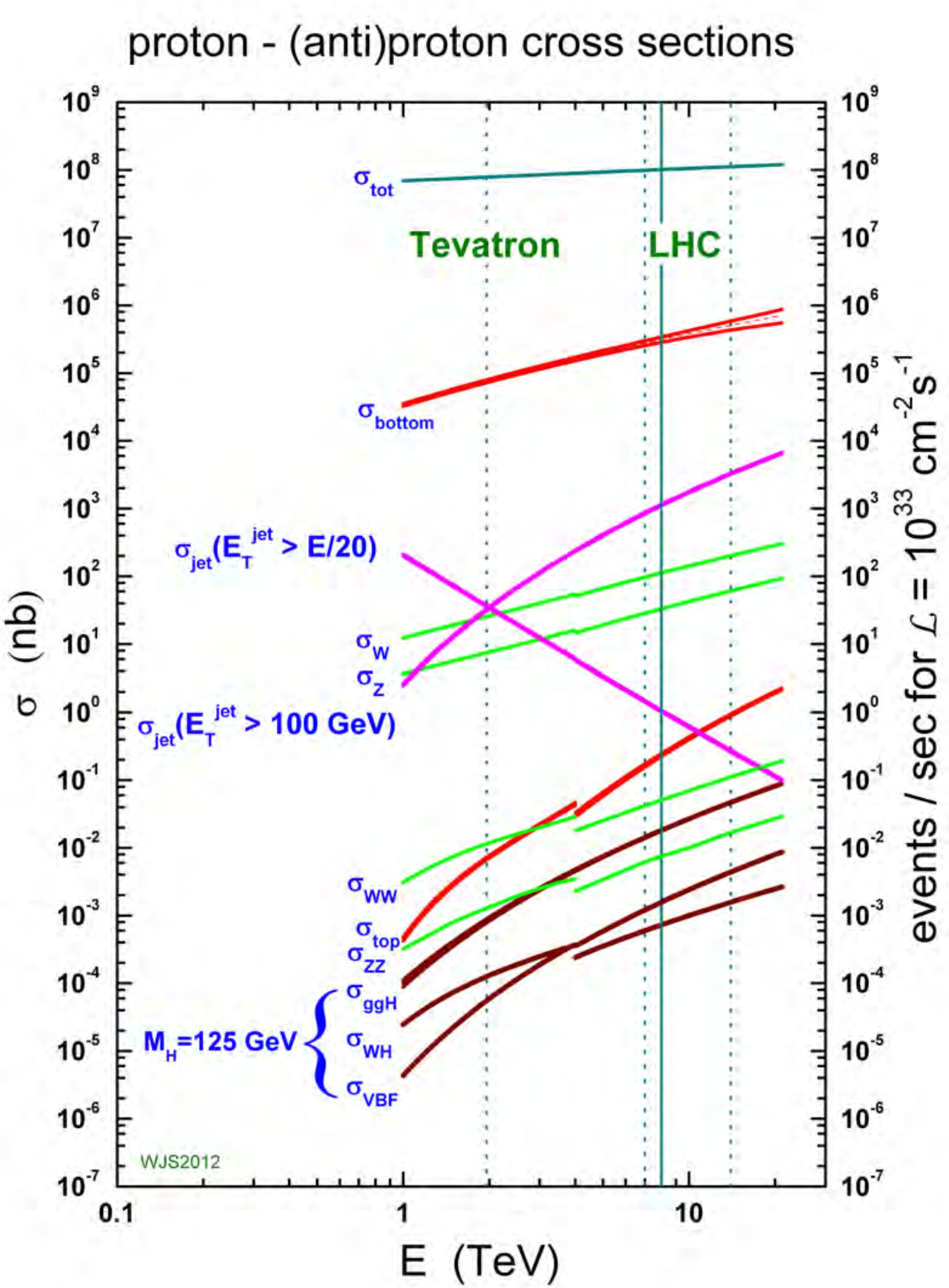
How to Simulate Without a Computer-
A Physics approach to the Brain

Karlheinz Meier
Ruprecht-Karls-Universität Heidelberg

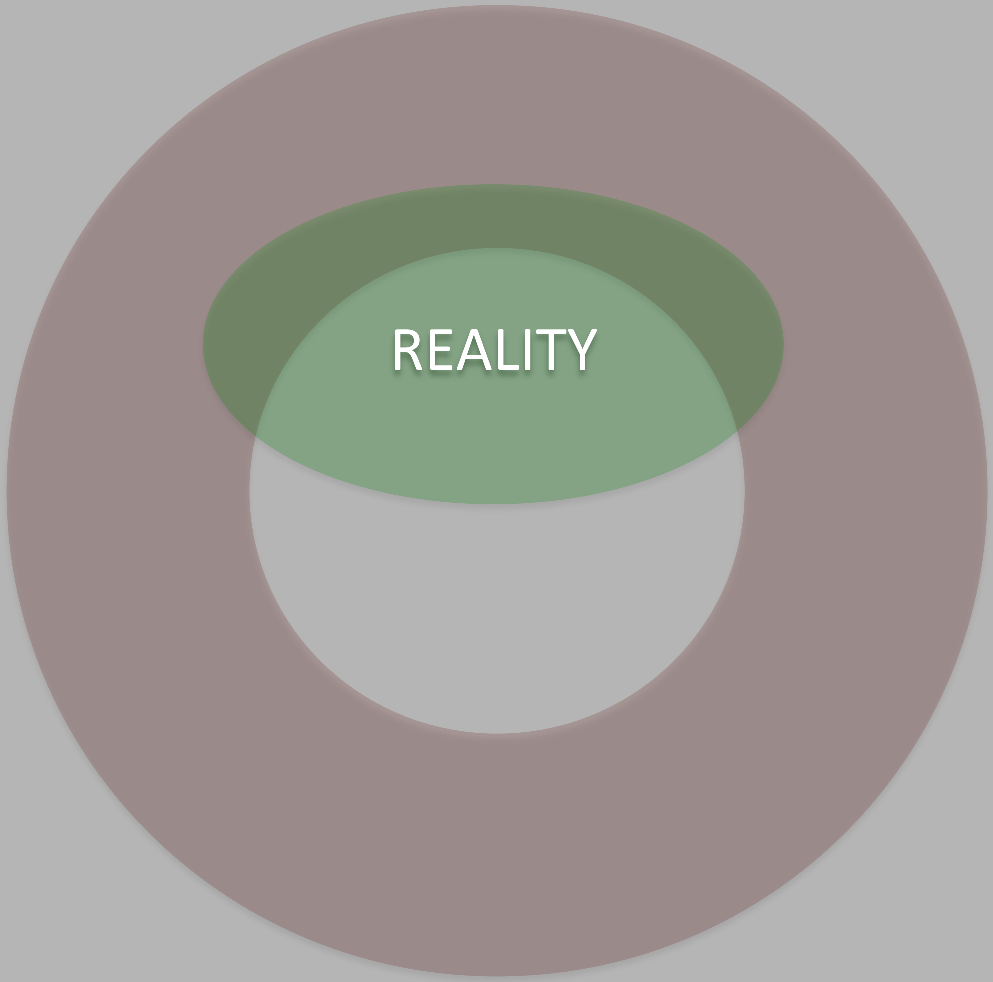
March 11th, 2014, (Lund universitet, Sweden)



proton - (anti)proton cross sections
σ (nb)
events / sec for ℒ = 10^33 cm^-2 s^-1
E (TeV)
0.1
1
10
10^9
10^8
10^7
10^6
10^5
10^4
10^3
10^2
10^1
10^0
10^-1
10^-2
10^-3
10^-4
10^-5
10^-6
10^-7
Tevatron
LHC
σ_tot
σ_bottom
σ_jet(E_T^jet > E/20)
σ_W
σ_Z
σ_jet(E_T^jet > 100 GeV)
σ_WW
σ_top
σ_ZZ
M_H=125 GeV
σ_ggH
σ_WH
σ_VBF
WJS2012

