

Simulating the Brain without a Computer

Achievements and Challenges of Brain Inspired Computing

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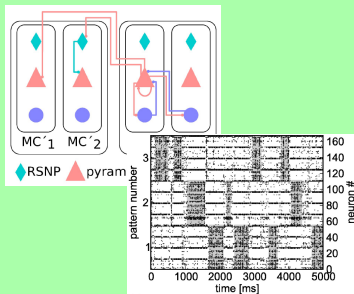
Kirchhoff-Institute for Physics
Heidelberg University

22. March 2013

BrainScale S
Scale S

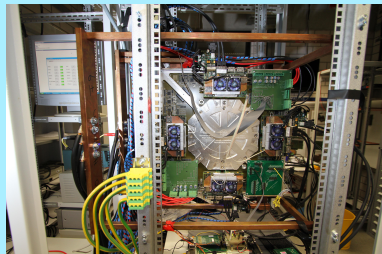
"Simulating the Brain"

Neuroscience



"Brain Inspired Computing"

Technology



Computing with a Physical Model

$$C \frac{dV}{dt} = -g_L (V - E_L) + g_L \Delta_T \exp\left(\frac{V - V_T}{\Delta_T}\right) - w - I$$
$$\tau_w \frac{dw}{dt} = a (V - E_L) - w$$

Mathematical model

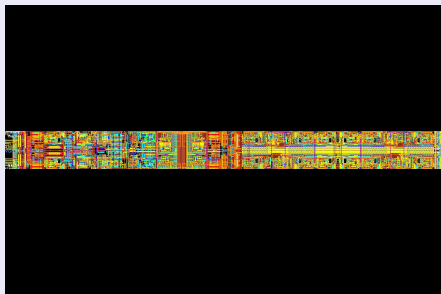
Biology

Hardware model



Physical model vs. software simulation

Physical model



- Inherent dynamics perform computation
- **Configurable dynamics**

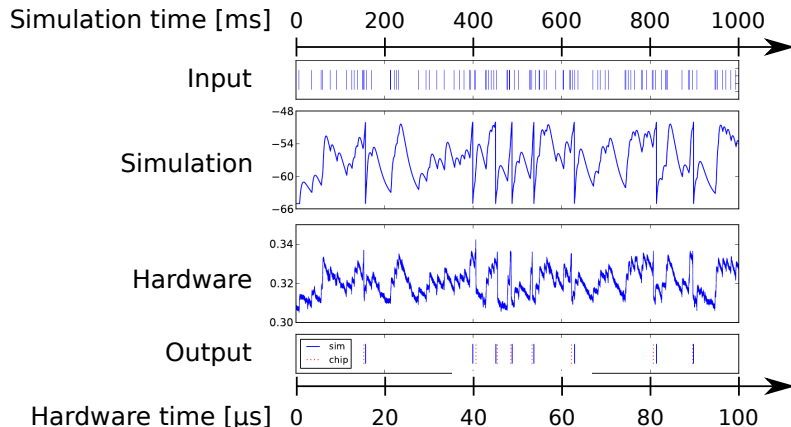
Classical computer



(Argonne National Laboratory, 2007)

- Numerically solve differential equations
- **Programmable dynamics**

Hardware model uses different scales



	Hardware	Biology
Voltage:	1 V	10 mV
Conductance:	100-1000 nS	10 nS
Capacitance:	1 pF	100 pF

→ Different time constants:
Hardware is **faster than**
biology

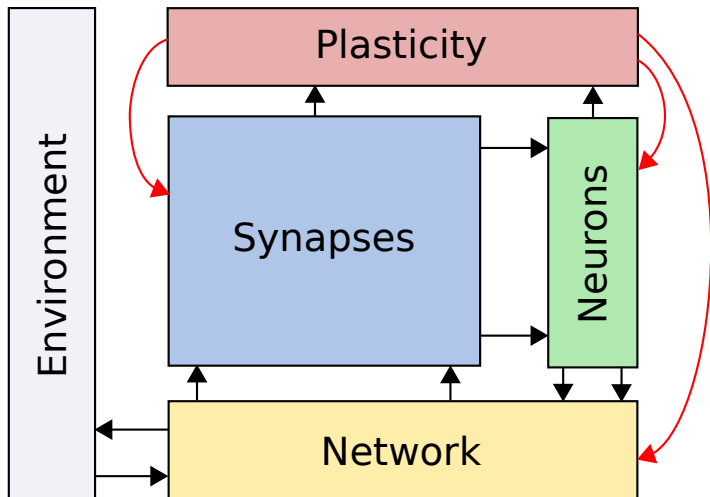
Accelerated time enables long-term learning studies

