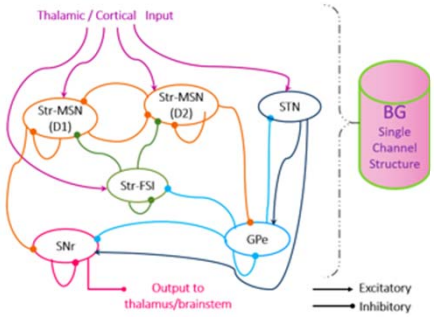
Computational Neuroscience

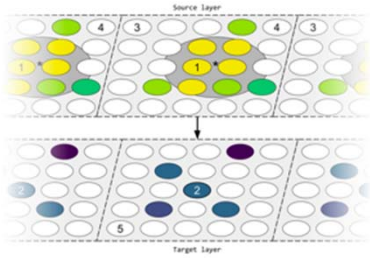


Neurorobotics

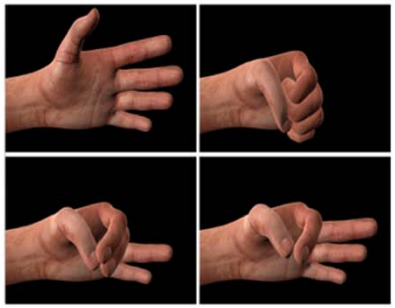
Theoretical Neuroscience

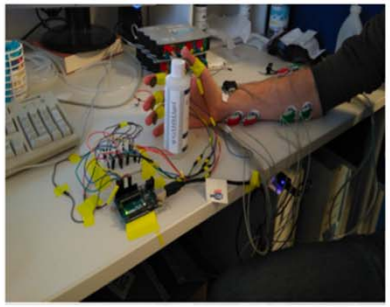




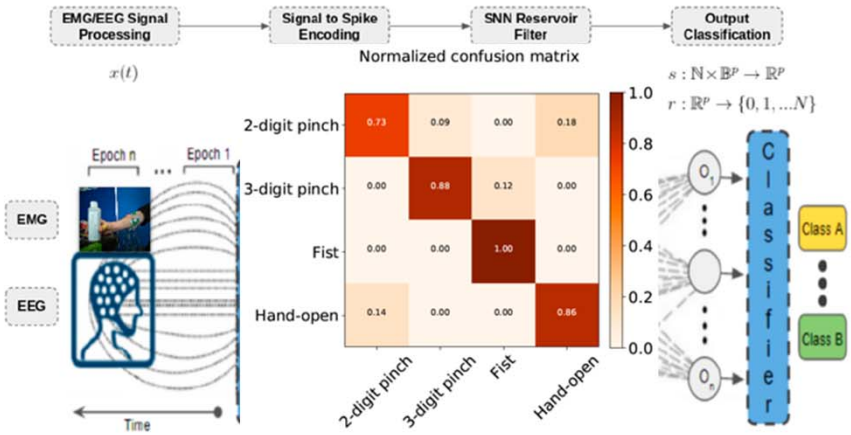


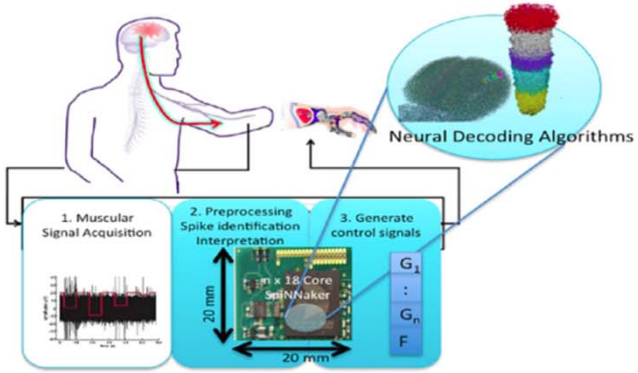
Neurorobotics





- Classification of electrical signals
  - real-time control of active prosthetics
  - low power
- Record electrical activity of participants during prescribed hand movements
- Classification with reservoir of spiking neurons
  - encode signals into spikes
  - train network (unsupervised)
  - readout to classify





Behrenbeck, J. et al. *Classication and Regression of Spatio-Temporal Signals using NeuCube and its realization on SpiNNaker Neuromorphic Hardware.* Journal of Neural Engineering. 2018

Neurorobotics

- Study vestibular ocular reflex in iCub robot
  - SpiNNaker as neural substrate
- Learn control via cerebellum inspired spiking neural network
  - Range of learning kernels based on relative spike timing + error
- Research embodiment of neural control systems

Francisco Naveros, Jesús A. Garrido, Angelo Arleo, Eduardo Ros, Niceto R. Luque. *Exploring vestibulo-ocular adaptation in a closed-loop neuro-robotic experiment using STDP. A simulation study.*