ATLAS Trigger Menu

Object	Examples of physics coverage	Nomenclature
Electrons	Higgs (SM, MSSM), new gauge bosons, extra dimensions, SUSY, W, top	e25i, 2e15i
Photons	Higgs (SM, MSSM), extra dimensions, SUSY	γ60i, 2γ20i
Muons	Higgs (SM, MSSM), new gauge bosons, extra dimensions, SUSY, W, top	μ20, 2μ10
Jets	SUSY, compositeness, resonances	j360, 3j150, 4j100
Jet+missing E_T	SUSY, leptoquarks	j60 + xE60
Tau+missing E_T	Extended Higgs models (e.g. MSSM), SUSY	τ30 + xE40


REALITY

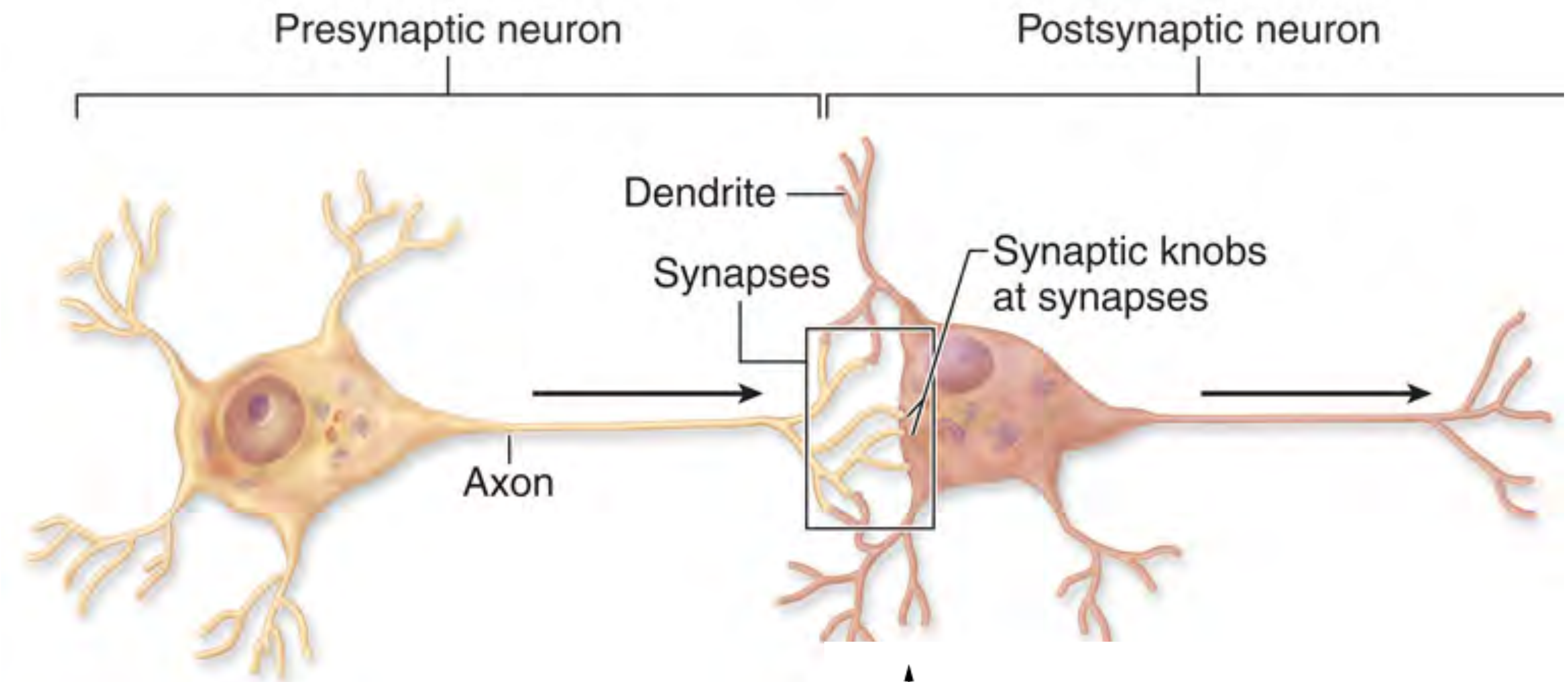
Santiago Ramon y Cajal
(1852-1934)

Individual cells in the brain are spatially separate objects

"interaction over a distance"

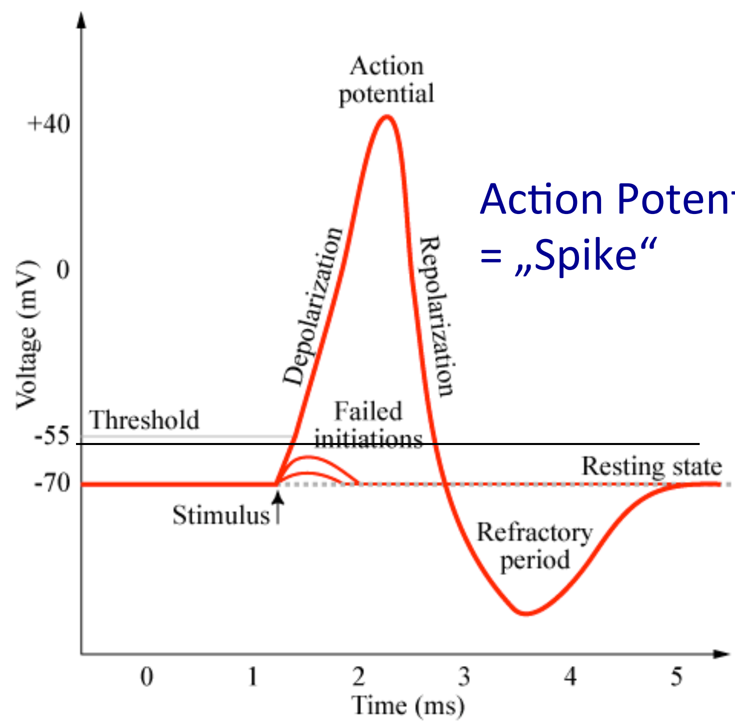
and

"spatial and temporal integration"

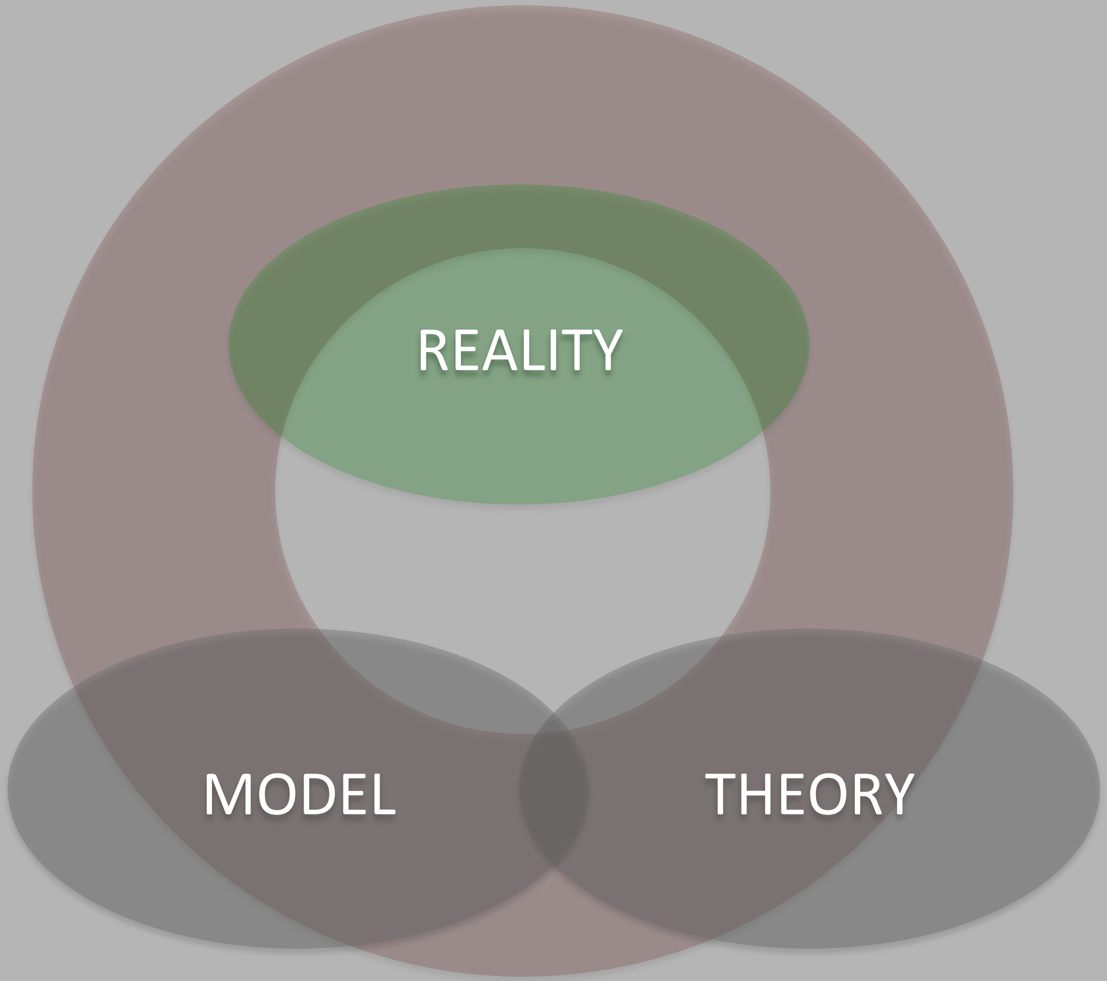


"Spike“ Communication across dynamic links (synapses)

