Human Brain Project

Physical Models of Neural Circuits in BrainScaleS and the Human Brain Project
Status and Plans

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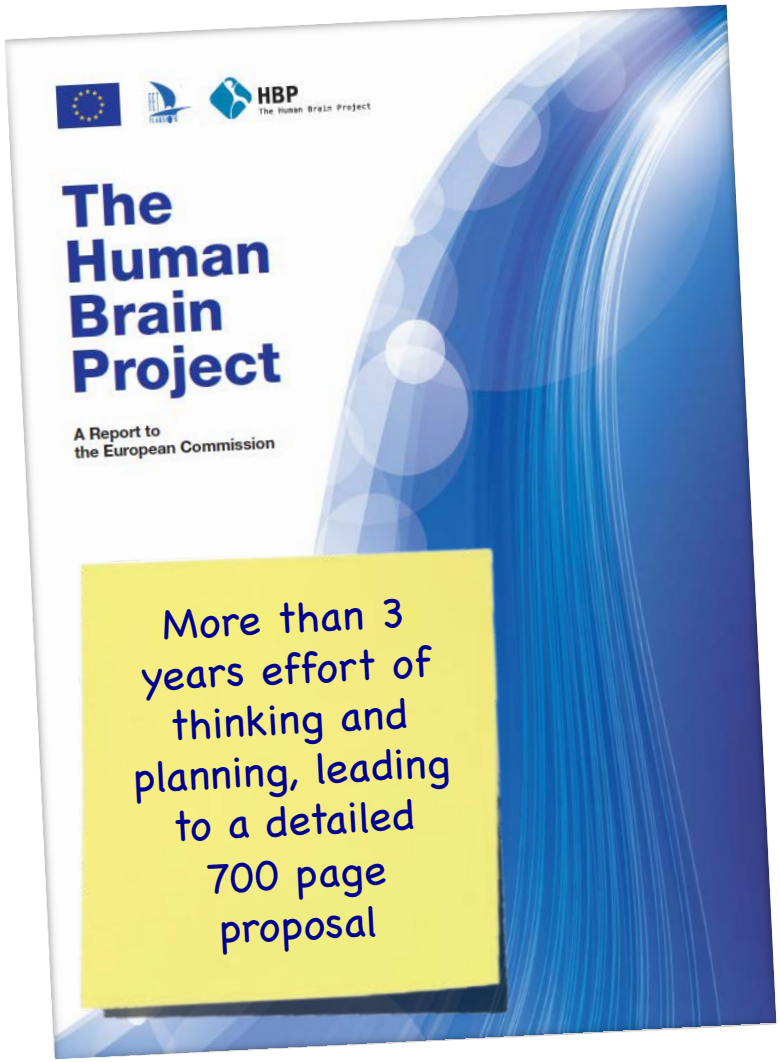
Ruprecht-Karls-Universität Heidelberg

Neuro-Inspired Computational Elements Workshop

February 2014
Sandia Labs NICE Workshop, Albuquerque, New Mexico, USA

The Human Brain Project



A coordinated effort to understand, improve and exploit the brain

Information and Public Report : www.humanbrainproject.org

- *Project Selection : January 2013*
- *Approval of 30 months ramp-up*
- *Starting date : October 1st, 2013*
- *Project Size : 80 Partners*
- *Initial EU Contribution : 54 M€*

The six Platforms in HBP

1. Neuroinformatics Platform
   Aggregate neuroscience data, deliver brain atlases
2. Medical Informatics Platform
   Aggregate clinical records, classify brain diseases
3. Brain Simulation Platform
   Derive brain models, run closed loop brain simulations
4. High Performance Computing Platform
   Develop and operate HPC systems optimized for brain simulations
5. Neuromorphic Computing Platform
   Develop and operate novel brain derived computing hardware
6. Neurorobotics Platform
   Develop virtual robotic systems for closed loop cognitive experiments

HBP : Two complementary neuromorphic computing concepts

MANY-CORE DIGITAL PROCESSOR SYSTEM

Many clocked. simplified ARM processors – address-based, small packet, asynchronous communication – effectively running at biological real-time

PHYSICAL MODEL SYSTEM

Many analogue elements with physical time constants – binary, asynchronous, continuous time, high density communication – effectively running at x10.000 biological real-time

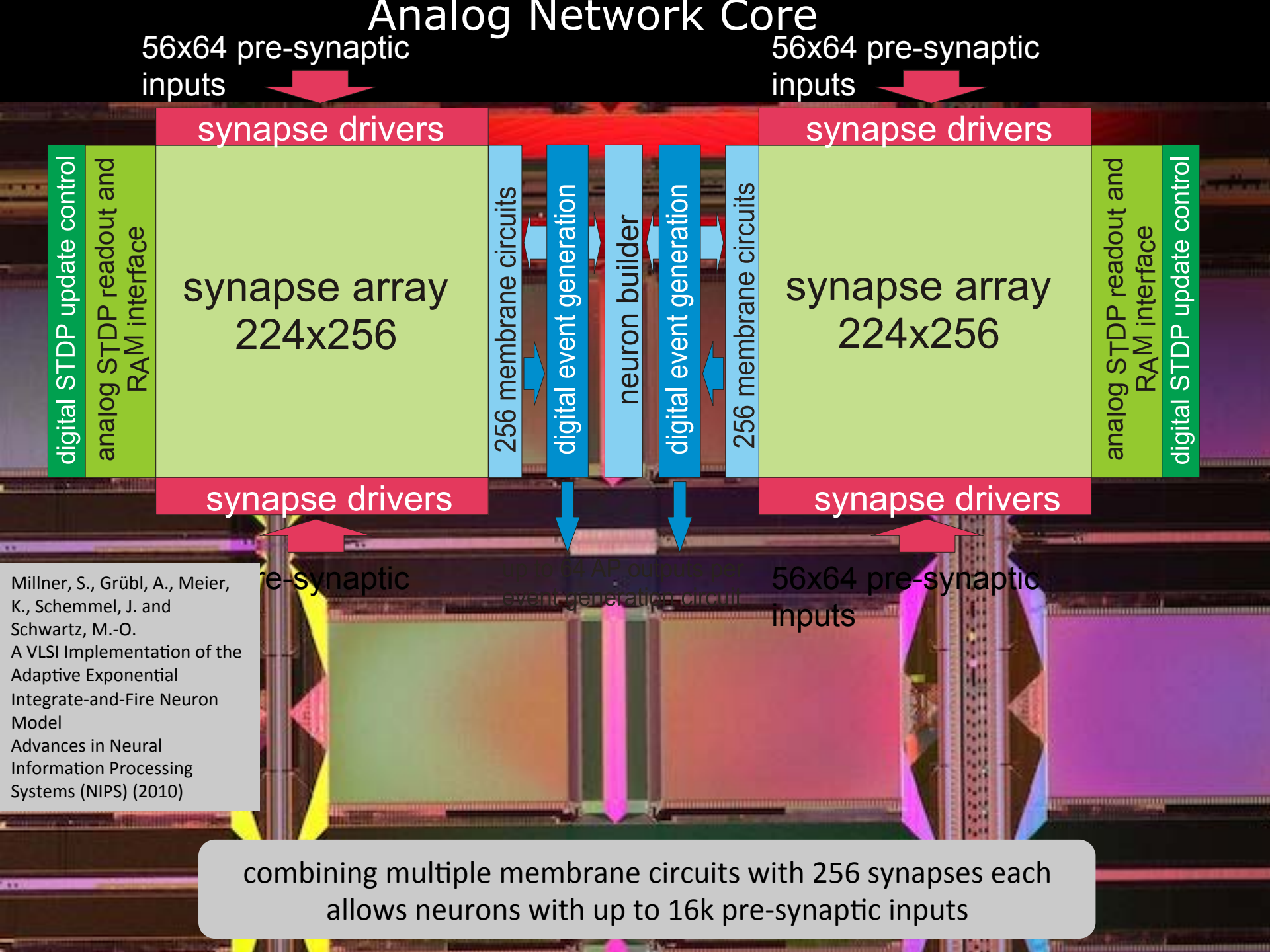
10 Rationales for the Physical Model System

- Mixed-Signal (Analog Cells, binary Spike Communication)
- Driven by architecture, not devices
- High Neuron Input Count
- Configurability (cells, connections) -> Universality
- Scalability : Chips (10^5) -> Wafers (10^8) -> Systems (10^9)
- Acceleration x 10.000 with consistent time constants
- Short Term und long Term Plasticity
- Upgradability with unchanged system architecture
- Hybrid Operation
- Non-Expert User Access

Objectives : Rapid Circuit Exploration

Study Structure and Dynamics

Analog Network Core



Millner, S., Grübl, A., Meier, K., Schemmel, J. and Schwartz, M.-O.
A VLSI Implementation of the Adaptive Exponential Integrate-and-Fire Neuron Model
Advances in Neural Information Processing Systems (NIPS) (2010)

combining multiple membrane circuits with 256 synapses each allows neurons with up to 16k pre-synaptic inputs

Millner, S., Grübl, A., Meier, K., Schemmel, J. and Schwartz, M.-O.
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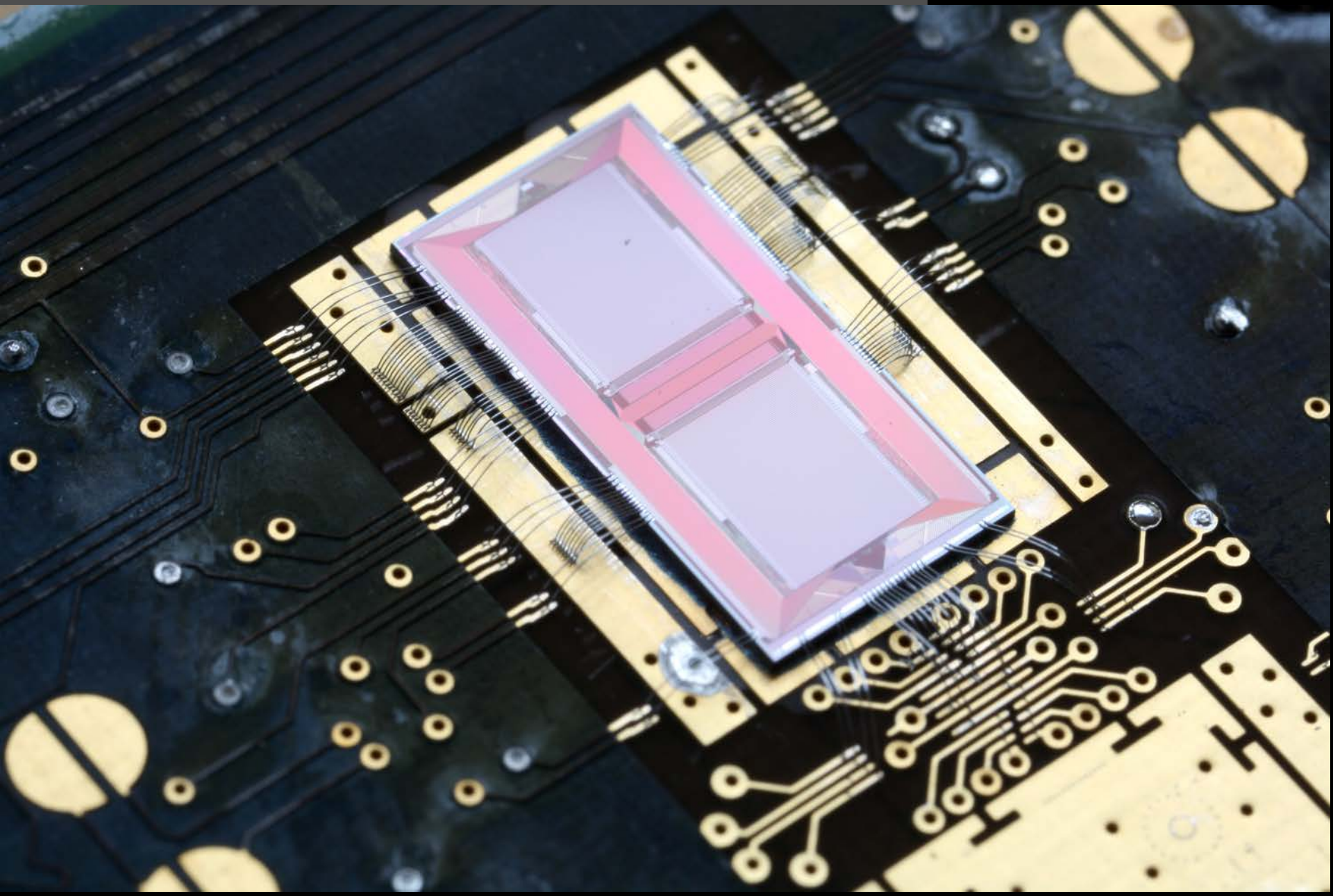
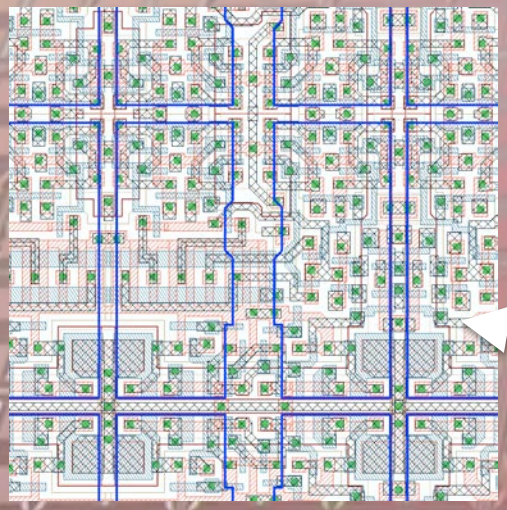
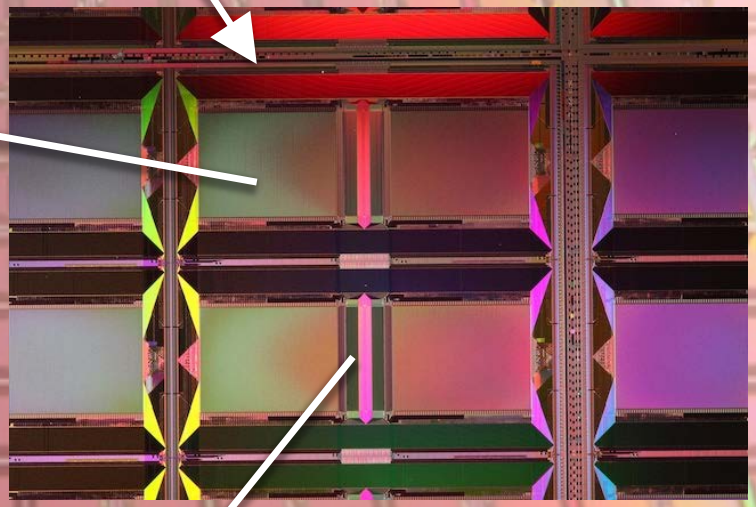