Time scales

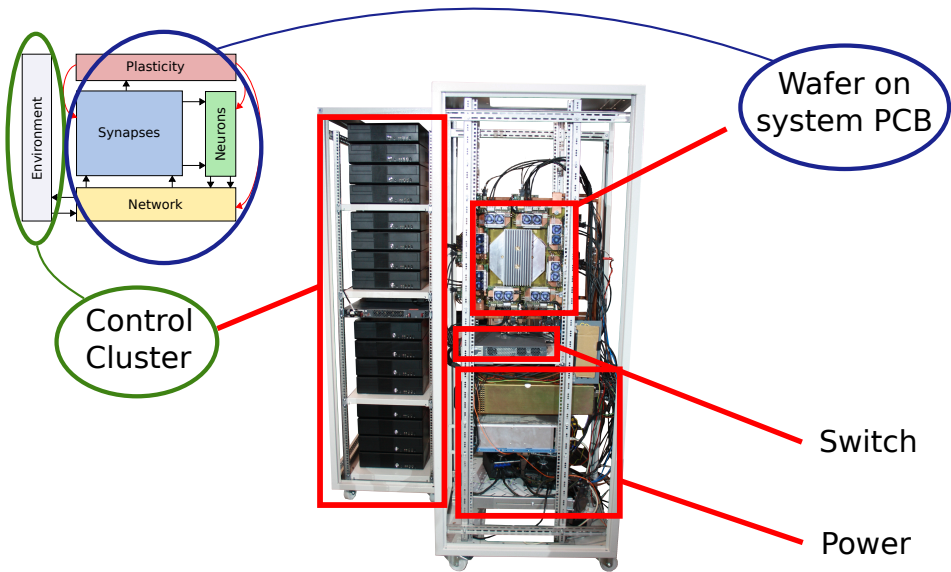
	Biological time	Hardware time ($\times 10^4$)
Plasticity	1 ms	$0.1 \mu s$
Learning Trial	1 min	1 ms
Training	1 h	100 ms
Development	1 month	1 min