Charge integration across cell membrane (neurons)

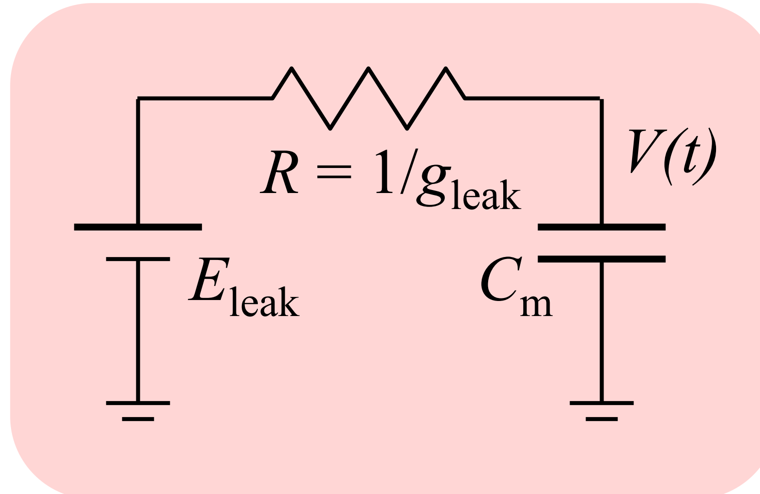


Action Potential = „Spike“


REALITY
MODEL
THEORY

From Ions to Abstraction to Electrons : Theoretical Approaches

$$C_m \frac{dV}{dt} = g_{\text{leak}}\left(E_{\text{leak}} - V\right)$$



Hodgkin-Huxley equations

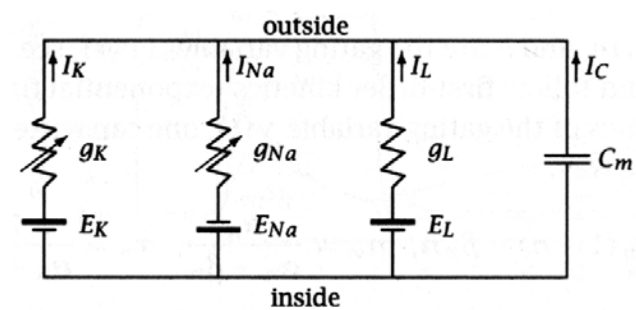
$$C_m \frac{dV}{dt} = -g_L\left(V - V_L\right) - \bar{g}_{Na} m^3 h\left(V - V_{Na}\right) - \bar{g}_K n^4\left(V - V_K\right)$$

$$\frac{dm}{dt} = \alpha_m(V)(1-m) - \beta_m(V)m$$

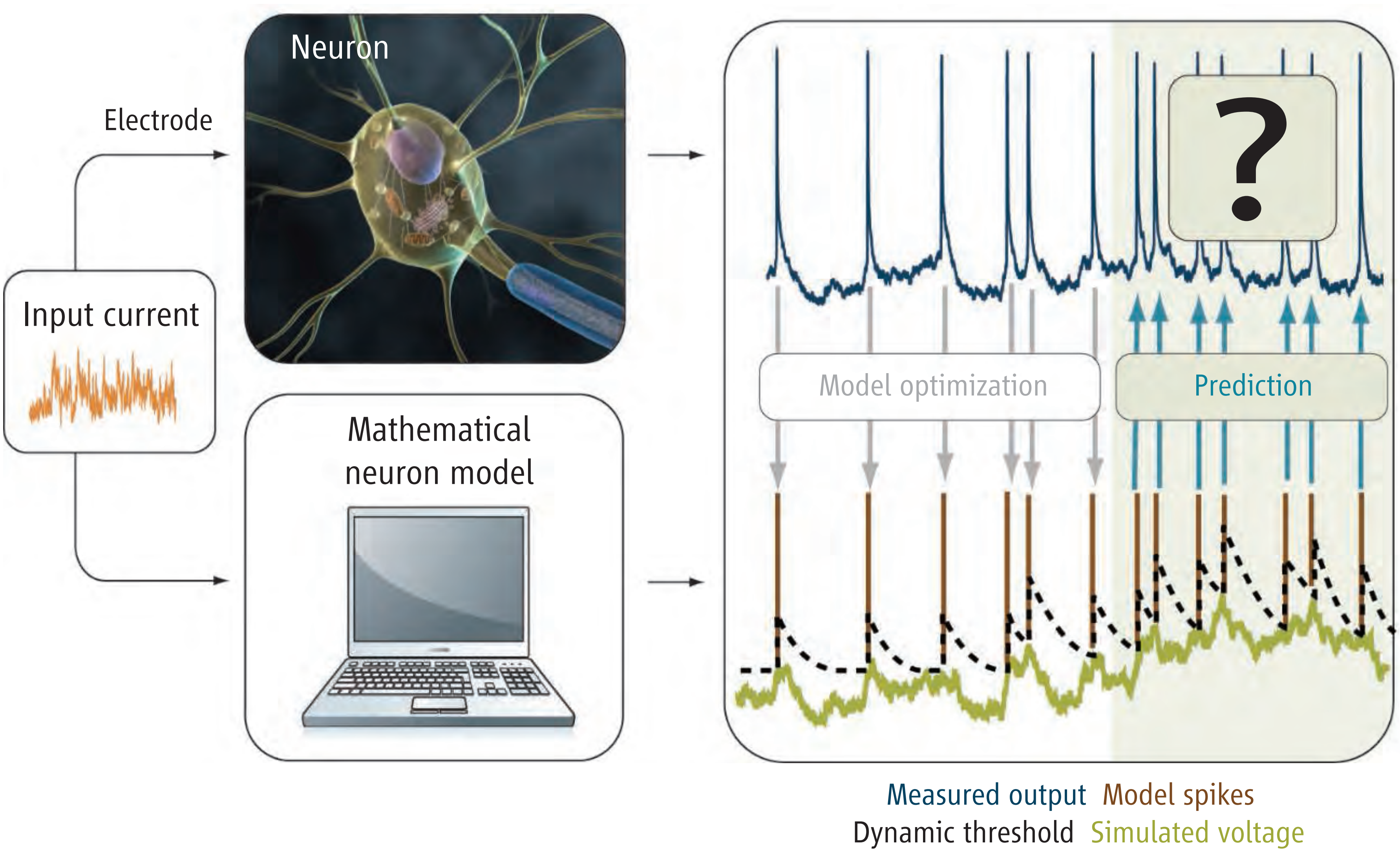
$$\frac{dh}{dt} = \alpha_h(V)(1-h) - \beta_h(V)h$$