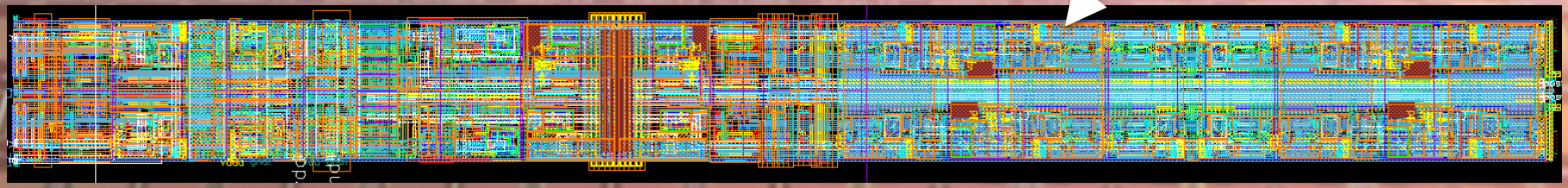
Multi-Scale Circuit Structure on 8 inch CMOS Wafer (180nm)



Plastic Synapses, 50.000.000 Million Instances on Wafer, Length Scale 10 µm 4-bit SRAM Weights

High Input Count Network Chips, 400 Instances on Wafer, Length Scale 1 cm network routing

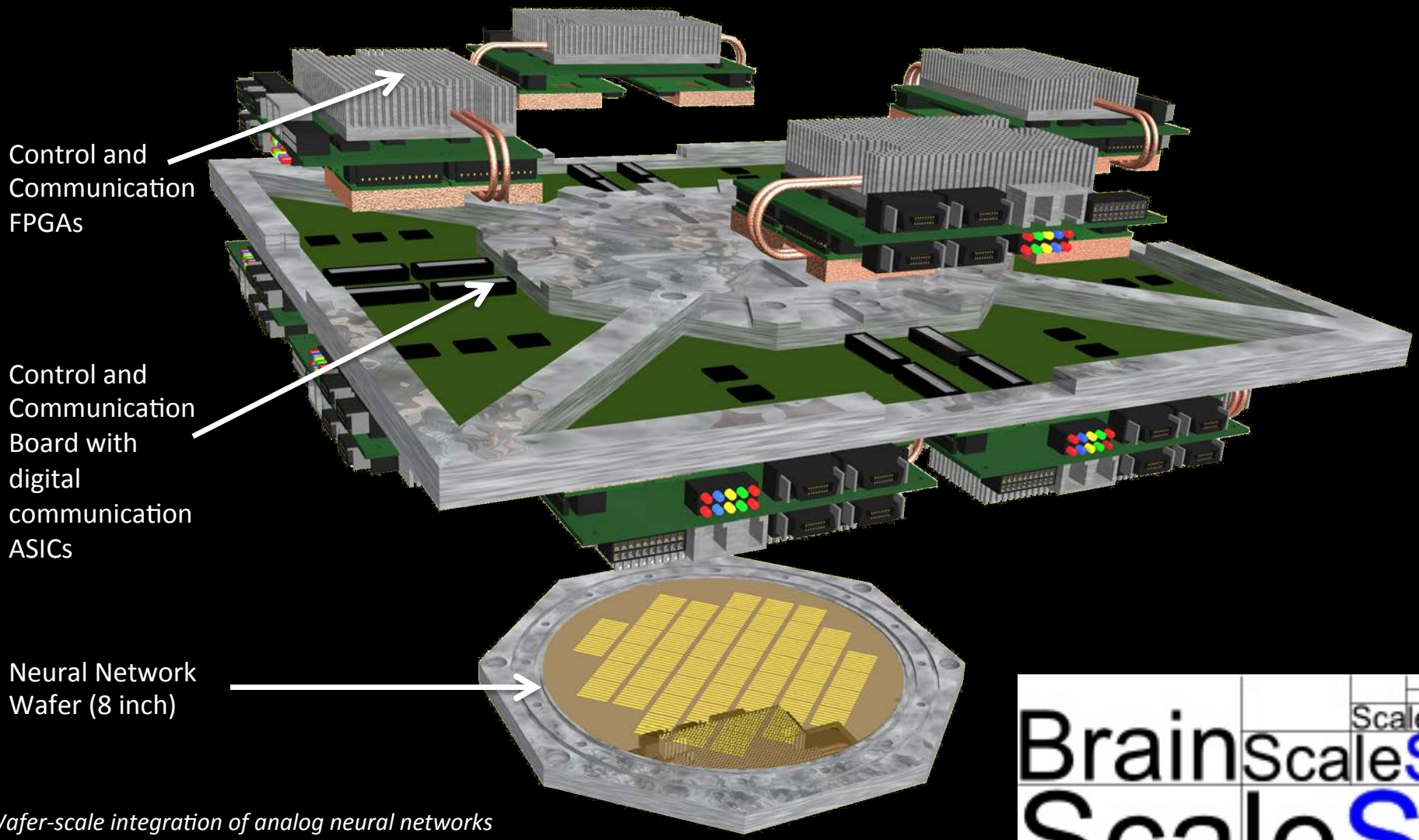




AdEx Neurons, 200.000 Instances on Wafer, Length Scale 300 µm,
Analog Floating Gate Parameter Storage
Poisson Noise Generators

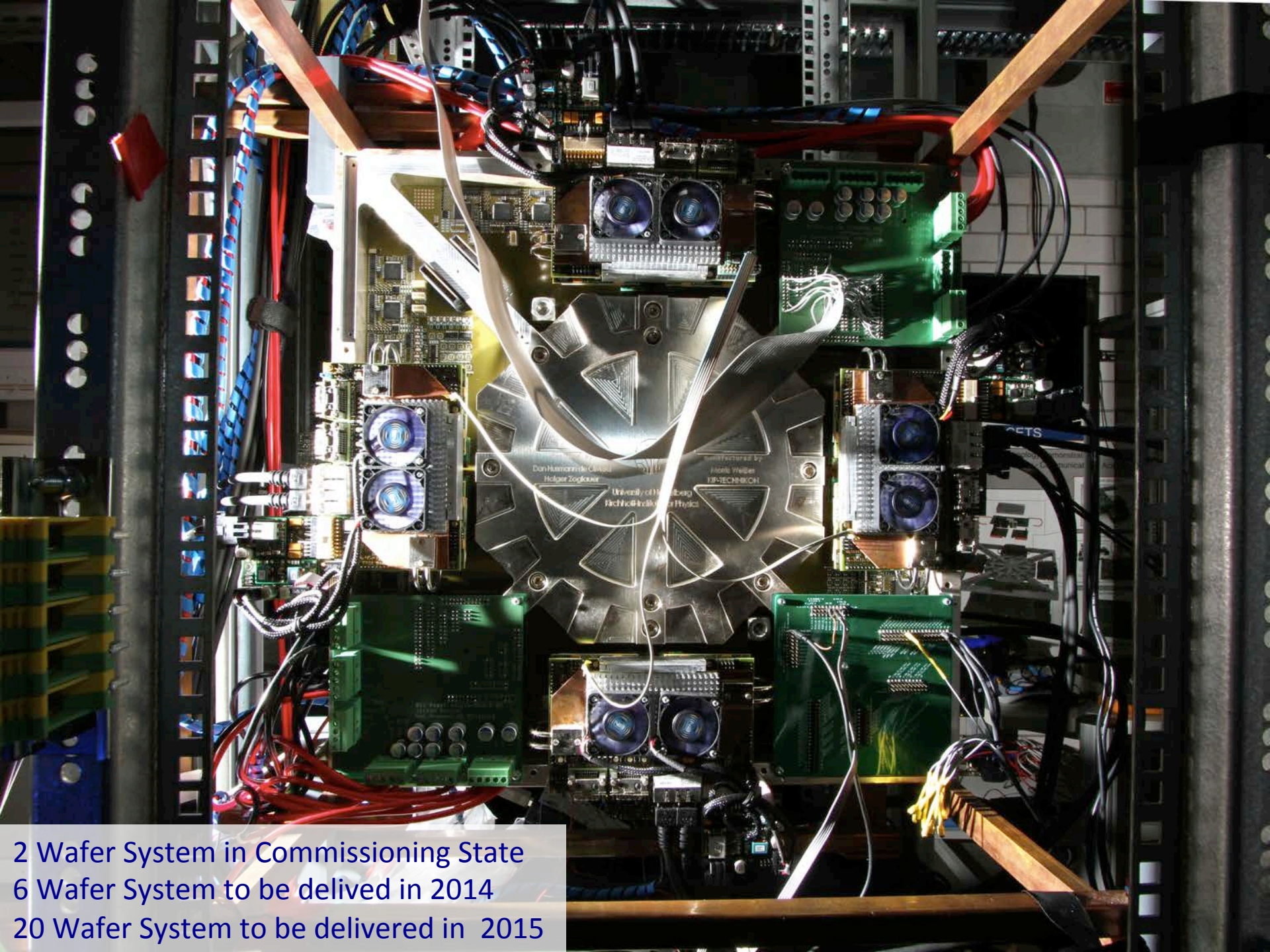
Neural Processing Unit, 200.000 Neurons, 50.000.000 plastic Synapses, 16.000 syn. I/P per neuron, accelerated by x 10.000

Separation of Neural Circuits and Monitoring/Readout/Control



Wafer-scale integration of analog neural networks
J. Schemmel, J, Fieres and K. Meier
In : Proceedings of IJCNN (2008), IEEE Press, 431

BrainScaleS

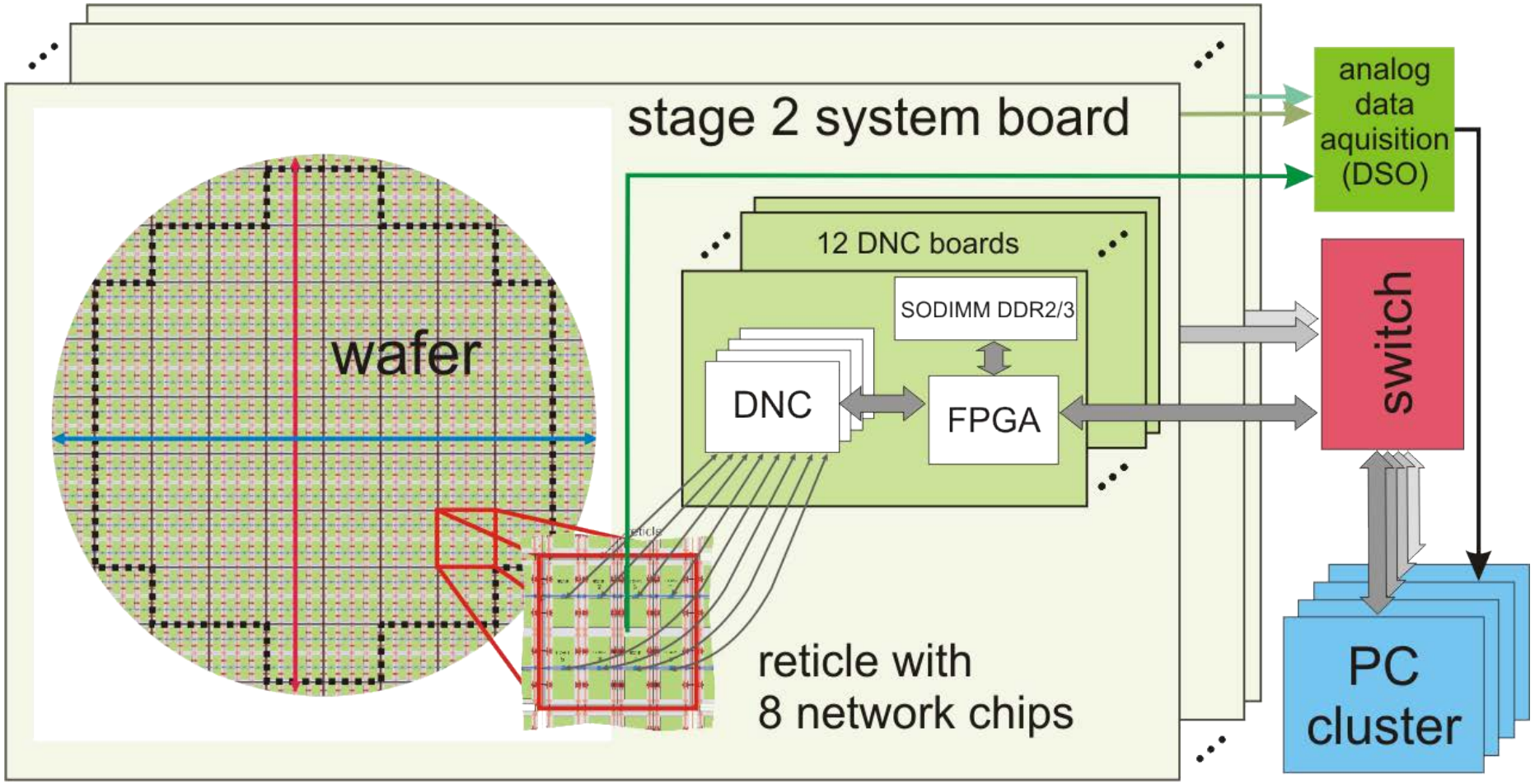


2 Wafer System in Commissioning State
6 Wafer System to be delived in 2014
20 Wafer System to be delivered in 2015

Communication Architecture Overview

Hierarchical 2 Layer Communication Setup

- Layer 1 : **On-Wafer** continuous, asynchronous, fixed delay spike transmission
- Layer 2 : **Off-Wafer** Packet based digital communication for medium and long-range spike transmission, network set-up, read-out and control.