- Large-scale software simulations typically **slower** than biological time

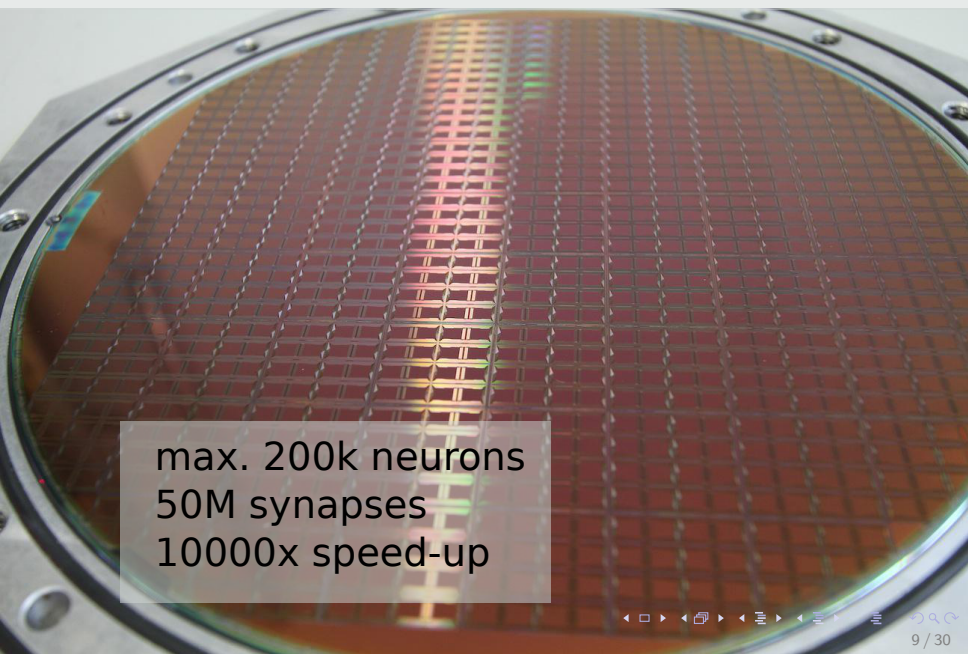
Structure of a hardware system



The BrainScaleS wafer-scale system

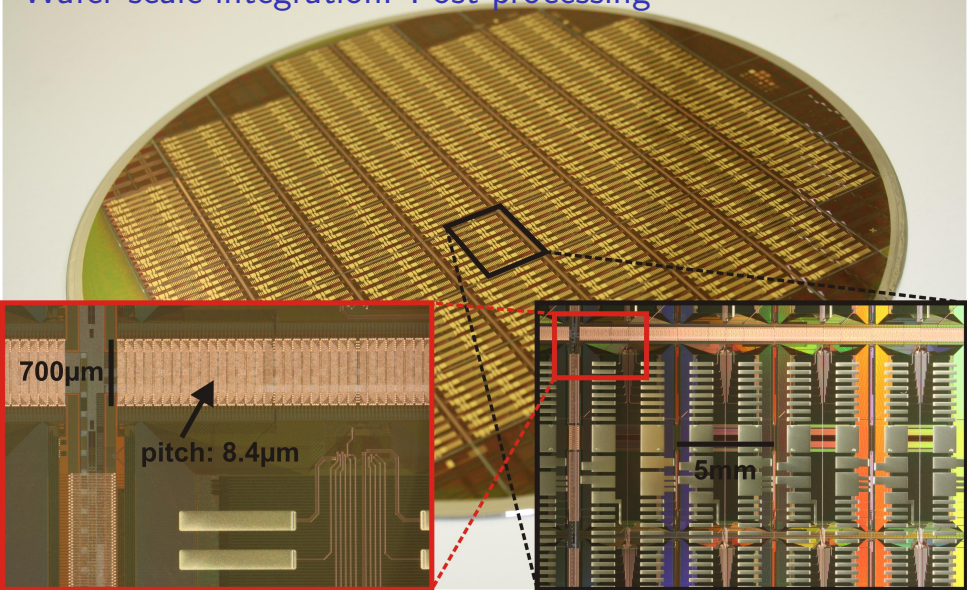


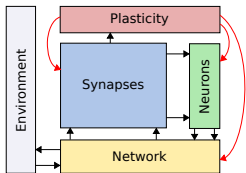
Wafer-scale integration



max. 200k neurons
50M synapses
10000x speed-up

Wafer-scale integration: Post-processing

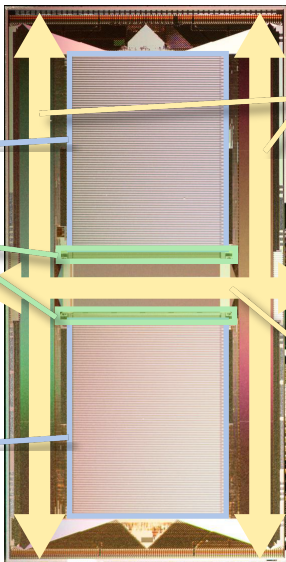




50k synapses

2x256 neurons