$$\frac{dn}{dt} = \alpha_n(V)(1-n) - \beta_n(V)n$$

Hodgkin-Huxley model

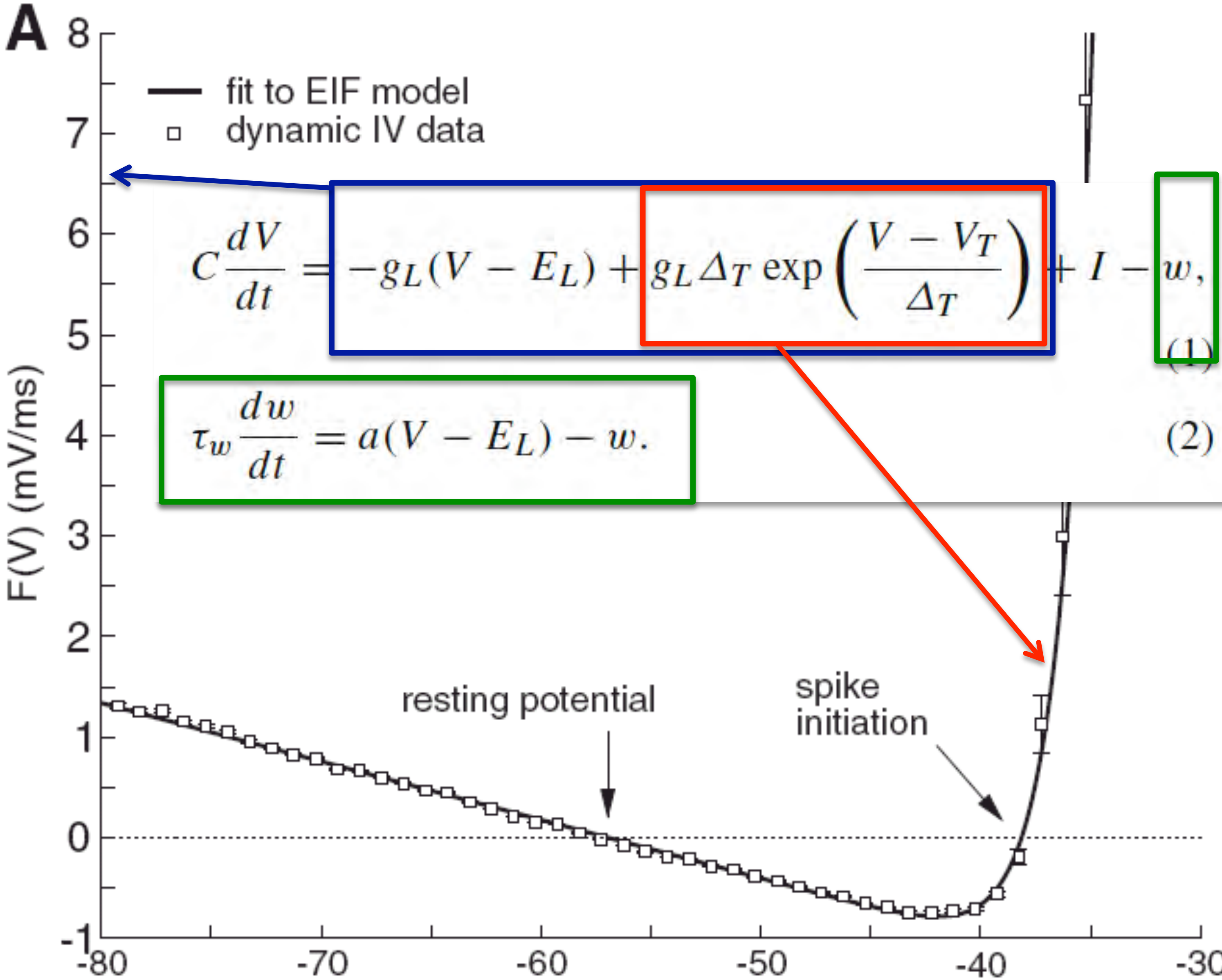


Developing and Tuning Neuron Models – From Ions to Mathematics



Gerstner et al. Science 326 (2009) 379 + references therein

Adaptive-Exponential Integrate-and-Fire Neuron Model



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

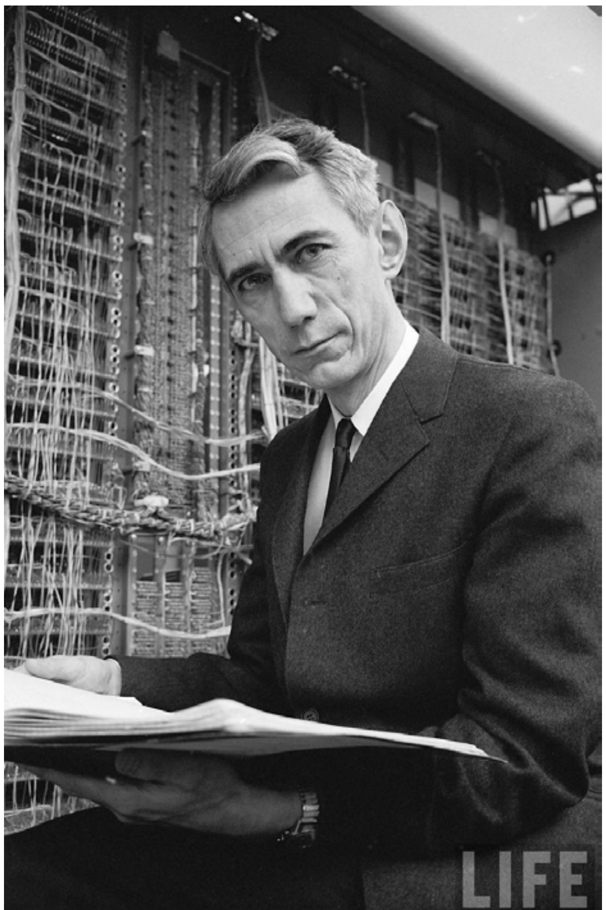
$$\tau_w \frac{dw}{dt} = a(V - E_L) - w. \quad (2)$$

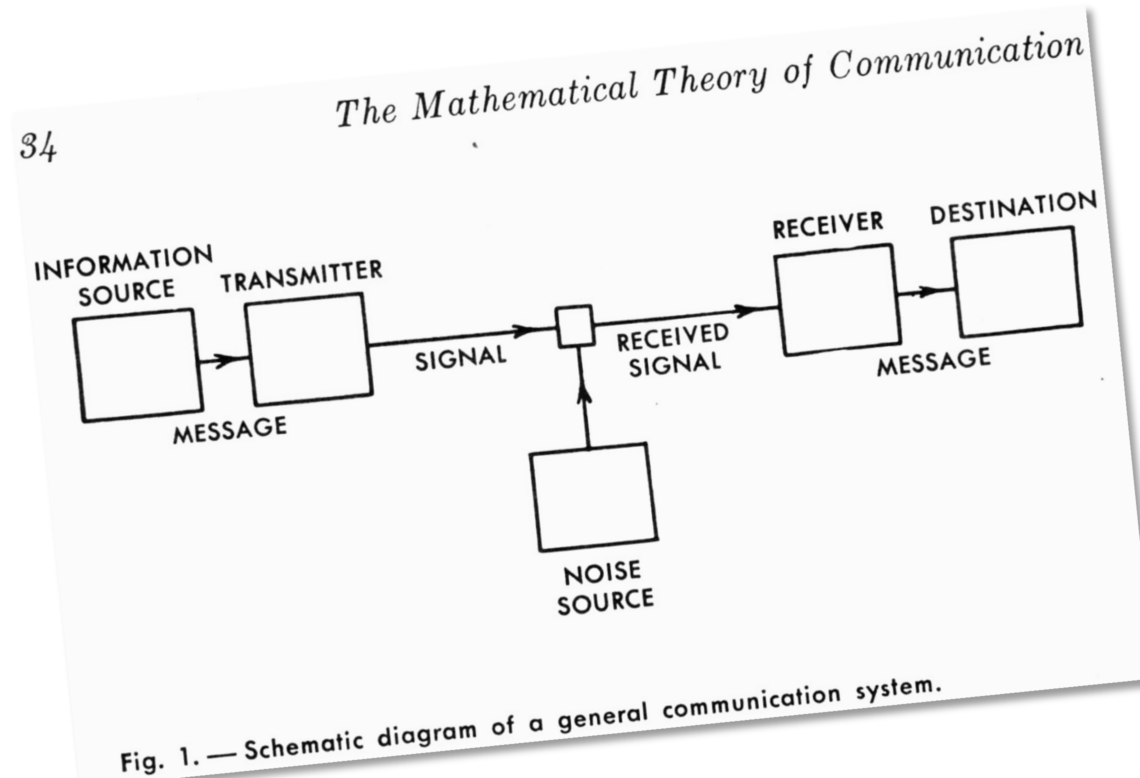
R. Naud et al., Biol Cybern (2008) 99:335–347

www.facets-project.org

Claude Shannon 1951 : What is Information ?

$$I(w_x) = -\log_a(w_x)$$





Habe nun, ach! Philosophie,
Juristerei und Medizin,
Und leider auch Theologie
Durchaus studiert, mit heißem Bemühn.
Da steh ich nun, ich armer Tor!
Und bin so klug als wie zuvor;
Heiße Magister, heiße Doktor gar
Und ziehe schon an die zehen Jahr
Herauf, herab und quer und krumm
Meine Schüler an der Nase herum-
Und sehe, daß wir nichts wissen können!
Das will mir schier das Herz verbrennen.