Typical Configuration Space for a Neuromorphic System approx. 40 MB for a full Wafer

Scope	Name	Type	Description
Neuron circuits (A)			embrane voltage
Synapse line drivers (B)			amp
Synapses (B)			
STP related (C)			on
STDP related (D)	n/a	i_l	Bias current controlling delay for presynaptic correlation pulse (for calibration purposes)
	$A_{+/-}$	s_l	Two voltages dimensioning charge accumulation per (anti-)causal correlation measurement
	n/a	s_l	Two threshold voltages for detection of relevant (anti-)causal correlation
	τ_{STDP}	g	Voltage controlling STDP time constants

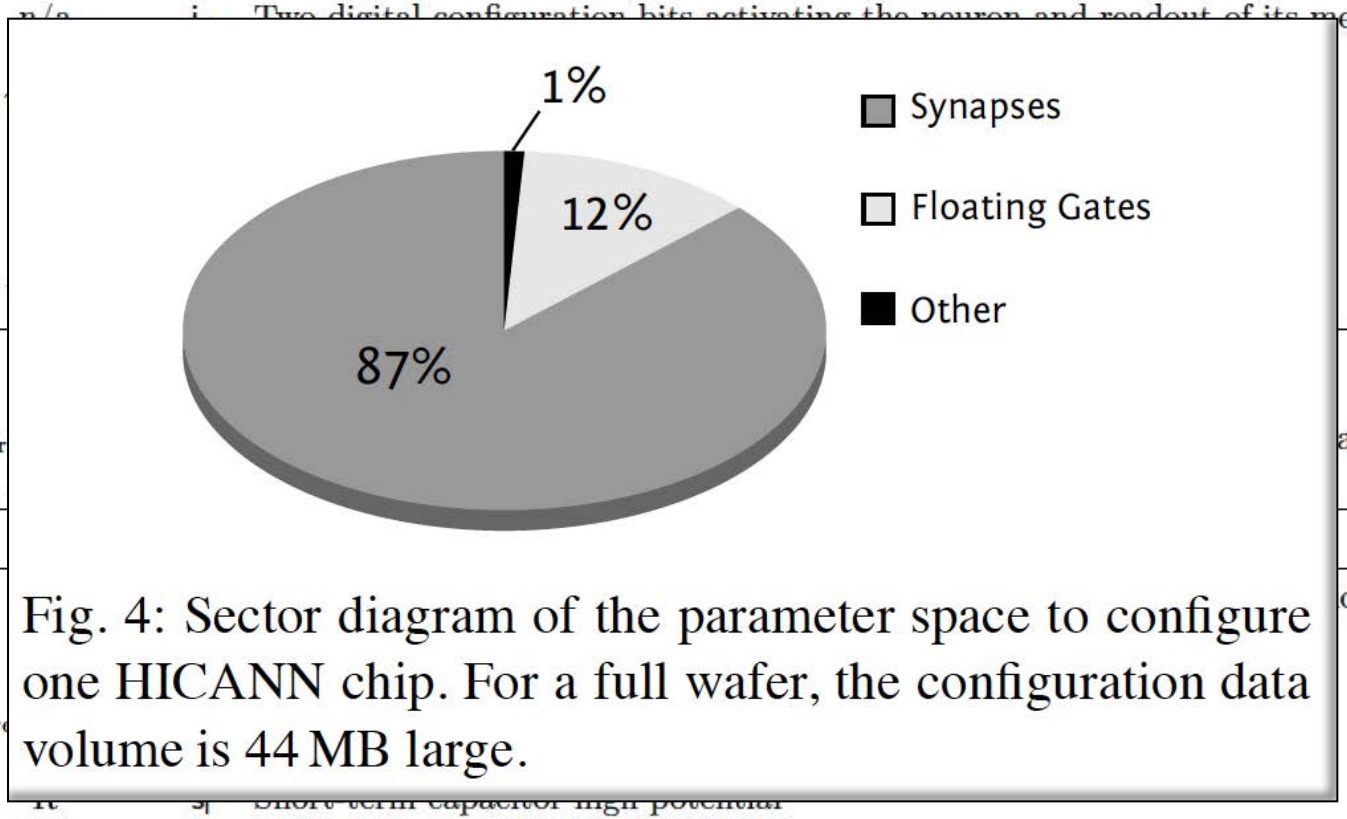
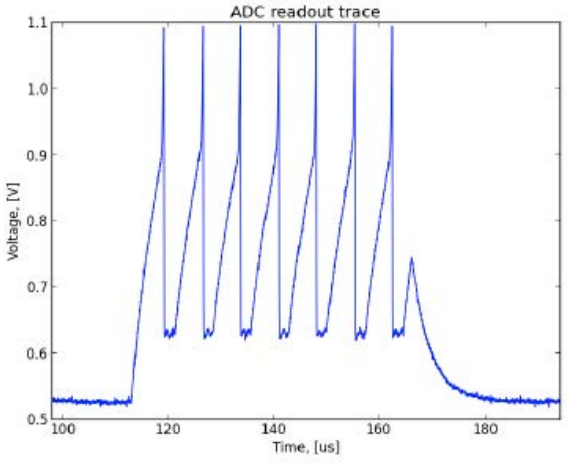
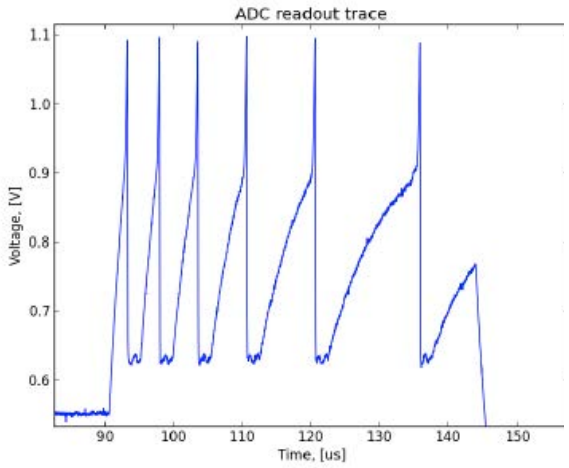
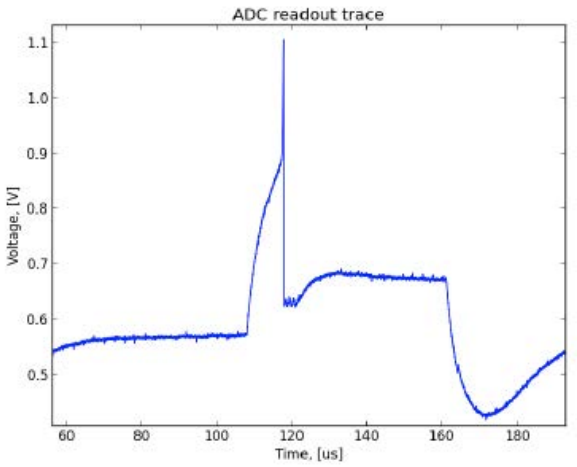
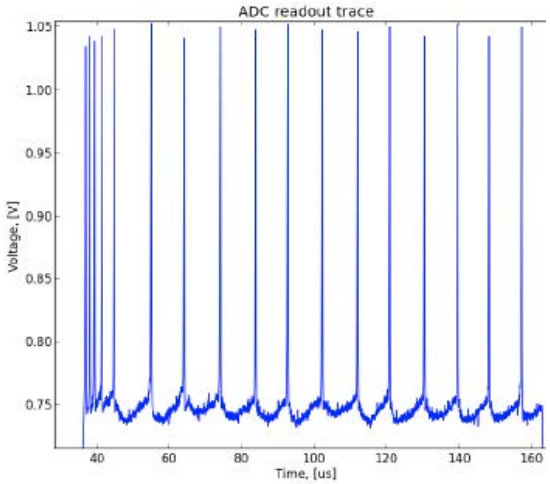


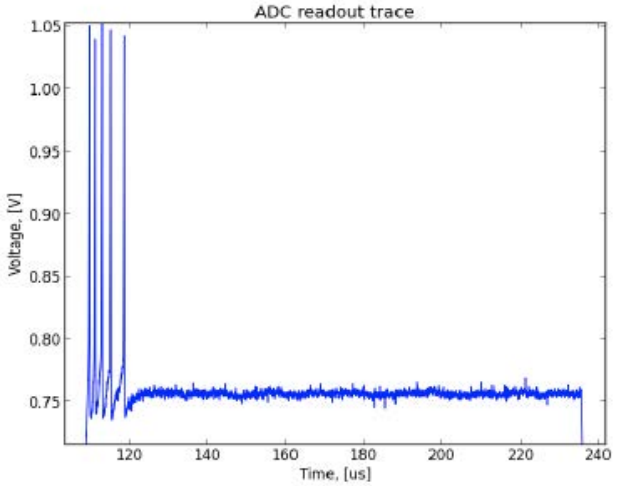
Fig. 4: Sector diagram of the parameter space to configure one HICANN chip. For a full wafer, the configuration data volume is 44 MB large.

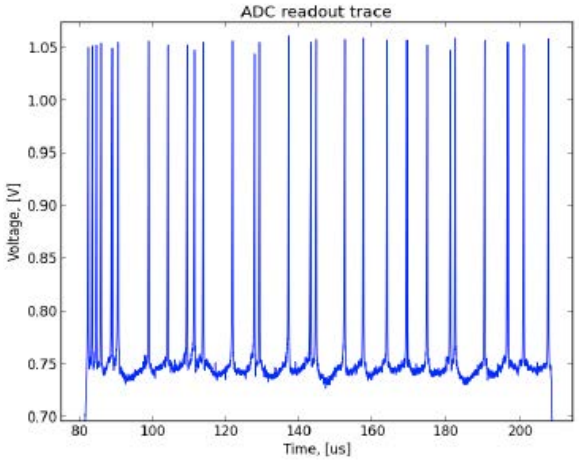






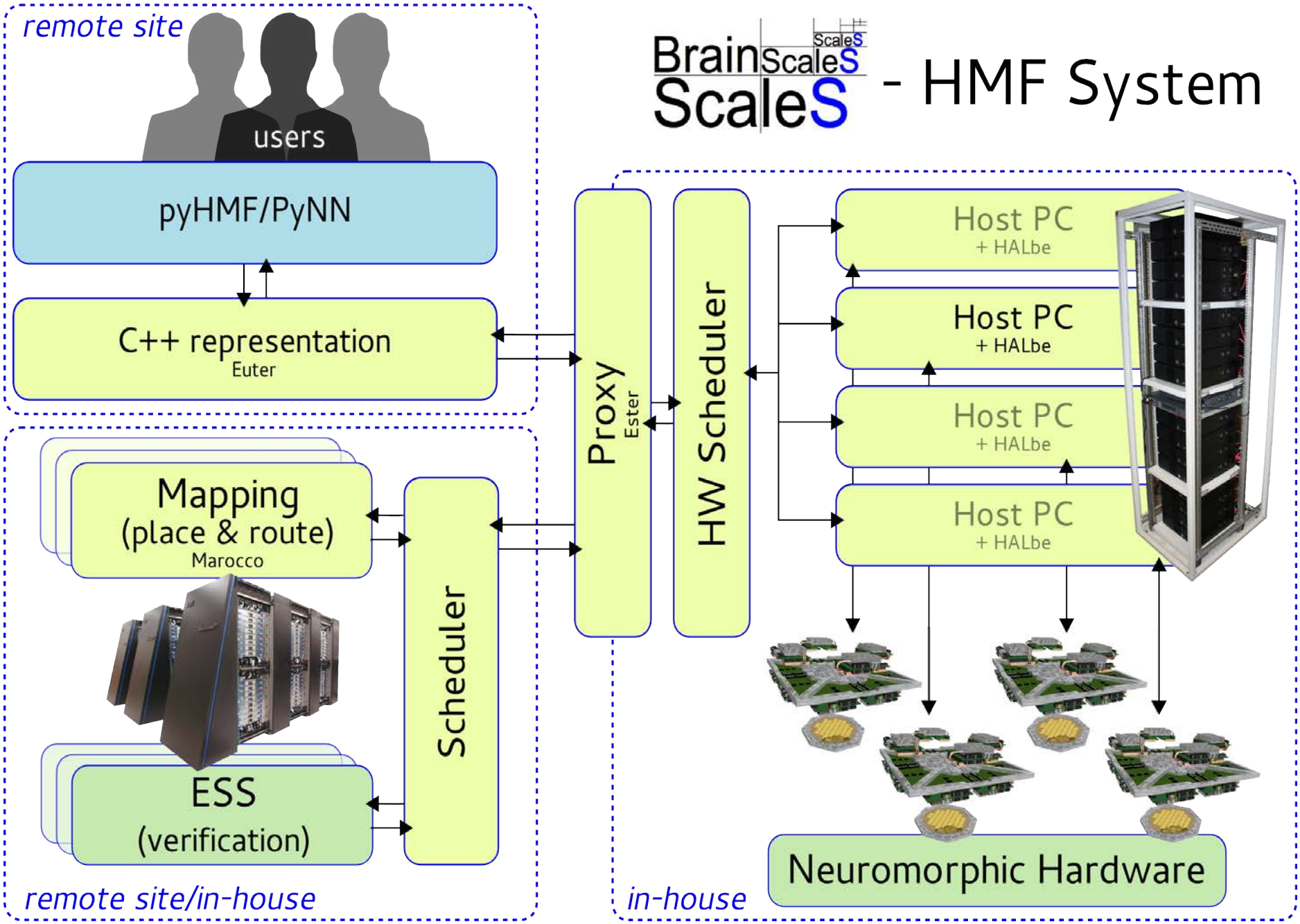






Phase Space Scan with VLSI Neurons (Bachelor Thesis Binh Tran, Heidelberg)