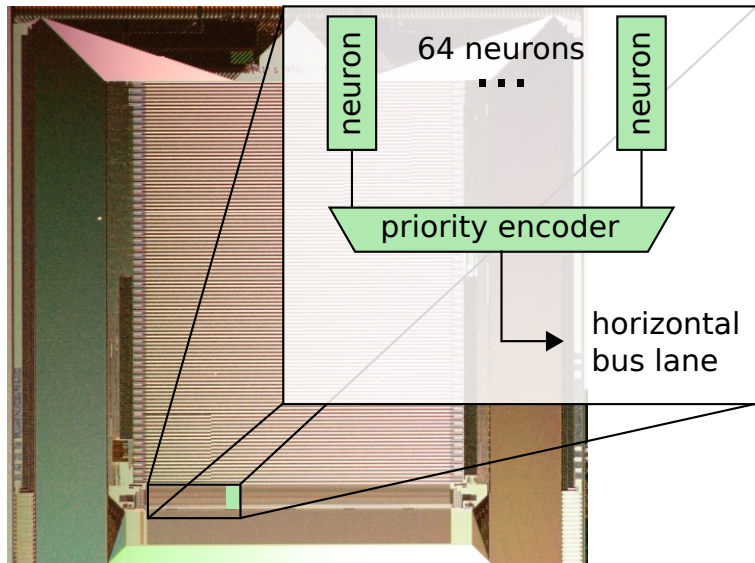
50k synapses



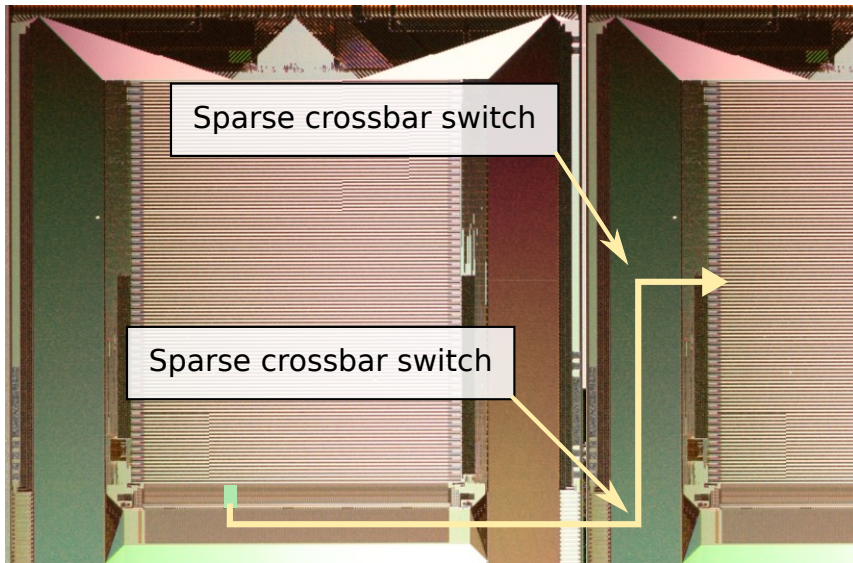
2x128 vertical
network lanes

64 horizontal
network lanes

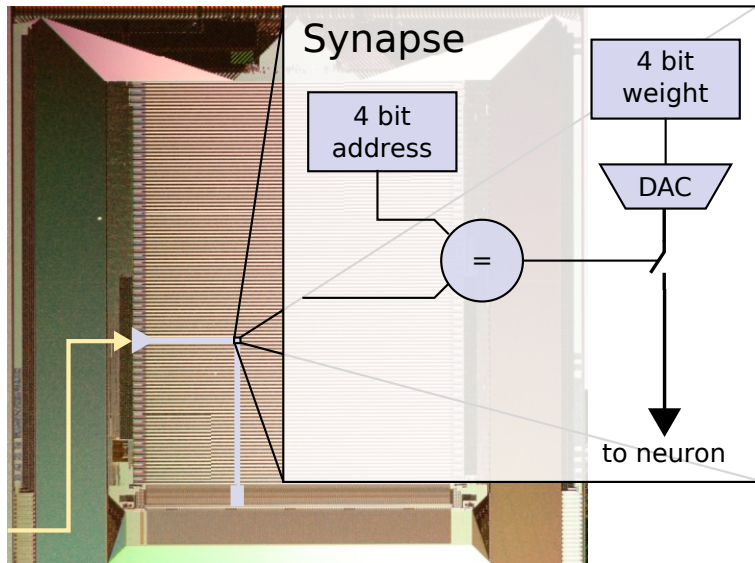
Event processing: Neuron output



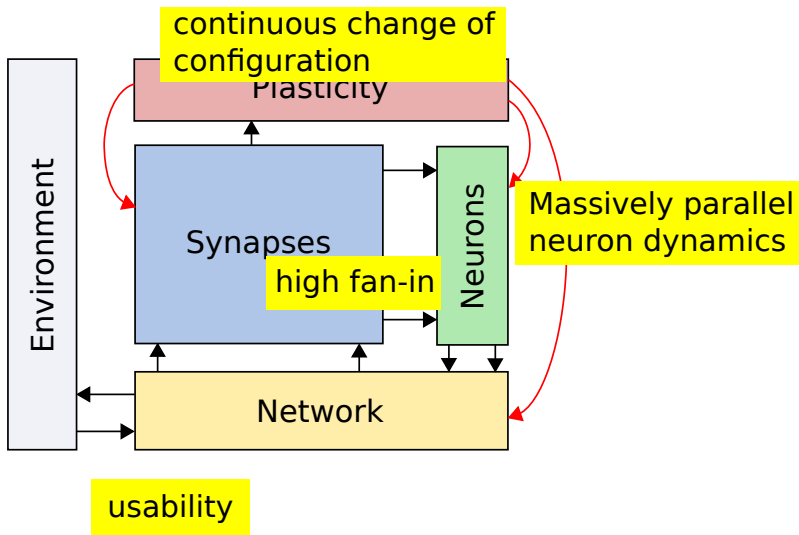
Event processing: Network



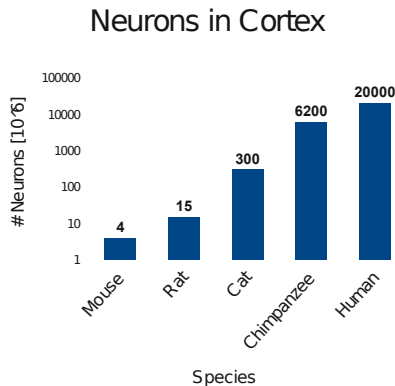
Event processing: Synapses



Challenges for hardware implementation



Challenge: Massively parallel neuron dynamics



Challenge