Ah! Now I've done Philosophy,
I've finished Law and Medicine,
And sadly even Theology:
Taken fierce pains, from end to end.
Now here I am, a fool for sure!
No wiser than I was before:
Master, Doctor's what they call me,
And I've been ten years, already,
Crosswise, arcing, to and fro,
Leading my students by the nose,
And see that we can know - nothing!
It almost sets my heart burning.

Habe nun, ach! Philosophie,
Juristerei und Medizin,
Und leider auch Theologie
Durchaus studiert, mit heißem Bemühn.
Da steh ich nun, ich armer Tor!
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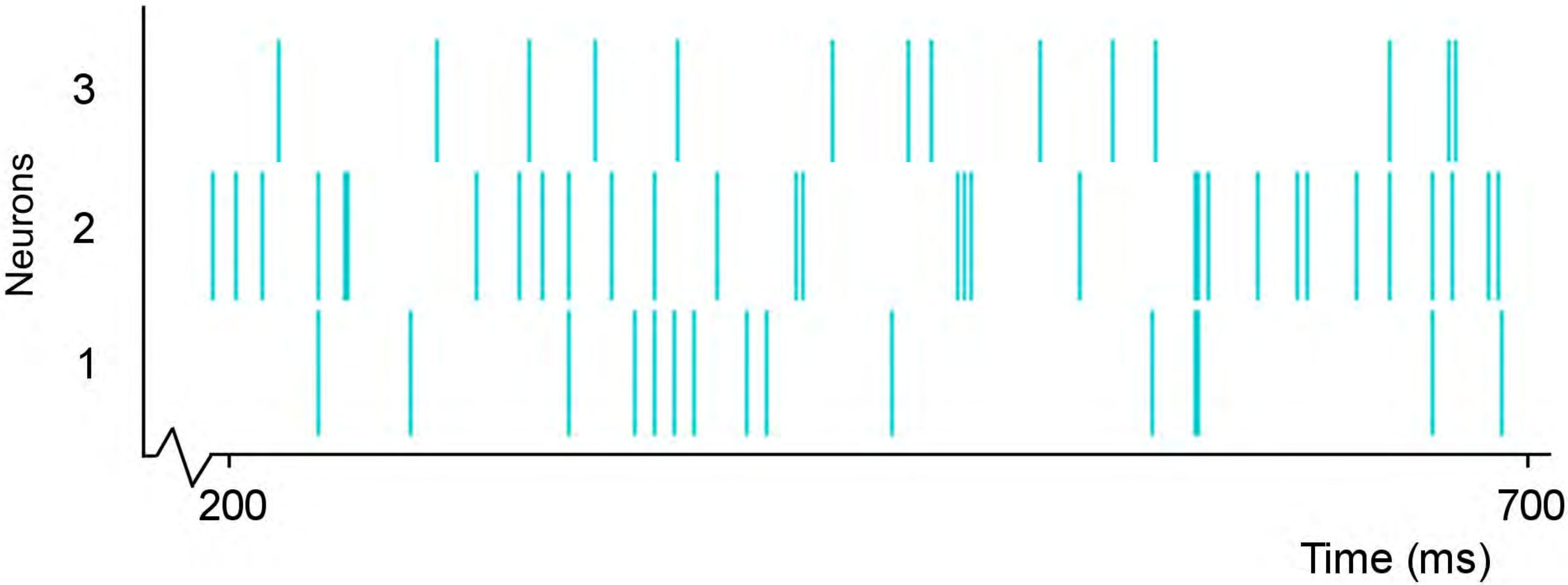
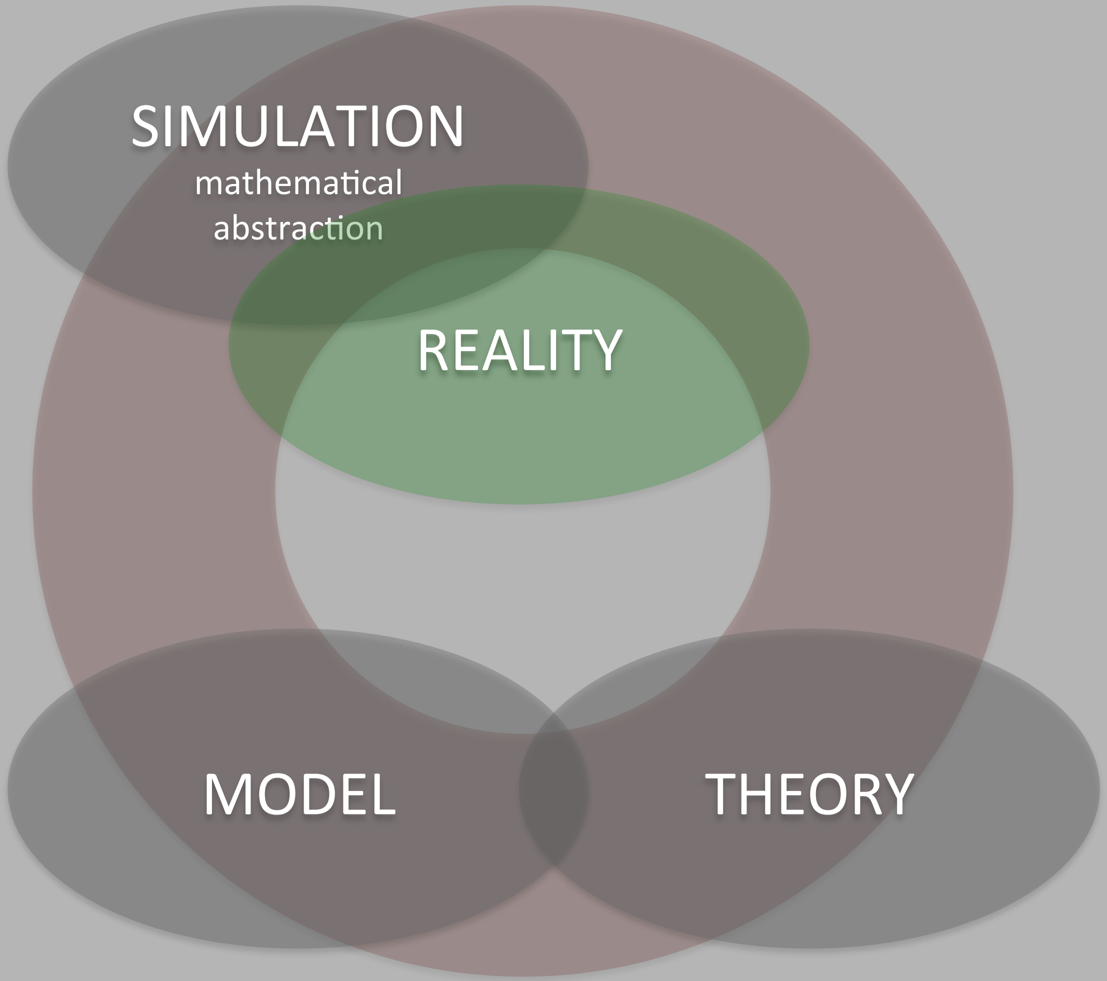
Meine Schüler an der Nase herum-
Und sehe, daß wir nichts wissen können!
Das will mir schier das Herz verbrennen.