BrainScaleS - HMF System



The HBP Physical Model Machine

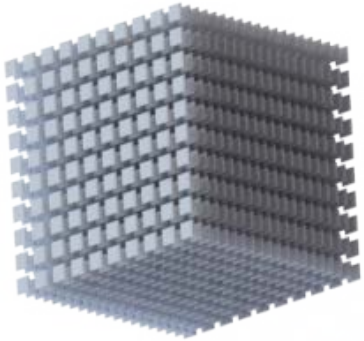
Neuromorphic Physical Model (NM-PM-1)

20
Neuronal Network Wafer
20 Peta-Connections/s

4 Million Neurons
1 Billion Synapses

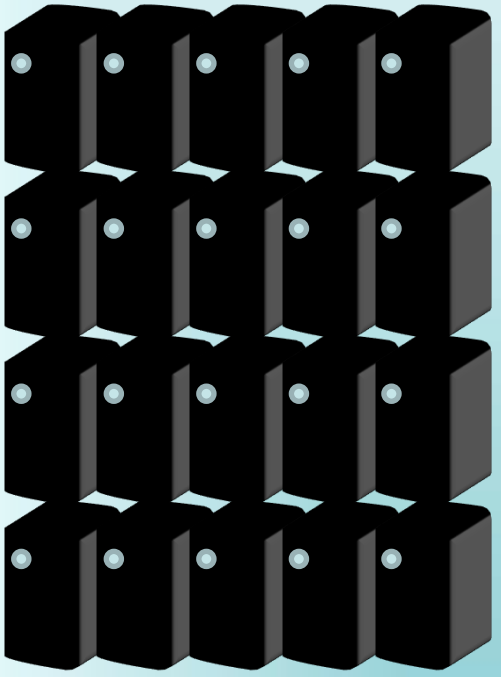
15
Tbit/s

1000 Kintex FPGAs



1 Tbit/s

Conventional
Computing Cluster
4 Tflop/s



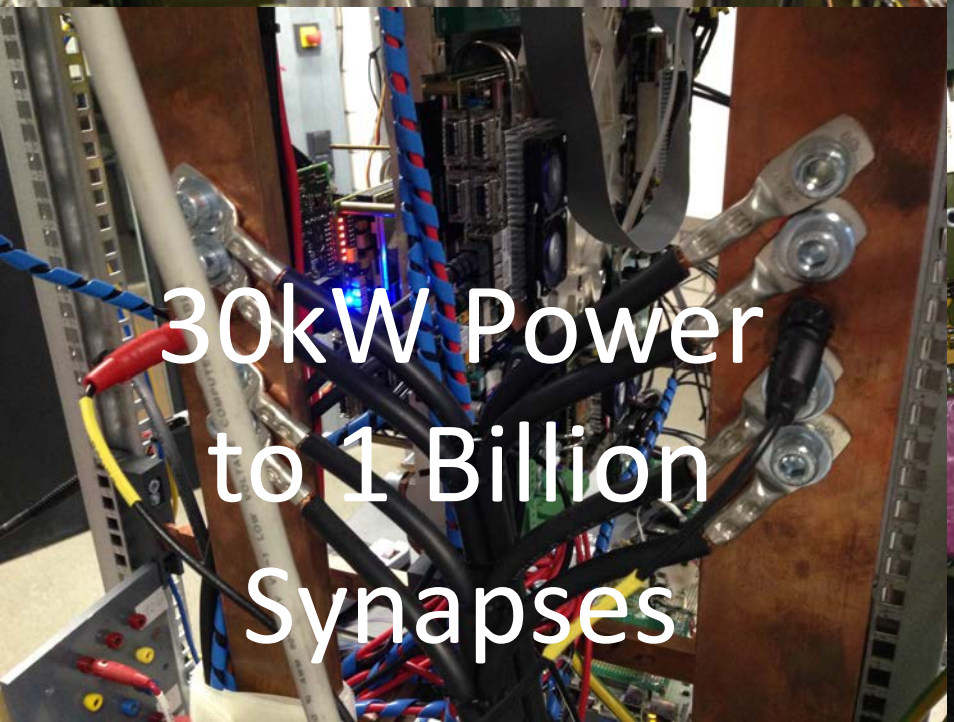
20 Intel Haswell

Scaling up : 20 Wafers, 4 Million Neurons, 1 Billion Synapses by October 2015

NEXT 18 MONTHS ……

50 kW Cooling

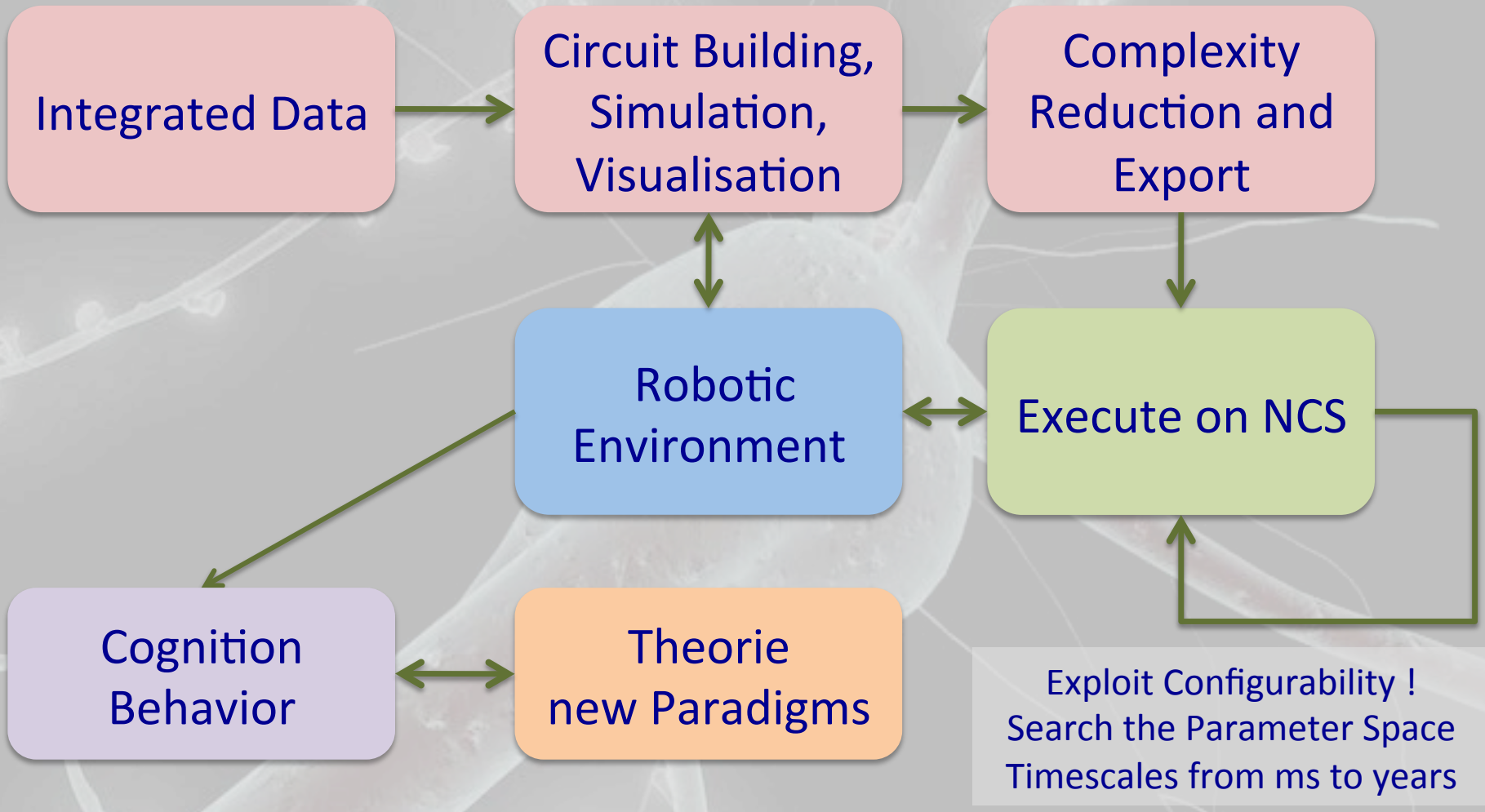
Tenthousand Cables and Connectors

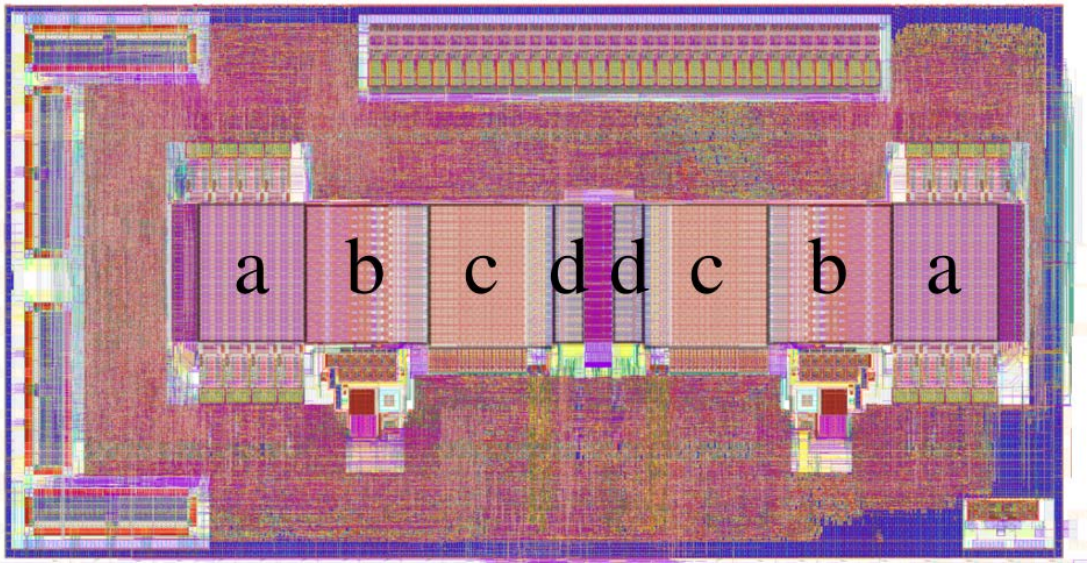


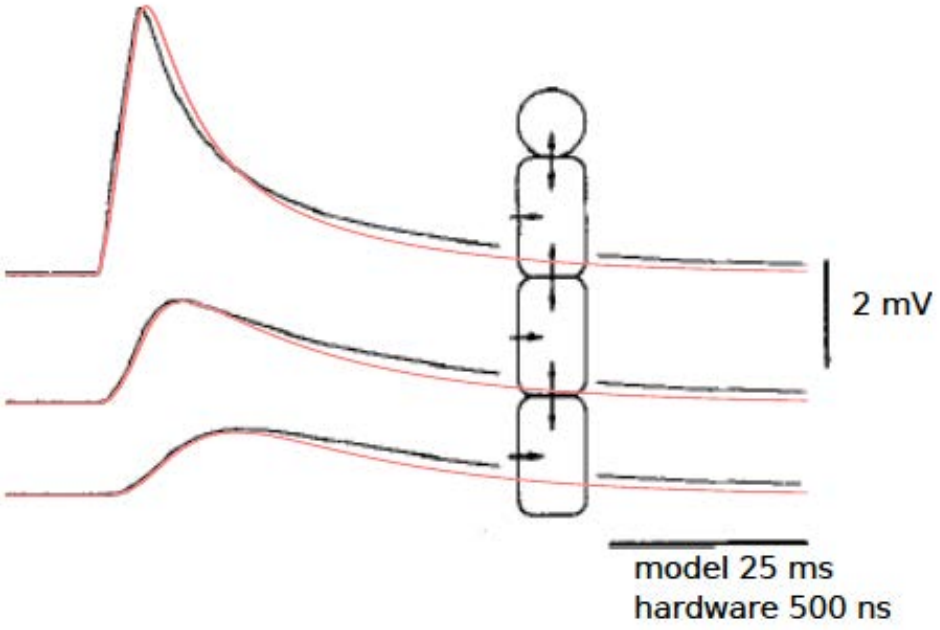
30kW Power to 1 Billion Synapses

2500 Support Boards

„Reducing Complexity – How far can we go ?“







Upgrade I

Multi-Compartment

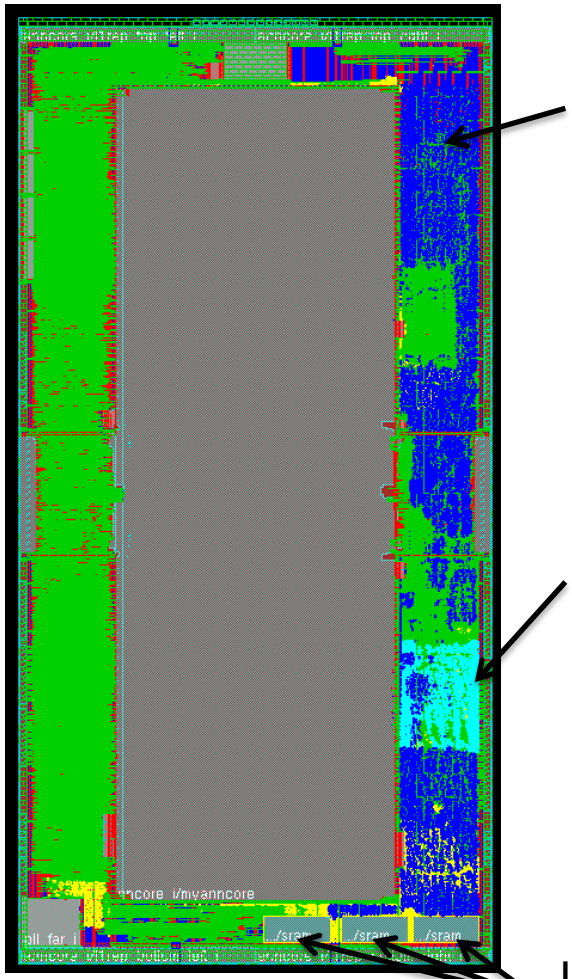
Introducing somatic membrane response to synaptic input at different parts of the dendrite

Dendritic Spikes
BP Action Potentials

Millner, Sebastian, et al. "Towards biologically realistic multi-compartment neuron model emulation in analog VLSI." *European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN)*. 2012.