- About $20 \cdot 10^9$ neurons in cortex
- Neurons show complex dynamics
- Need area & power efficient solution

Approach

- Neurons as physical model
- Analog computing

BrainScaleS neurons

$$-C_m \frac{dV}{dt} = g_l (V - E_l) - g_l \Delta_t e^{\left(\frac{V - V_t}{\Delta_t}\right)} + w$$

$$+ I$$

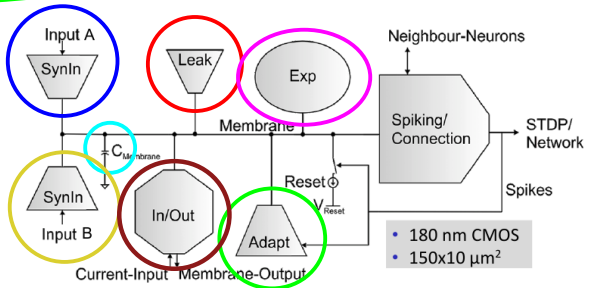
$$+ g_e(t) (V - E_e)$$

$$+ g_i(t) (V - E_i)$$

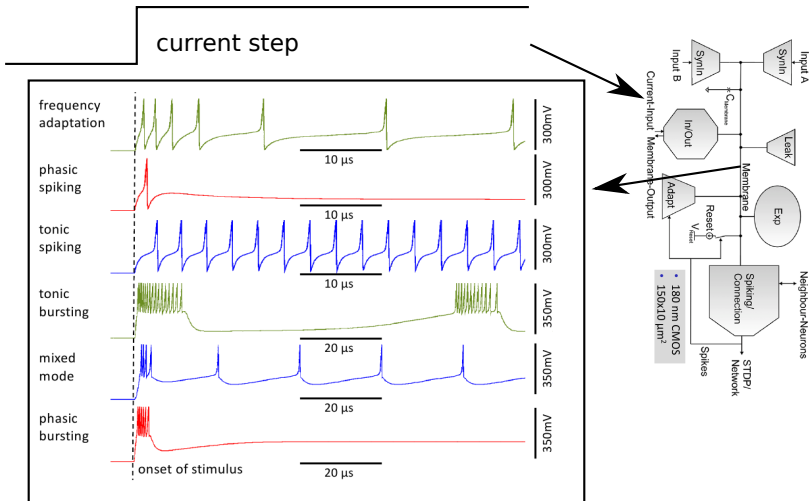
$$-\tau_w \frac{dw}{dt} = w - a (V - E_l)$$