Bartolozzi, C., et al. *A Cerebellum Inspired Vestibular Occular Reflex in and iCub Robot with SpiNNaker as the Neural Substrate.* In Prep

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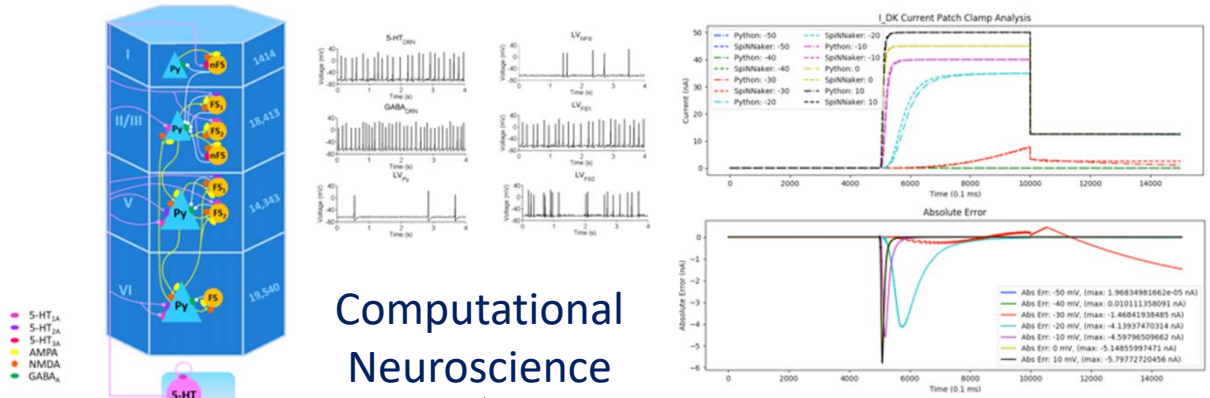
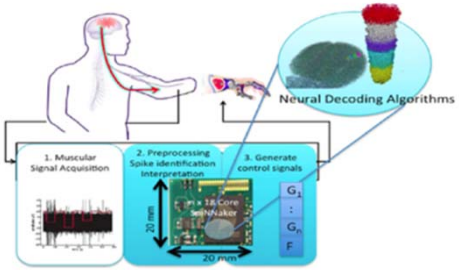
SpiNNaker applications