Upgrade II : Algorithmic synaptic processing

Plasticity Processor



- General purpose processor
- PowerPC instruction set
- Programmable in C++
- Specialized instructions
- 400 processors on wafer
- Working 65nm prototype

- Arbitrary local update rules
- Structural plasticity
- External reward signals
- Gated STDP

Friedmann, Simon, et al. "Reward-based learning under hardware constraints—using a RISC processor embedded in a neuromorphic substrate." *Frontiers in neuroscience* 7 (2013).

Pfeil, Thomas, et al. "Six networks on a universal neuromorphic computing substrate." *Frontiers in neuroscience* 7 (2013).

Spikey

384 Neurons
100.000 plastic synapses
10.000 -100.000 Real-Timp
Plugs into Laptop via USB

Increasing number of published applications covering a wide spectrum of networks

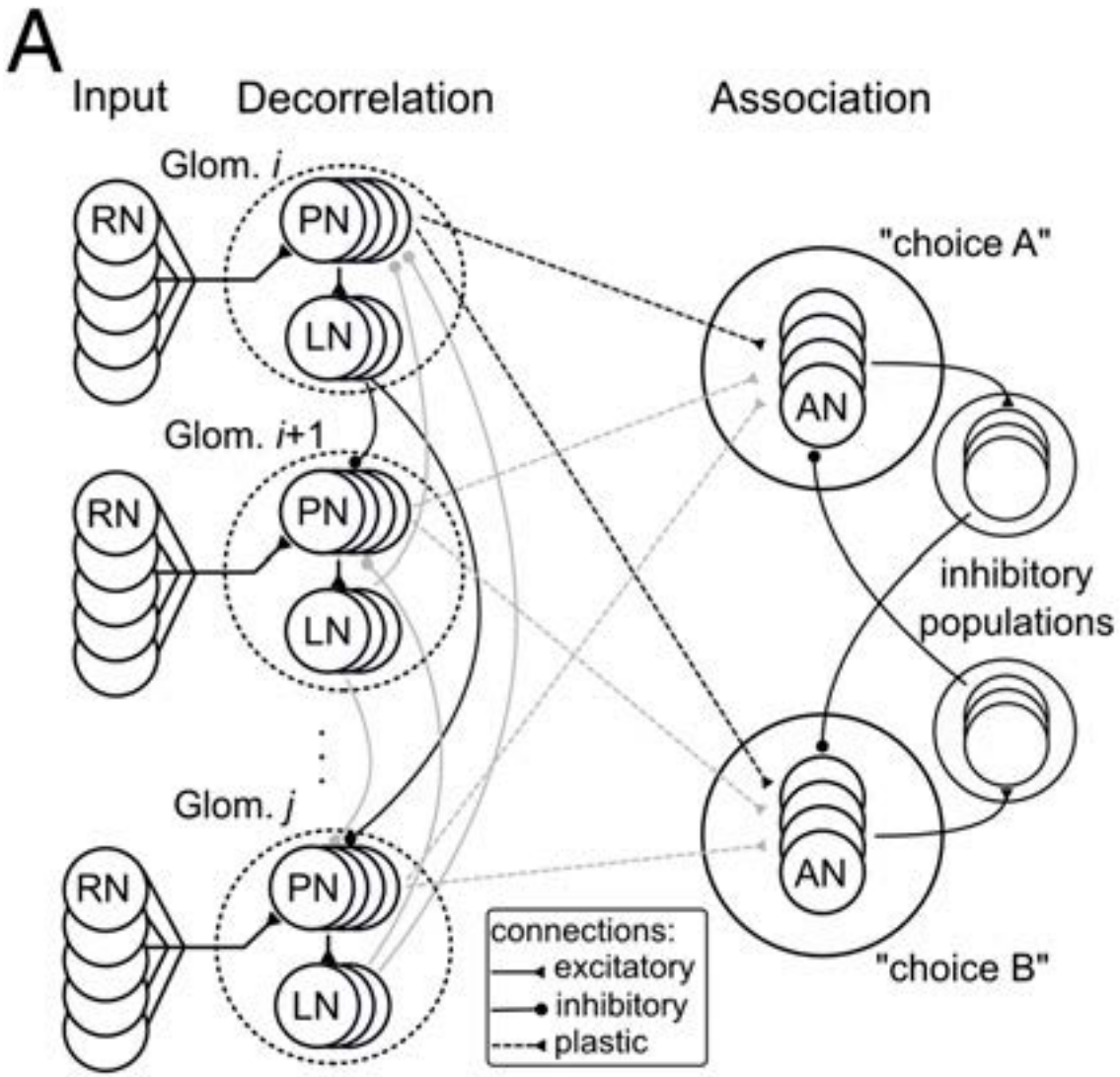
Exploiting Substrate UNIVERSALITY

- *Synfire chains*
- *Balanced random networks*
- *Liquid computing, temporal pattern identification*
- *Winner-take-all circuits*
- *Minicolumn L2/3 attractor networks*
- *Olfactory system of insects*
- *Barn owl echolocation, applying STDP*

Pfeil, Thomas, et al. "Six networks on a universal neuromorphic computing substrate." *Frontiers in neuroscience* 7 (2013).

Schmuker, Michael, Thomas Pfeil, and Martin Paul Nawrot. "A neuromorphic network for generic multivariate data classification." *Proceedings of the National Academy of Sciences* (2014): 201303053.

Pfeil, Thomas, et al. "Neuromorphic learning towards nano second precision." *Neural Networks (IJCNN), The 2013 International Joint Conference on Neural Networks*. IEEE, 2013.



3 Layer Spiking Neuron Network derived from Insect Olfactory System

L I : Receptor Neurons

L II : Decorrelation through lateral inhibition (Glomeruli)

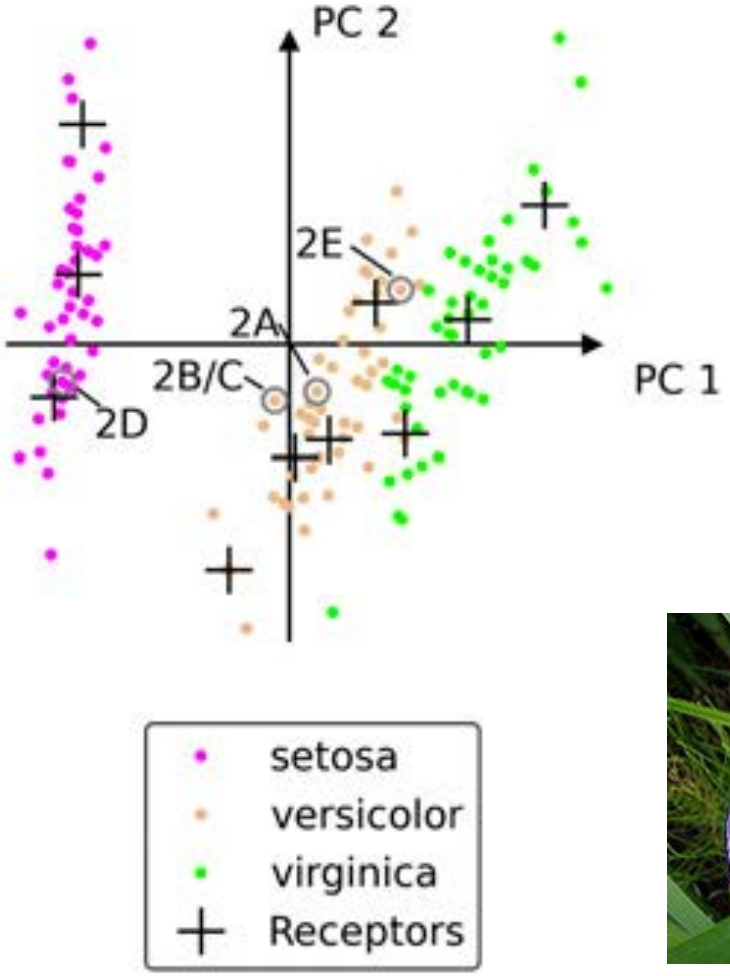
L III : Association (Soft WTA through strong inhibitory populatuions)

Supervised Learning

Synaptic Projections from Layer 2 to Layer 3

Schmuker, Michael, Thomas Pfeil, and Martin Paul Nawrot. "A neuromorphic network for generic multivariate data classification." *Proceedings of the National Academy of Sciences* (2014): 201303053.

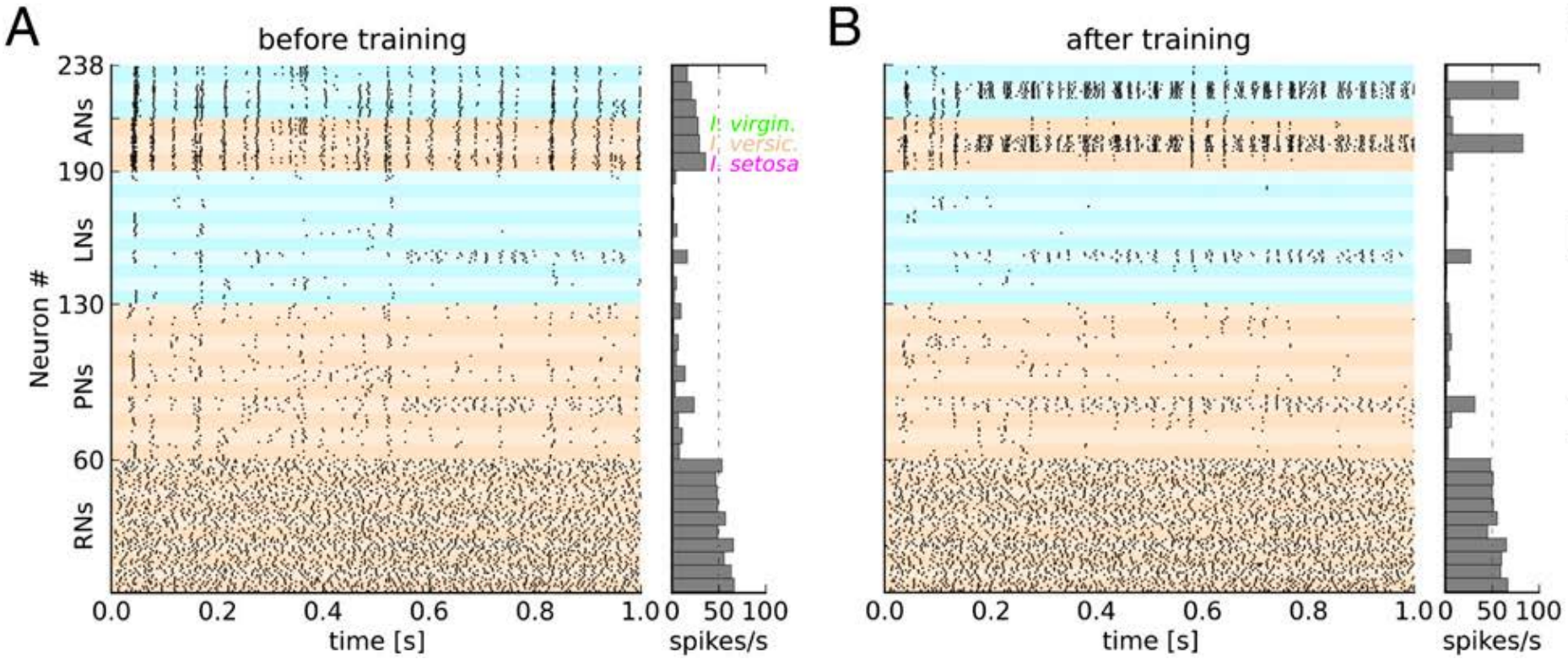
Iris Dataset, First 2 Principal Components