Adaptive Exponential Integrate & Fire neuron model
(Brette & Gerstner, 2005)

Hardware model
(Millner, 2012)

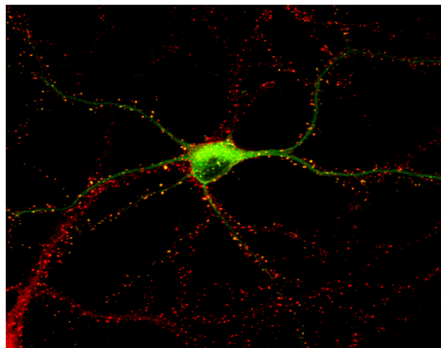


BrainScaleS neurons



- Configurable: Different firing modes
- Reproduce behavior from biology

Challenge: High synaptic input count



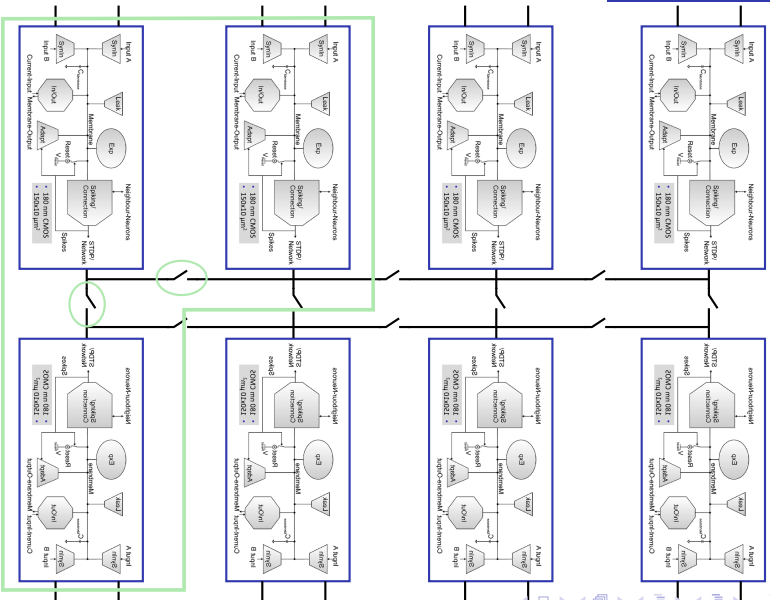
(Paul De Koninck, 2004)

Challenge

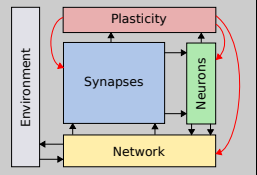
- $10^4 - 10^5$ synapses per neuron in neocortex
- Much more synapses than neurons

Approach

- Simple synapses
- Combinable neurons

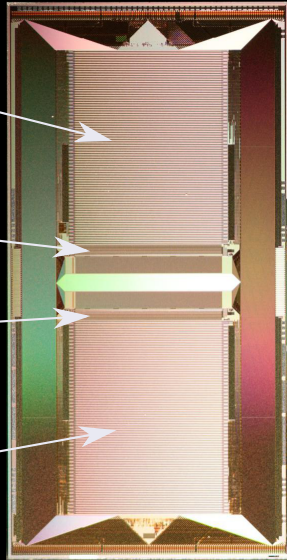
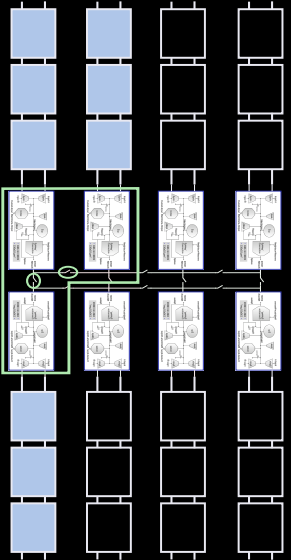