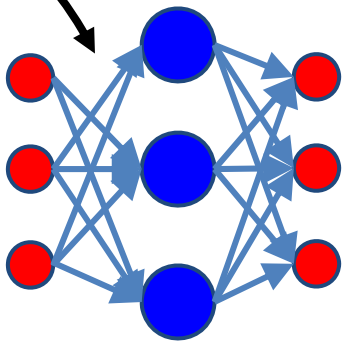


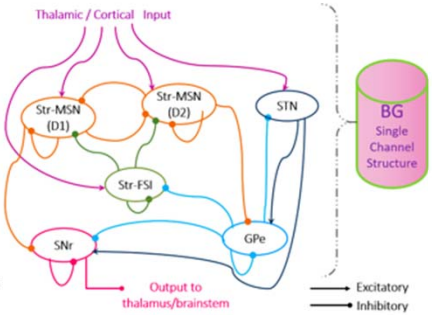
Computational Neuroscience

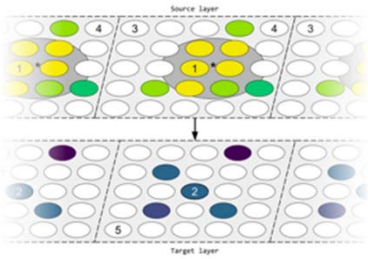
Neurorobotics



Theoretical Neuroscience







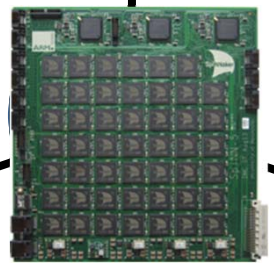
SpiNNaker collaborators

Prof. Markus Diesmann
Dr. Sacha van Albada
Prof. Abigail Morrison

Dr Alok Joshi

Prof. Johan Storm
Dr. Ricardo Murphy

Computational Neuroscience



Dr Chiara Bartolozzi

Neurorobotics

Theoretical Neuroscience

Prof Nikola Kasabov

Jan Behrenbeck
Zied Tayeb
Prof. Jorg Conradt

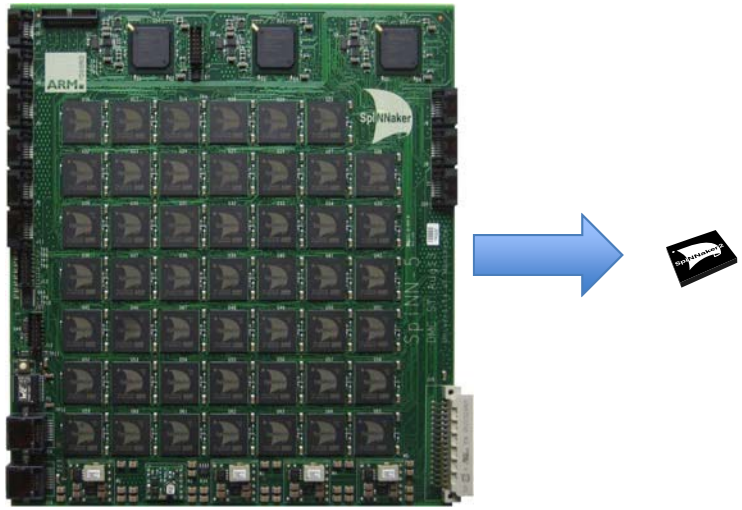
Prof. Wolfgang Maass

Dr Andre Grüning

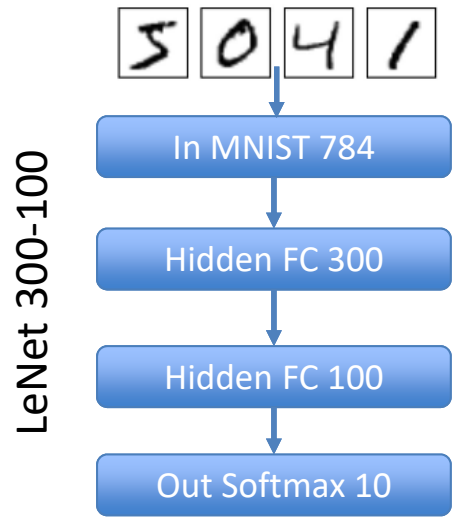
SpiNNaker2

- **Approach: Neuromorphic Many Core System**
  - Processor based → flexibility
  - Fixed digital functionality as accelerators → performance
    - High quality random numbers (including stochastic rounding)
    - Exponential/Log functions
    - Machine Learning multiply-accumulate unit
  - Low voltage (near threshold) operation enabled by 22FDX technology and adaptive body biasing (ABB) → energy efficiency
  - Event driven operation with fine-grained dynamic power management and energy proportional chip-2-chip links → workload adaptivity

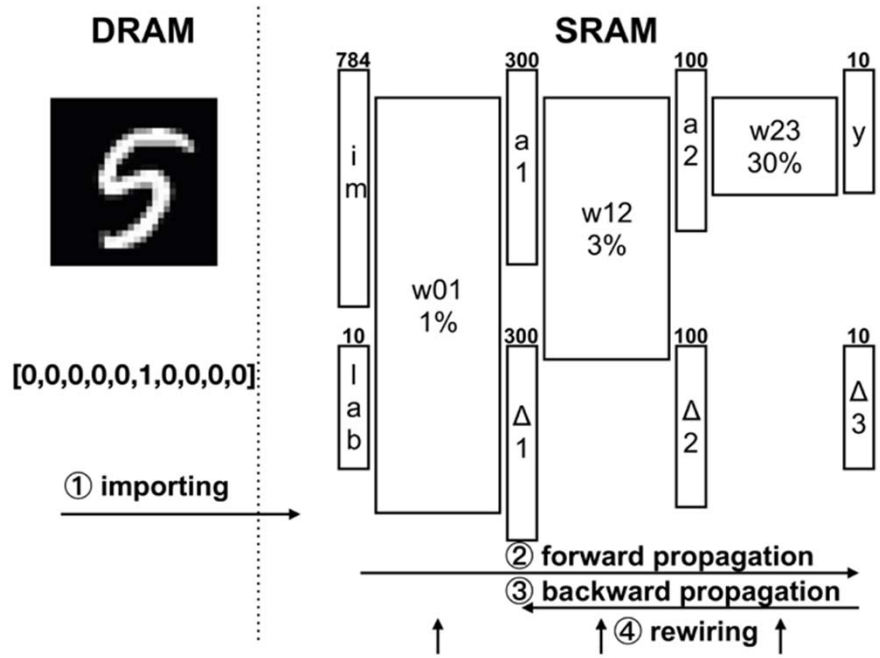
- **Scaling Target:**
  - **>x10** capacity compared to SpiNNaker1
  - Enabled by new hardware features and modern CMOS process



Deep Rewiring



- Synaptic sampling as dynamic rewiring for rate-based neurons (deep networks)
- Ultra-low memory footprint even during learning
- Uses PRNG/TRNG, FPU, exp
  - → **speed-up 1.5**
- Example: **LeNet 300-100**
  - 1080 KB → 36 KB
  - training on local SRAM possible
  - ≈ 100x energy reduction for training on SpiNNaker2 prototype (28nm) compared to X86 CPU
  - → **96.6% MNIST accuracy for 1.3% connectivity**