Placement of „Virtual Receptors (VR)“

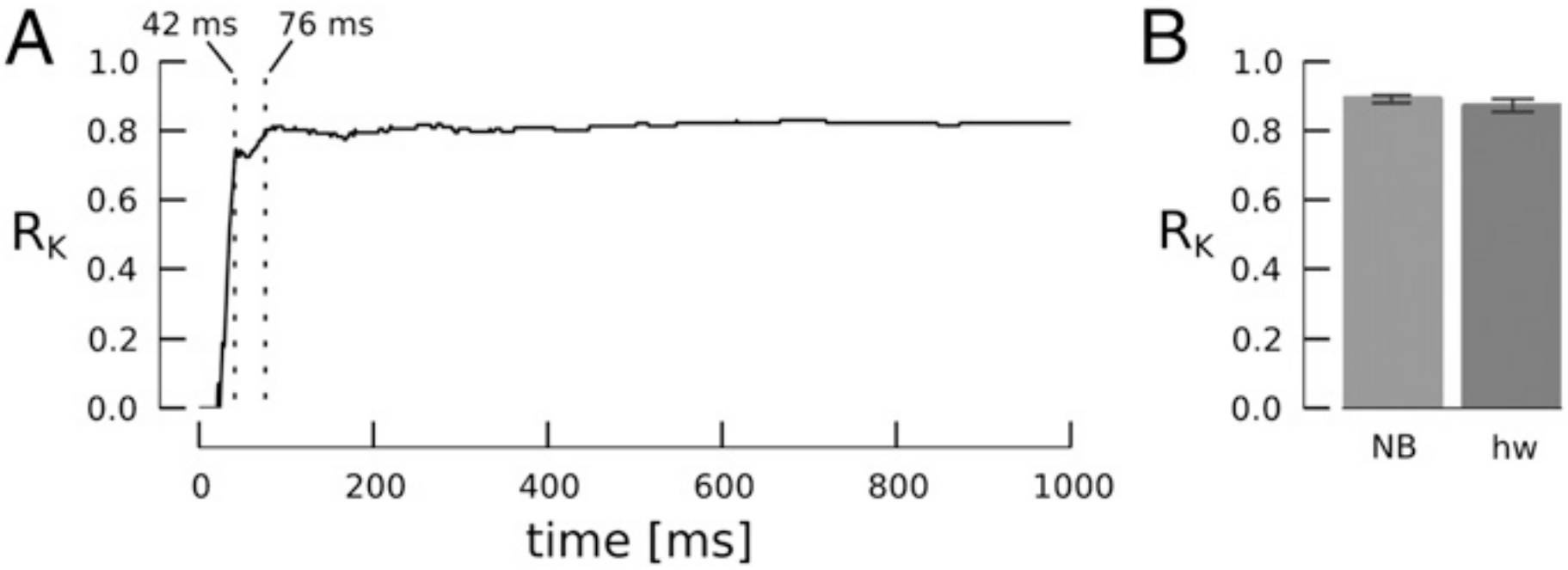
Schmuker, Michael, Thomas Pfeil, and Martin Paul Nawrot. "A neuromorphic network for generic multivariate data classification." *Proceedings of the National Academy of Sciences* (2014): 201303053.

Neuromorphic Network Activity before and after Learning



Schmuker, Michael, Thomas Pfeil, and Martin Paul Nawrot. "A neuromorphic network for generic multivariate data classification." *Proceedings of the National Academy of Sciences* (2014): 201303053.

Classification Performance compared to Software Bayesian Classifier with 5-fold cross-validation

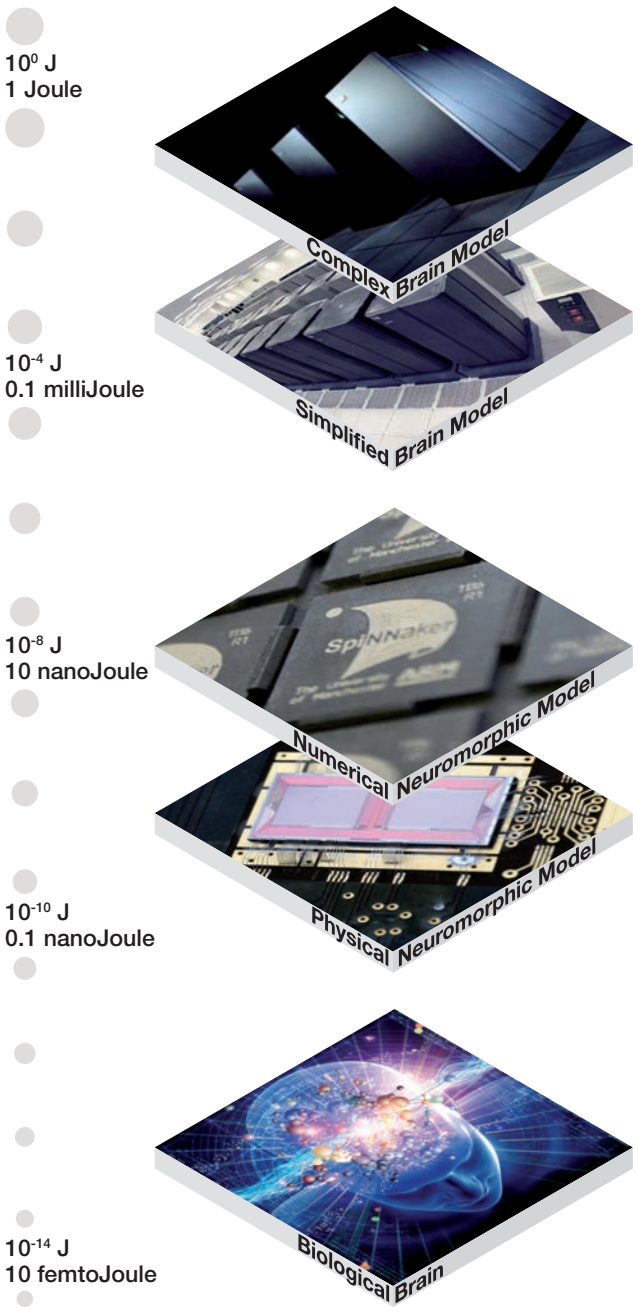


Boring ?

Probably .....

What so magic about Neuromorphic Computing ? Remember the Buzzwords ??

- Energy efficiency
- Simulation Speed
- Generalisation outside Biology
- Using faulty, diverse Devices
- Use Learning and Plasticity



Energy*Scales*

Energy used for a synaptic transmission

14 orders of magnitude difference for *„the same thing“*

Physical models (*Neuromorphic*)

- Typically 10.000.000 times more energy efficient than state-of-the art HPC (comparable model)
- 10.000 less efficient than biology

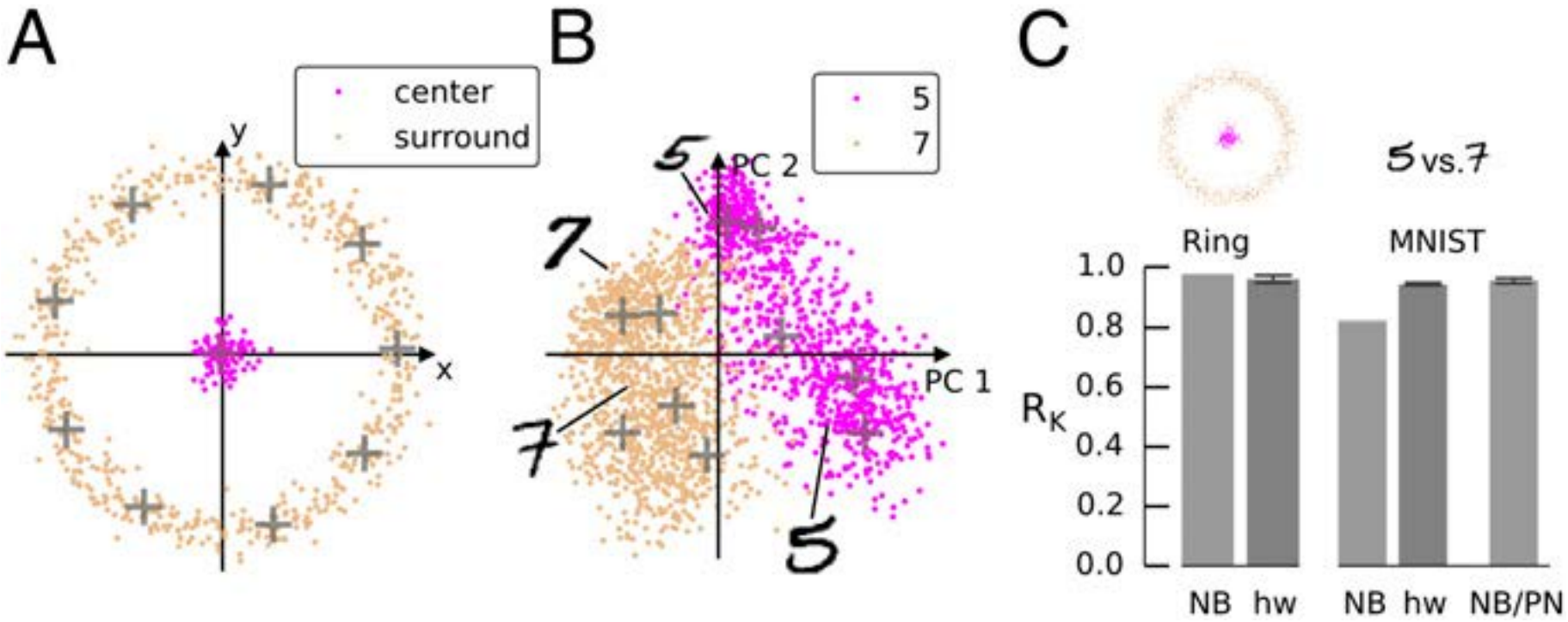
From : HBP project report

Time*Scales*

	Nature	Simulation	Accelerated physical model
Detection of causality	10^{-4} s	0.1 s	10^{-8} s
Plasticity	1 s	100 s	10^{-4} s
Learning	day	100 days	10 s
Development	year	100 years	3000 s
12 Orders of magnitude			
Evolution	> millenia	> 100 millenia	> month
> 15 Orders of magnitude			

Temporal dynamics is key to understanding (and using) the computational paradigms of the brain

Generic Data Analysis with a biologically derived Neuromorphic System



Schmuker, Michael, Thomas Pfeil, and Martin Paul Nawrot. "A neuromorphic network for generic multivariate data classification." *Proceedings of the National Academy of Sciences* (2014): 201303053.

2011 EDITION : EMERGING RESEARCH DEVICES, Chapter 5.3

The appeal of neuromorphic architectures lies in

i) their potential to achieve (human-like) intelligence based on unreliable devices typically found in neuronal tissue
ii) their strategies to deal with anomalies, emphasizing not only tolerance to noise and faults, but also the active exploitation of noise to increase the effectiveness of operations
iii) their potential for low-power operation.

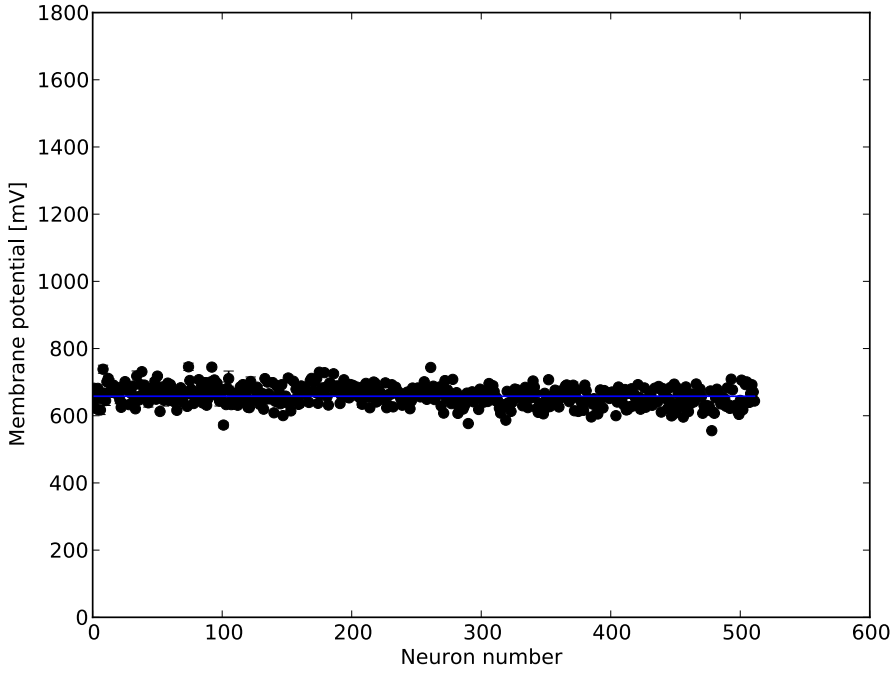
Traditional von Neumann machines are less suitable with regard to item i), since for this type of tasks they require a machine complexity (the number of gates and computational power), that tends to increase exponentially with the complexity of the environment (the size of the input). Neuromorphic systems, on the other hand, exhibit a more gradual increase of their machine complexity with respect to the environmental complexity.