Combined neuron

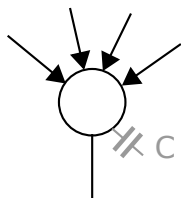


224 synapses per column

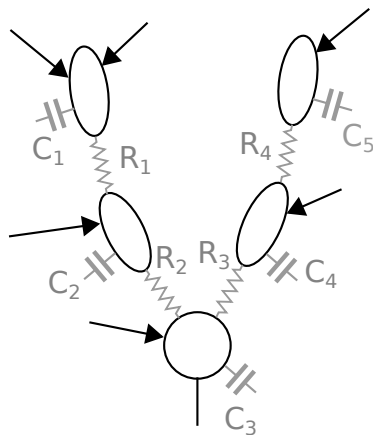
max. 14k synapses per neuron



Outlook: Multi-compartment neurons

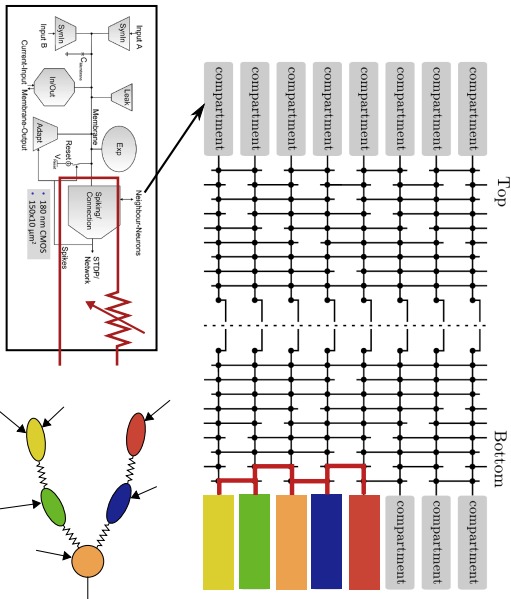


Point Neuron



Multi-compartment
Neuron

Outlook: Multi-compartment neurons

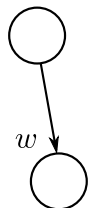


- Configurable resistances
 - Routing matrix
 - Implement dendritic tree
- ⇒ **Biologically more realistic**

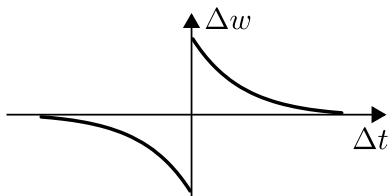
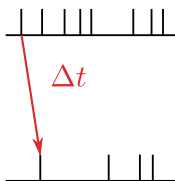
(Millner, 2012)

Challenge: Synaptic plasticity

presynaptic
neuron



postsynaptic
neuron



**Spike Timing Dependent
Plasticity**

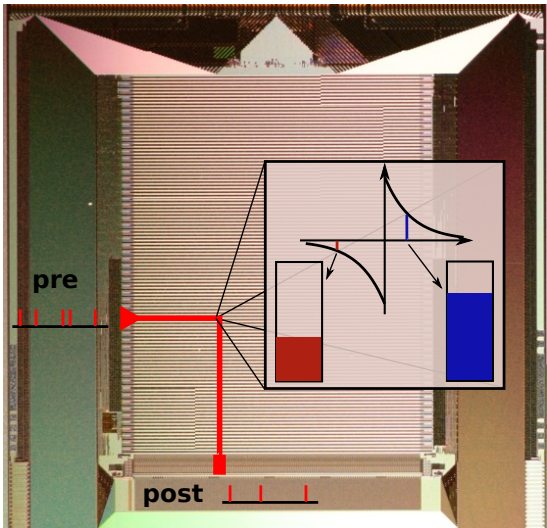
Challenge

- Every synapse subject to change
- Plasticity is foundation of learning
- Timing dependency with millisecond precision

Approach

- Analog timing measurement
- Digital weight modification

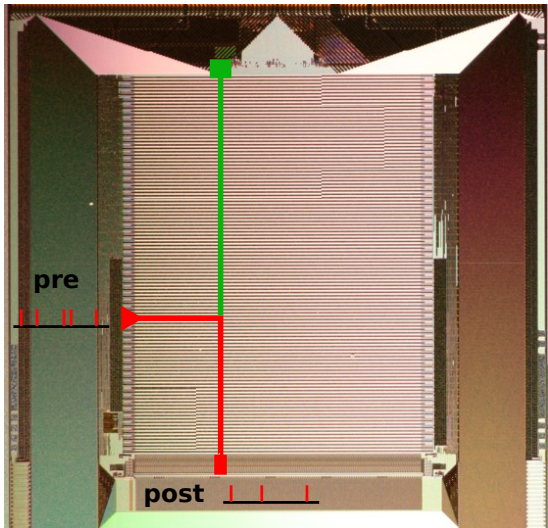
BrainScaleS STDP



Synapse:

- Measure spike timing
- Exponential weighting
- Local accumulation on capacitors

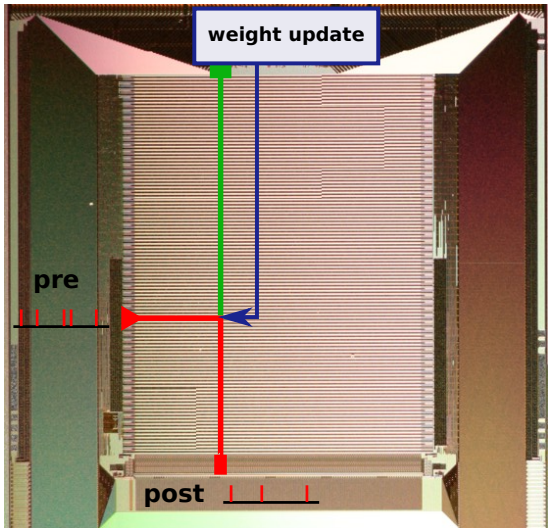
BrainScaleS STDP



Evaluation:

- Configurable comparison operation
- e.g. compare difference to threshold

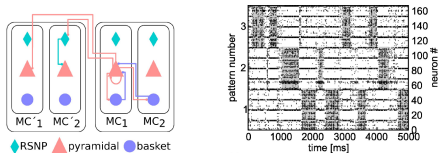
BrainScaleS STDP



Digital weight update:

- 4 bit weights
- Calculate new weight
- Uses look-up tables

Challenge: Usable by neuroscientists



Challenge

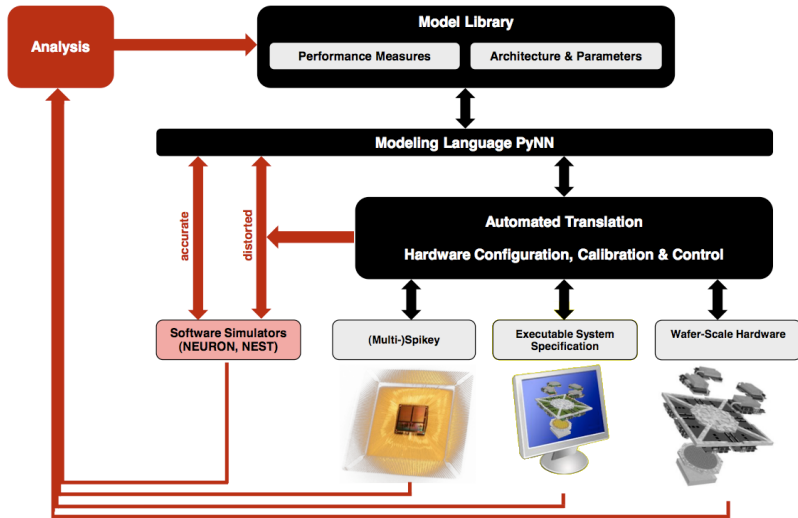
- Large configuration space
- Lots of technical detail
- Neuroscientists are not hardware engineers

Approach

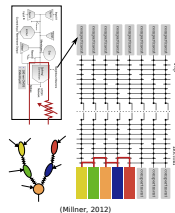
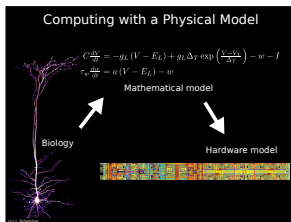
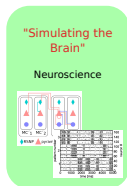
- Network described in biological terms
- Modeling language PyNN
- Automatic configuration



Usage Workflow



Conclusion



- Goals: **"Simulating the Brain"** and **"Brain inspired Computing"**
- Workflow: Biology → Model → Hardware
- **Acceleration**: Important for studies of learning
- Improved **neuron model** in future systems