$I_{Shannon}(B,b) = 5.79$ bits



$I_{shannon}(\text{spike}, 50\text{Hz}, \partial t=1\text{ms}) = 5.79 \text{ bits}$


SIMULATION
mathematical
abstraction
REALITY
MODEL
THEORY

Simulation (U Zürich)

M 74

Biology and Computer Simulation

BlueBrain Projekt, H. Markram, EPFL

Cortical Column – 10.000 Neurons
0.000003 Watt
100.000 Watt

Mouse Brain – 100.000.000 Neurons
0.03 Watt
1.000.000.000 Watt

Human Brain – 100.000.000.000 Neurons
30 Watt
1.000.000.000.000 Watt

Installed in Germany (2010) : 170.000.000.000 Watt

AND : 100 to 1000 times slower than biology

How much does a Neural Computation „cost“ ?
A rough (and incomplete) estimate of 2 contributions

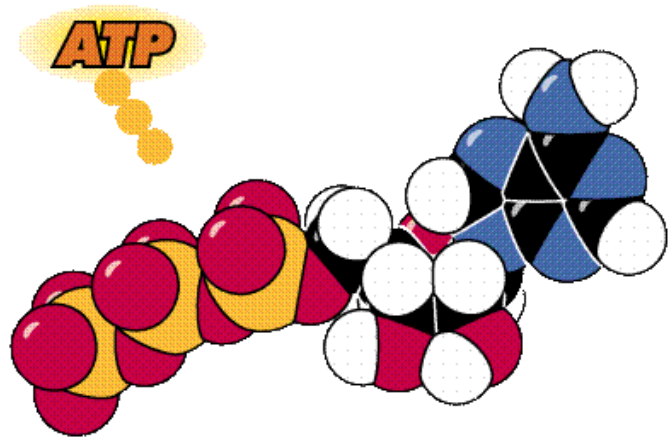
Approx. 10^9 ATP molecules to be hydrolyzed for action potential

Approx. 10^5 ATP molecules to be hydrolyzed for synaptic transmission

D. Attwell and S. B. Laughlin

Obtain 10^{-19} Joule per ATP molecule

Bray, Dennis. Cell Movements. New York: Garland, 1992



10^{-10} Joule (100.000 fJ = 0.1 nJ) per action potential

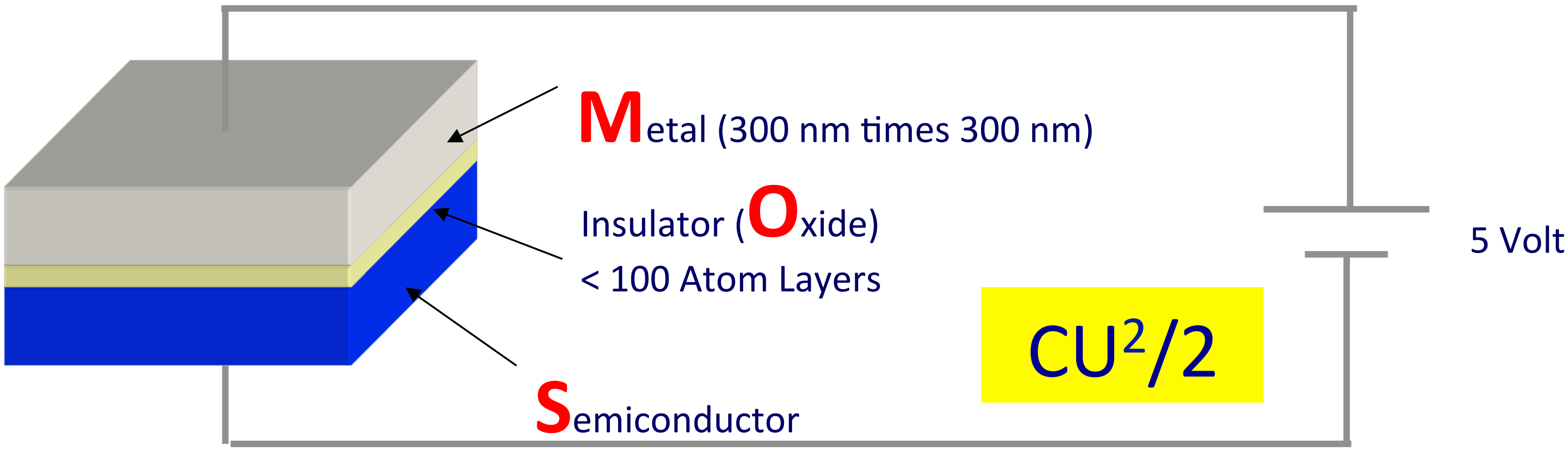
10^{-14} Joule (10 fJ) per synaptic transmission

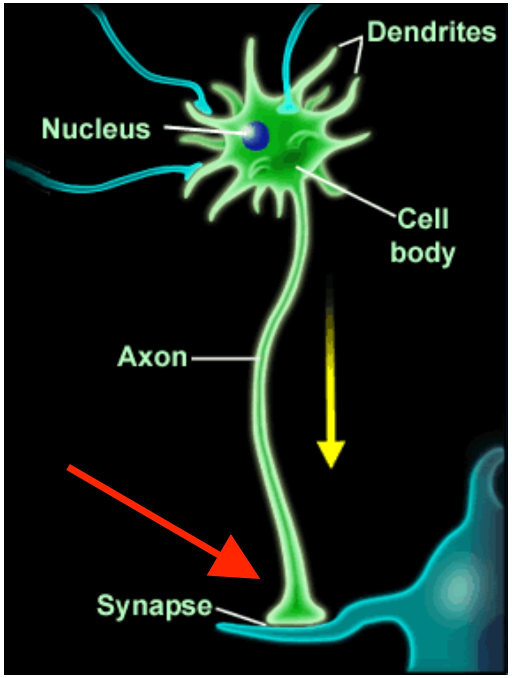
100 Billion neurons firing at 1 Hz : 10 J / s = 10 W

10^{15} Synapses transmitting at 1 Hz : 10 J / s = 10 W

SMALL, even realistic numbers

Electronics vs. Biology on the device level - Not a big difference !



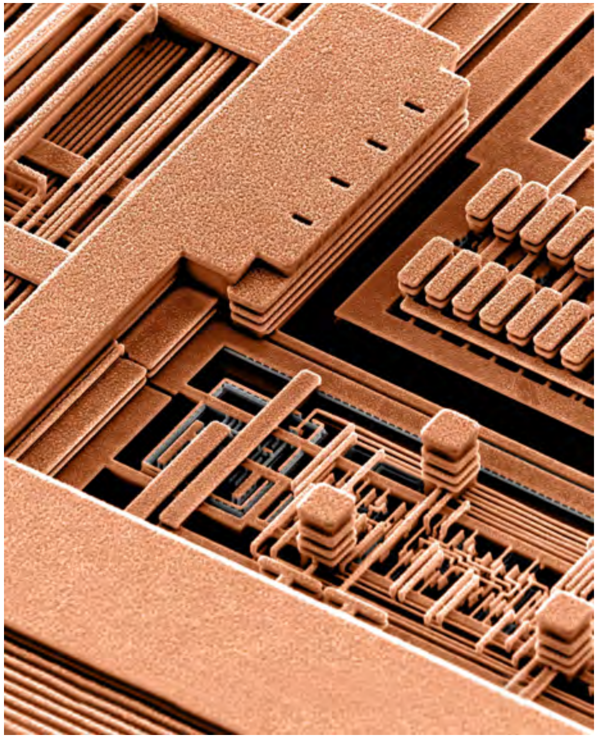


„Charging" of a MOS element : approximately 1 fJ (much less today)

Synaptic Transmission : approximately 10 fJ

„10 low-tech Transistors"

The communication problem



IBM G5 Processor

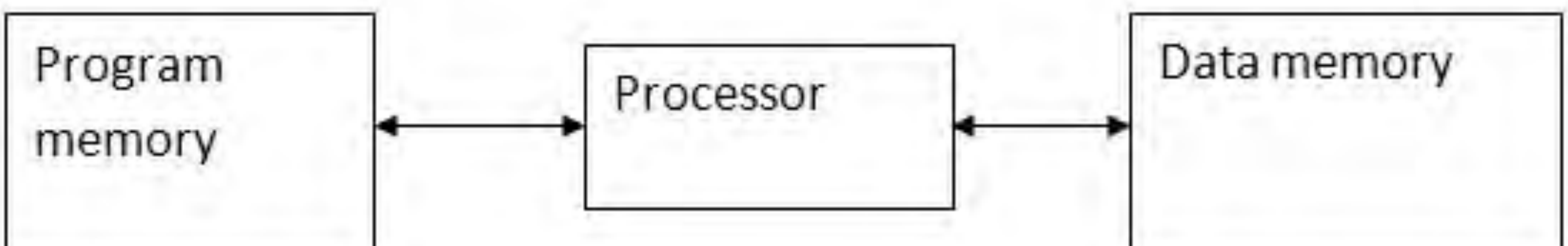
(almost) twodimensional system of „connecting wires“