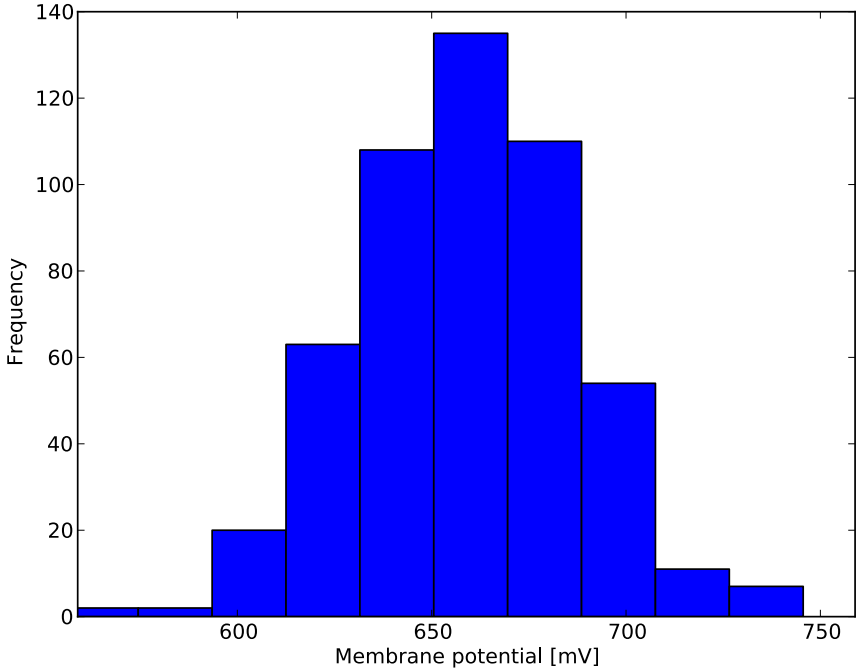
Therefore, at the level of human-like computing tasks, neuromorphic machines have the potential to be superior to von Neumann machines.

Full chip E_L calibration

BrainScaleS Project
M.O. Schwarz PhD Thesis

Target : $E_L = 655$ mV



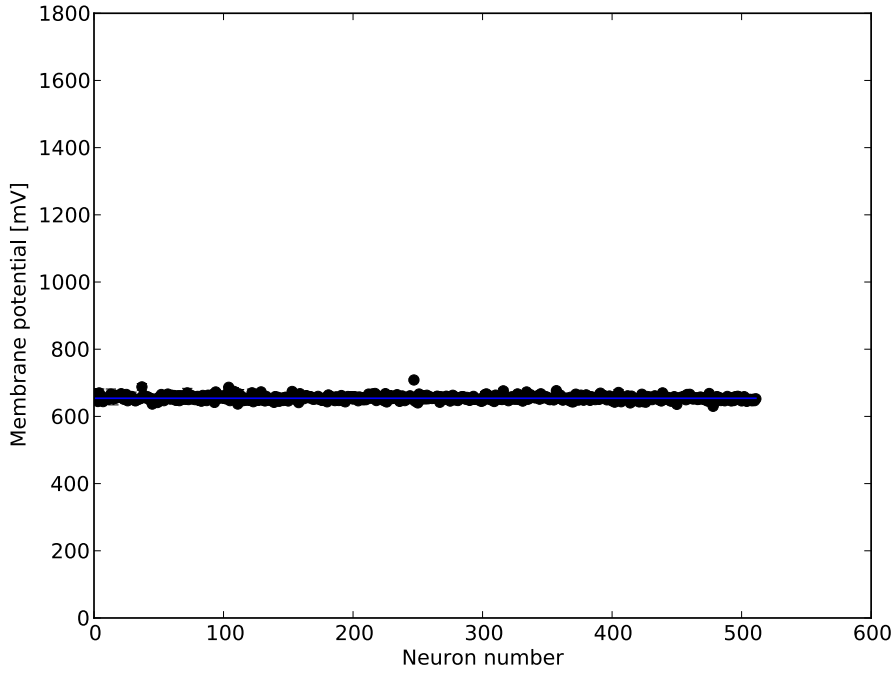


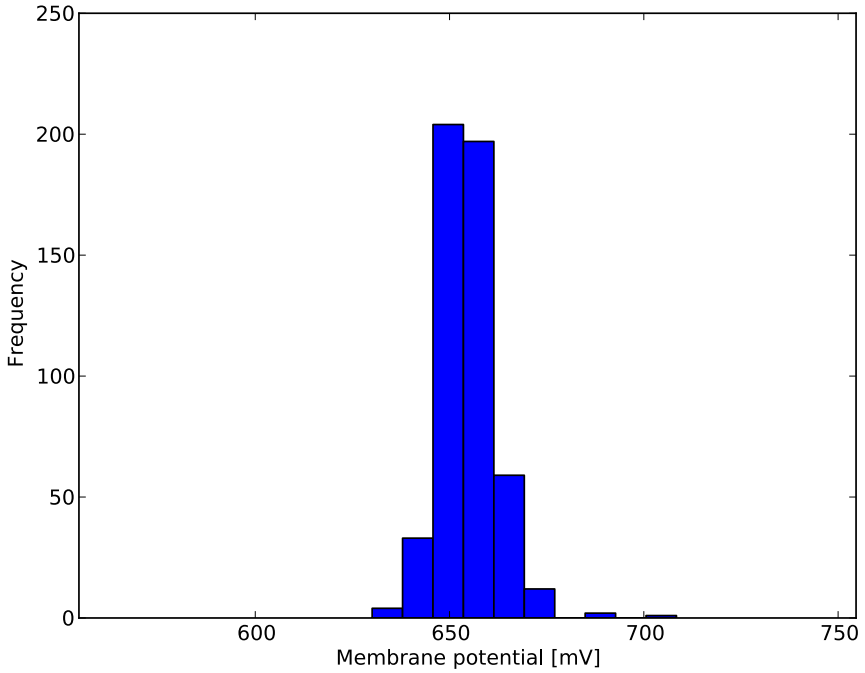
Mean = 658.9 mV | Std = 28.5 mV

Full chip EL calibration

BrainScaleS Project
M.O. Schwarz PhD Thesis

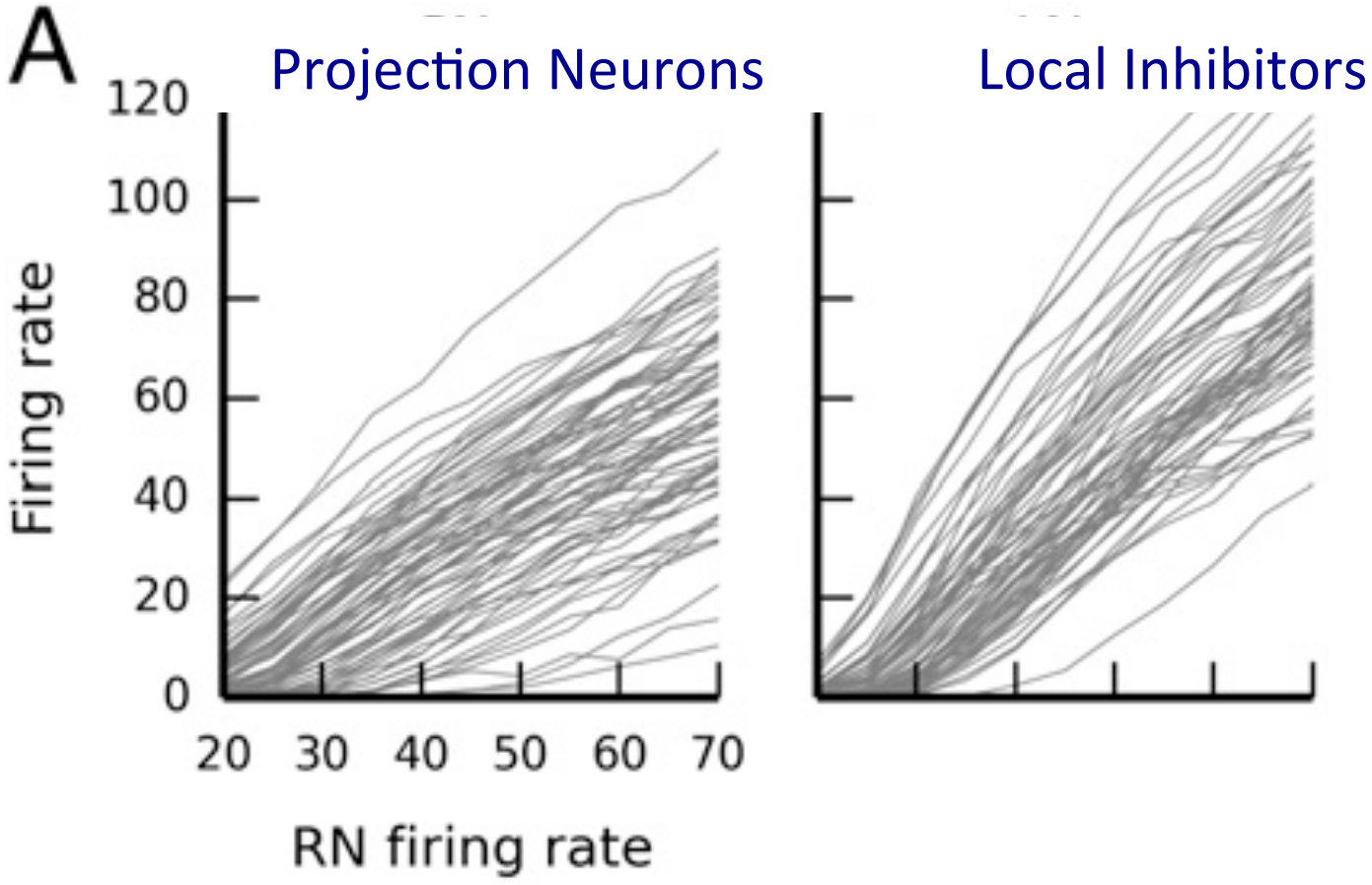
Target : EL = 655 mV



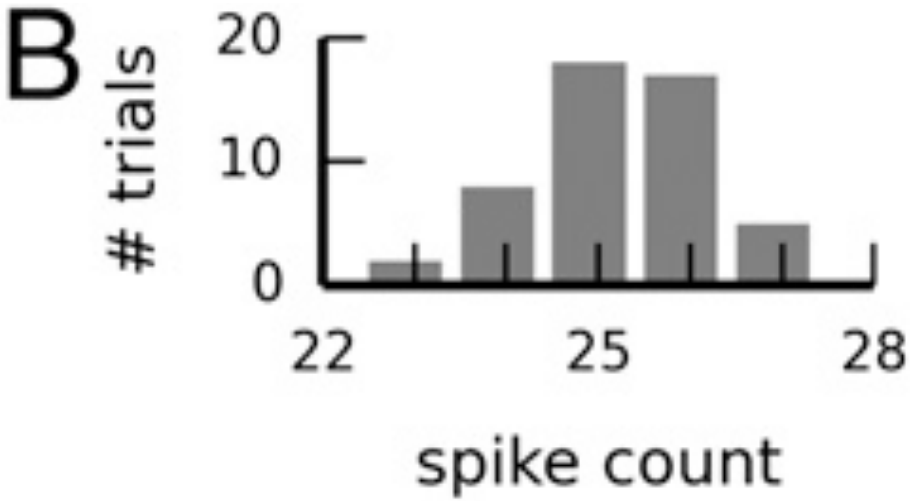


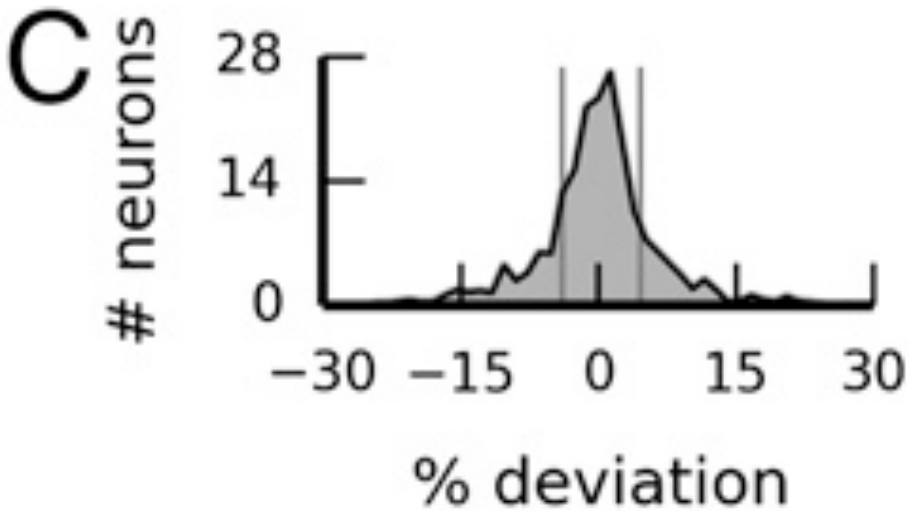
Mean = 654.3 mV | Std = 5.1 mV

Fixed Pattern Noise in the Neuromorphic Glomeruli Populations



Schmuker, Michael, Thomas Pfeil, and Martin Paul Nawrot. "A neuromorphic network for generic multivariate data classification." *Proceedings of the National Academy of Sciences* (2014): 201303053.