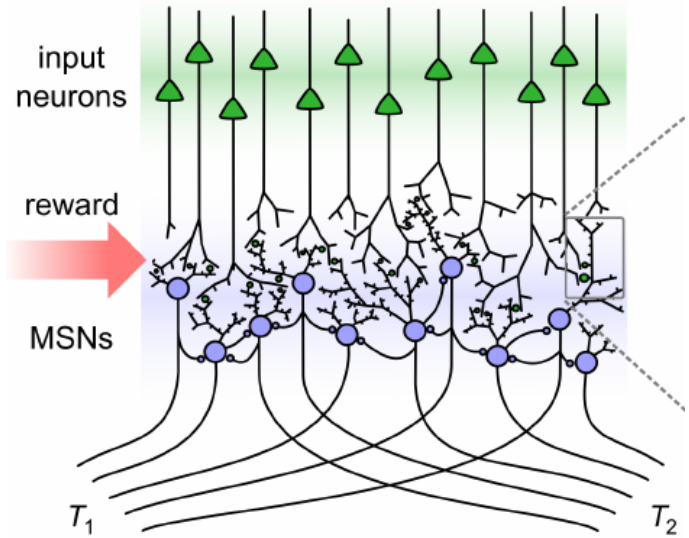
→ *G. Bellec et al., "Deep rewiring: Training very sparse deep networks", arXiv, 2018*

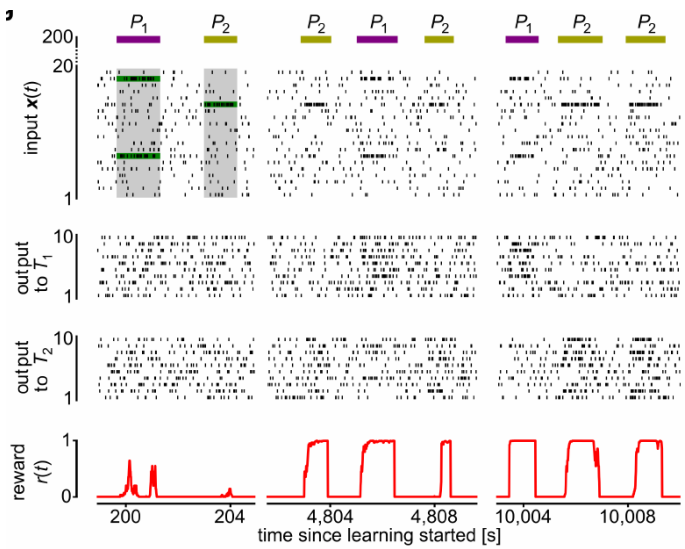
→ *Chen Liu et al., "Memory-efficient Deep Learning on a SpiNNaker 2 prototype", Frontiers in Neuromorphic Engineering*

Reward-Based Synaptic Sampling

- Characteristics:
  - Spiking reward-based learning
  - Synaptic sampling of network configuration
- Benchmark: task-dependent routing
  - 200 input neurons, 20 stochastic neurons, 12k stochastic synapses
- Main results:
  - random, float&exp, **speed-up factor 2** of synapse update every time step
  - Use of Accelerators + local computation (no DRAM): **62% less energy**
  - Modified version of synaptic rewiring "**Random reallocation of synapse memory":** More efficient implementation, Faster exploration of parameter space

→ *Yexin Yan et al., "Efficient Reward-Based Structural Plasticity on a Spinnaker 2 Prototype", IEEE Trans BioCAS*





Reviewer: I rarely review papers like this that build so well on related work, that are comprehensive, and that present a significant result.

Adaptive Robotic Control with the Neural Engineering Framework

Theory:

Self-learning adaptive control algorithm realized through the Neural Engineering Framework (NEF)

Task: Control of robotic arm

Neural Adaptive Controller superior to PID Controller for simulated aging

Low-latency between robot and chip required for real-time execution

Hardware Setup:

FPGA-prototype / JIB-1 (planned) + Lego Mindstorms Ev3 + Host PC

Target:

Demo for neuro-based processing in low-latency application

- Evaluate use of Machine Learning Accelerator (MLA))
- > 10x speed-up from MLA

Conclusions

- ***SpiNNaker:***
  - has been 20 years in conception…
  - …and 10 years in construction,
    - and is now ready for action!
  - ~100 boards with groups around the world
  - 1M core machine built
  - HBP is supporting s/w development
- ***SpiNNaker2:***
  - 10x performance & efficiency
  - tape-out April 2020
    - prototype test-chips available now