Spend typically 1000 times more energy in wires compared to transistors (as long as leakage currents are still small)

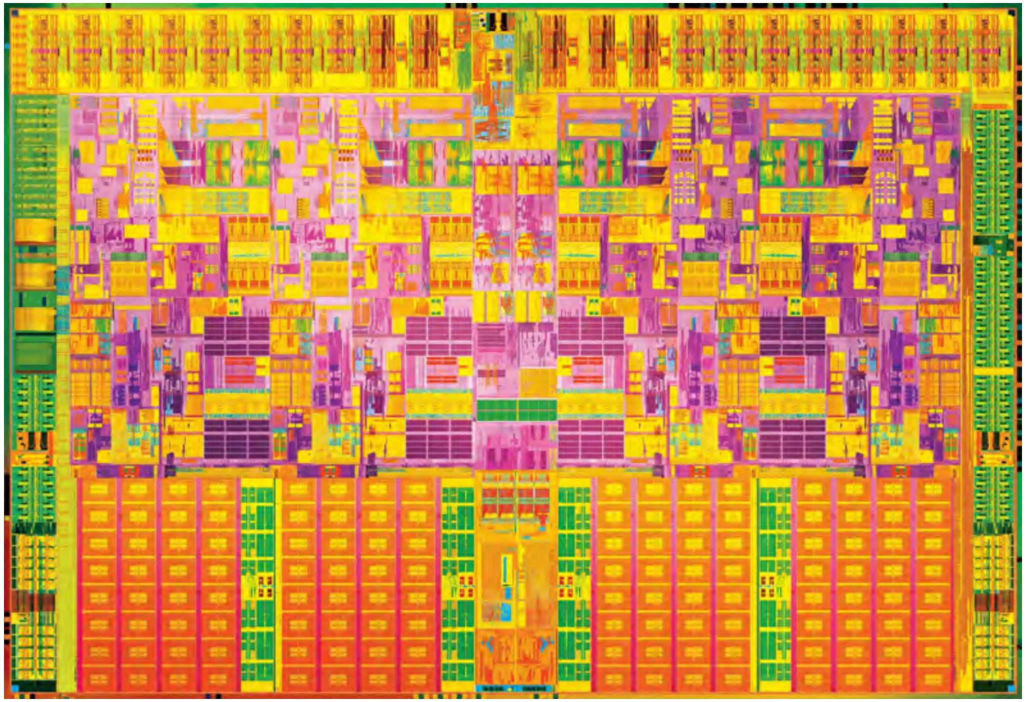
Energy Problem

Use this network to transport information

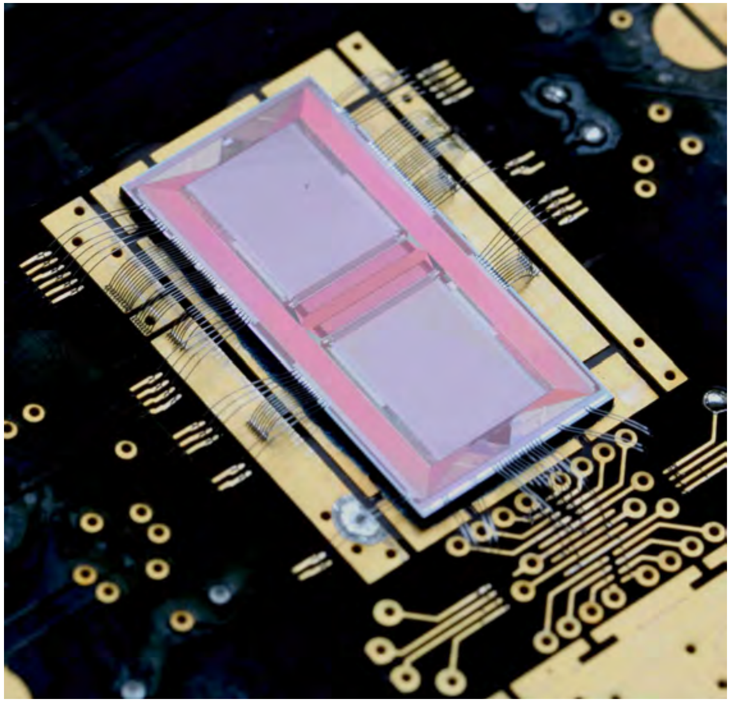
Architecture Problem



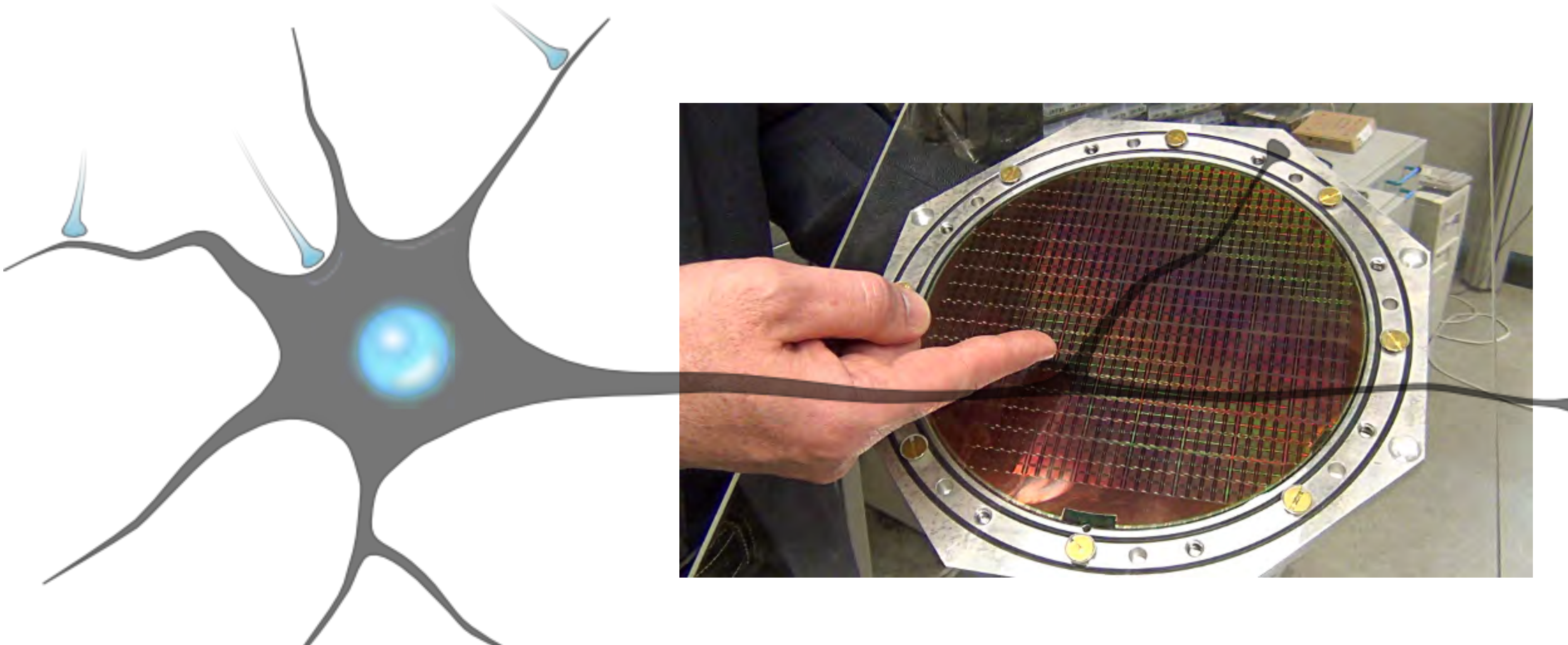
The Brain, Computers and Bottom-up Synthesis



The Brain in a Computer ?



Computers like Brains ?