Temporal Noise in the Neuromorphic Glomeruli

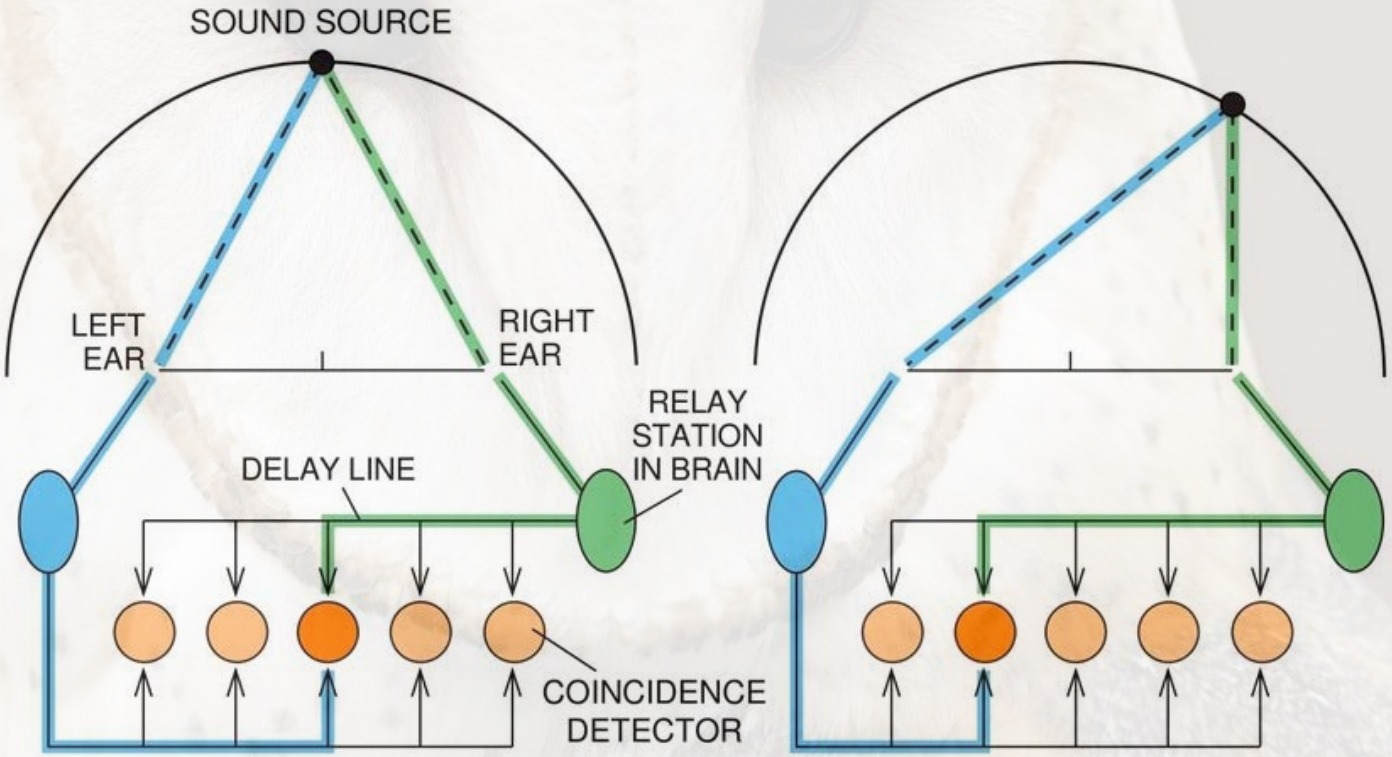
Populations

Schmuker, Michael, Thomas Pfeil, and Martin Paul Nawrot. "A neuromorphic network for generic multivariate data classification." *Proceedings of the National Academy of Sciences* (2014): 201303053.

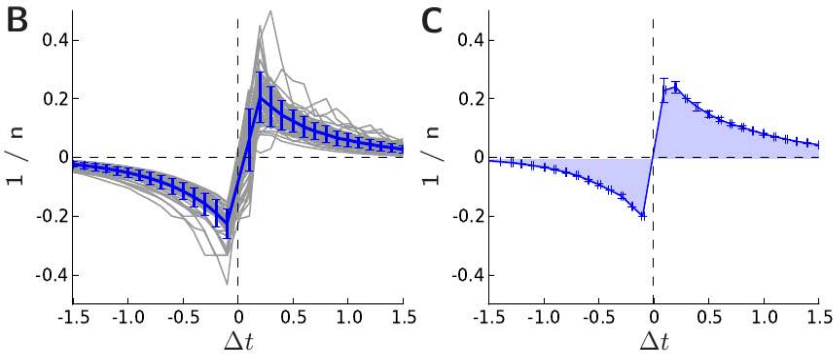
STDP based Neuromorphic Localization of Sound Sources

Thesis A.C. Scherzer

- Barn Owl Model (Carr&Konishi, 1990)
- Arrival Times proportional to path length
- Compensating delay lines in the circuits trigger coincidence detectors (Jeffress, 1948)
- Spatial Coding of interaural time differences (ITDs) by coincidence detectors



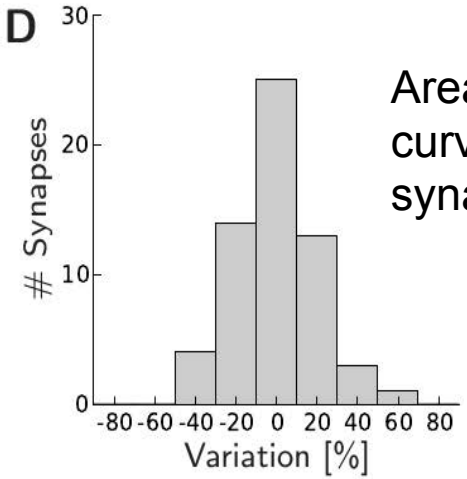
Analogue Synapse Precision



Average over 60 synapses

One synapse

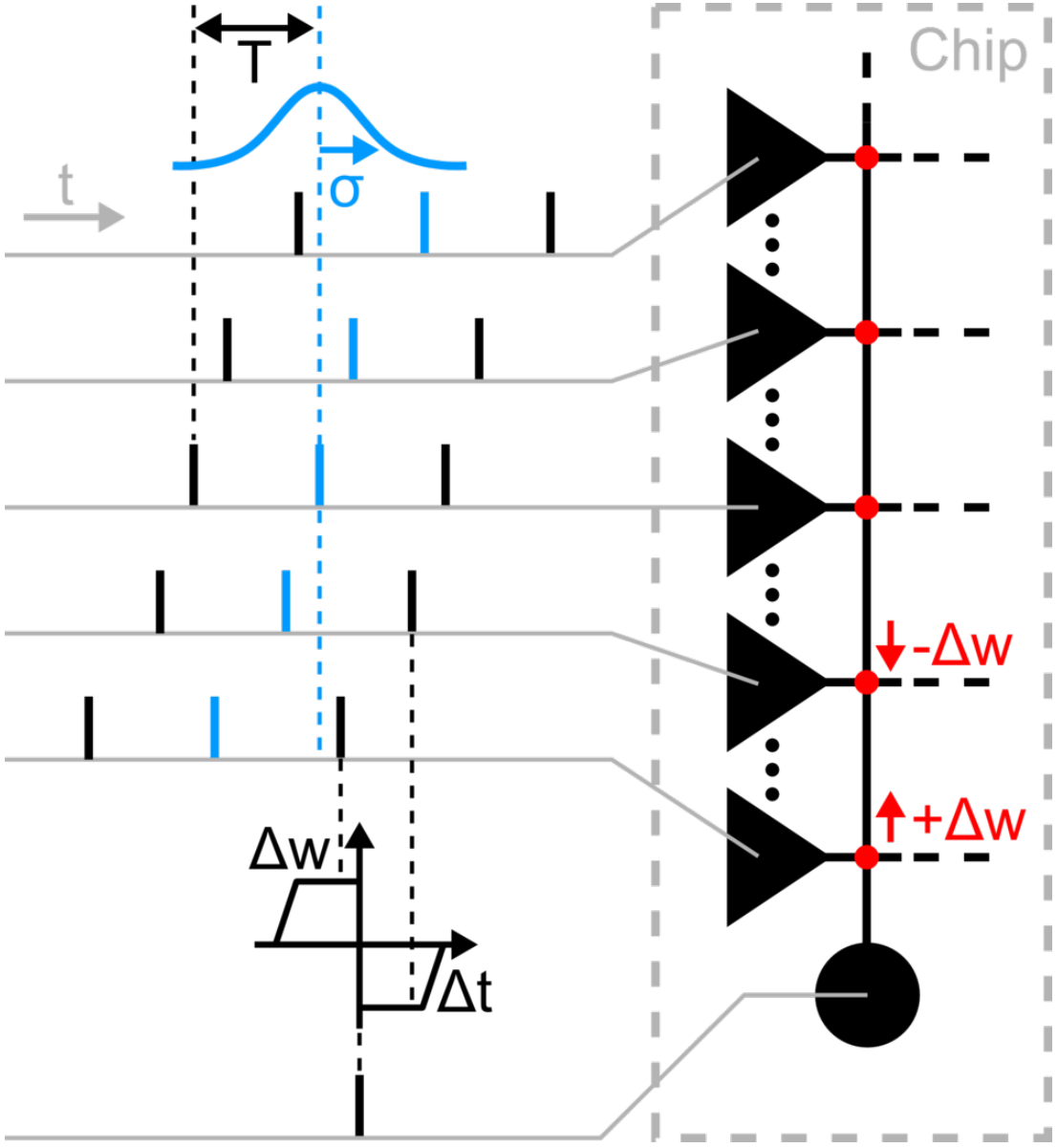
- Correlation measurement in synapses
- Characterization of fixed-pattern noise



Area under the curve for 60 synapses

- Typically 20% synapse-to-synapse variation
- Individual synapses are precise

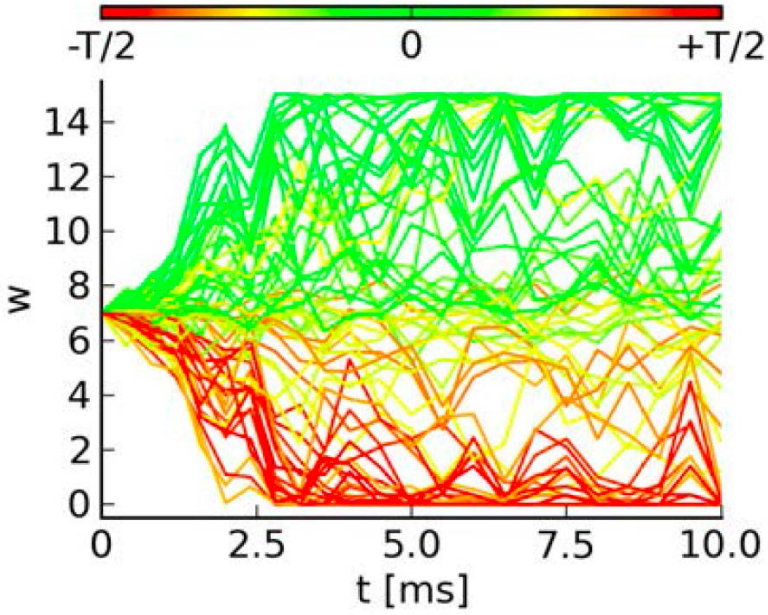
Pfeil, Thomas, et al. "Is a 4-bit synaptic weight resolution enough?–constraints on enabling spike-timing dependent plasticity in neuromorphic hardware." *Frontiers in neuroscience* 6 (2012).



NM Hardware

- 64 neuronal spiking signal sources (nucleus magnocellularis) correspond to presynaptic inputs
- Receiving postsynaptic neuron (nucleus laminaris) performs phase locking by STDP learning (Gerstner, 1996)
- T = 1 µs stimuli with σ = 600 ns spread of axonal delays
- Run 100 emulations with 20ms duration each

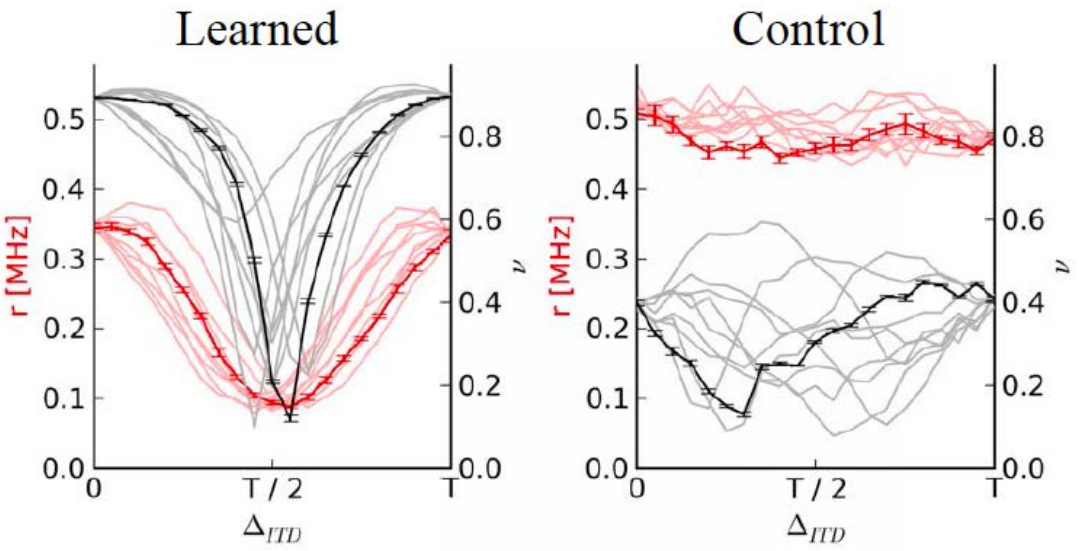
Pfeil, Thomas, et al. "Neuromorphic learning towards nano second precision." *Neural Networks (IJCNN), The 2013 International Joint Conference on Neural Networks*. IEEE, 2013.



Synaptic adaptation O(ms) in biological time

Timing presion of O(10 ns) in electronics time

Bachelor Thesis
Anne-Cathrin Scherzer
Heidelberg



Pfeil, Thomas, et al. "Neuromorphic learning towards nano second precision." *Neural Networks (IJCNN), The 2013 International Joint Conference on Neural Networks*. IEEE, 2013.

BRAIN-DERIVED COMPUTING

- Consistent concept for a novel, brain derived, non-von Neumann, non-Turing computer architecture
- Accessible to available technologies (CMOS) and attractive application for future component technologies (nanoelectronics)
- Key features : Universality, scalability, fault tolerance, power efficiency, speed, learning
- Accelerated operation : Only known approach to bridge all timescales relevant for circuit dynamics
- Important next step : Give up simulation as a reference, exploit device mismatch and noise

BrainScaleS
Week of BrainScaleS
2nd plenary meeting
JÜLICH

Human Brain Project