Neural Cell = Entity on Silicon Substrate

No global Synchronization

Continuous Time

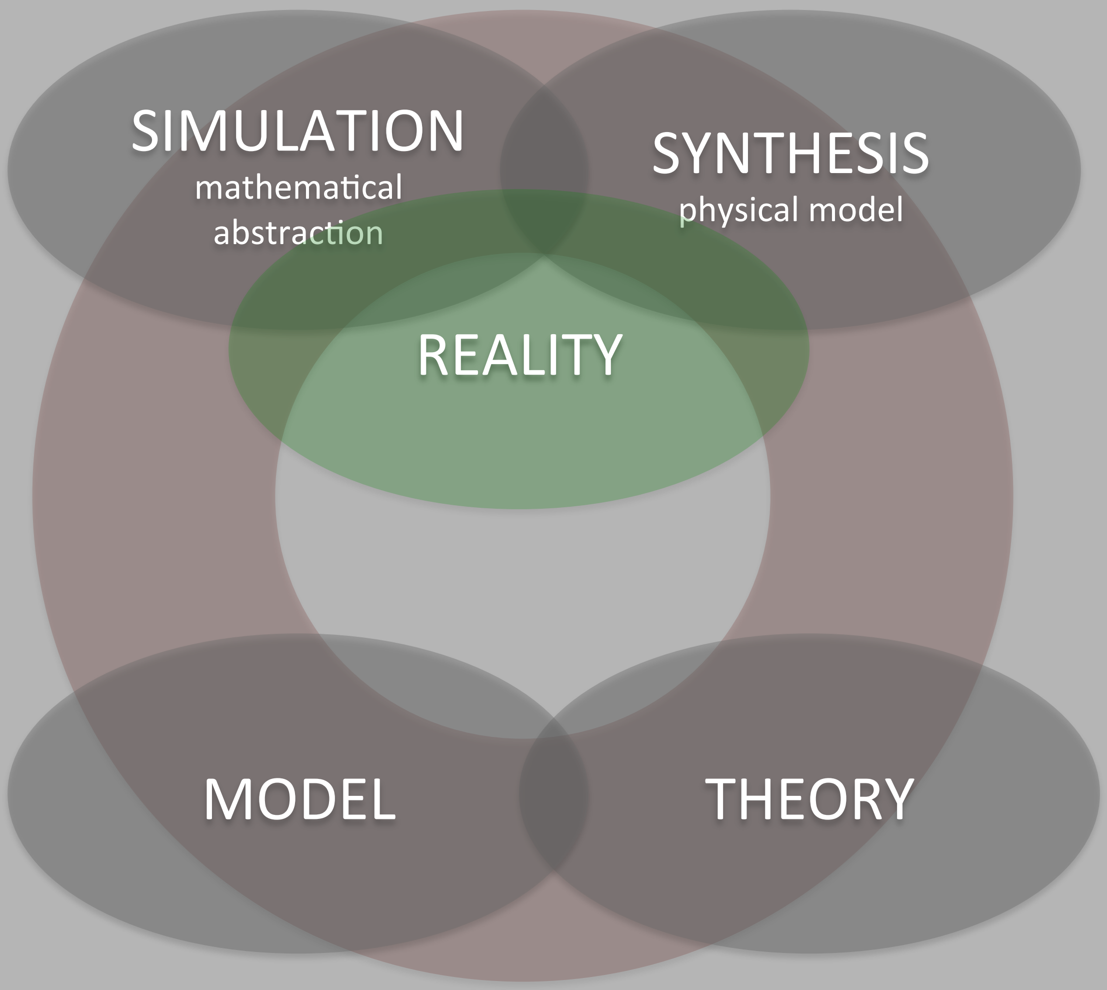
Neuromorphic Computing

Why …… ?

Neuromorphic Systems should be …

Low Power	solving the energy problem
Fault Tolerant	solving the reliability problem
Self Organized	solving the software problem
Fast	solving the simulation time problem
Compact	solving the size problem

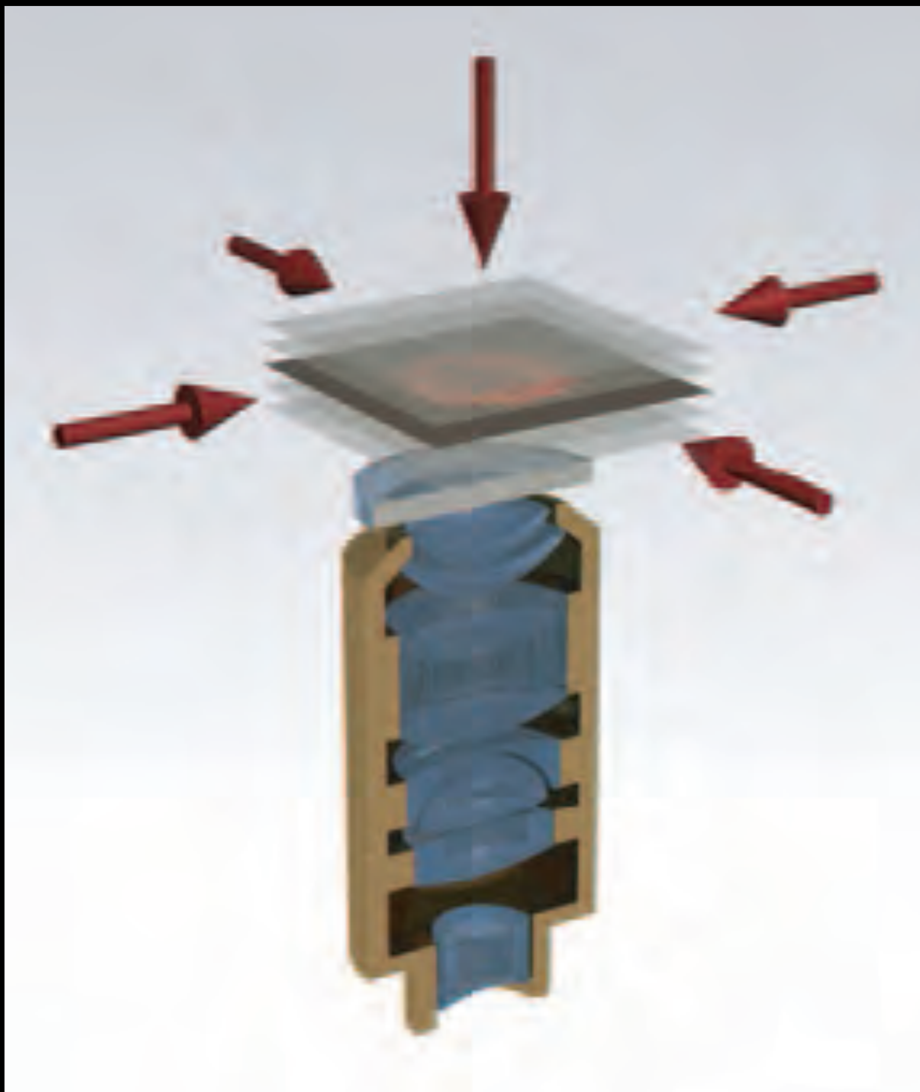
….. of traditional computing


SIMULATION
mathematical
abstraction
SYNTHESIS
physical model
REALITY
MODEL
THEORY

Joseph Wright of Derby
"A Philosopher giving that Lecture on the Orrery, in which a lamp is put in place of the Sun" (1766)

Quantum Emulators – Synthesize what you cannot compute

Bloch, Dalibard, Nascimbène, Nature Physics, Vol. 8, April 2012
Feynman, Int. J. Theor. Phys., Vol. 21, Nos. 6/7, 1982

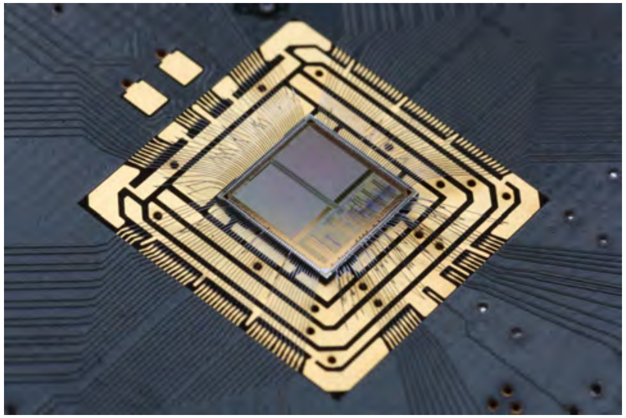


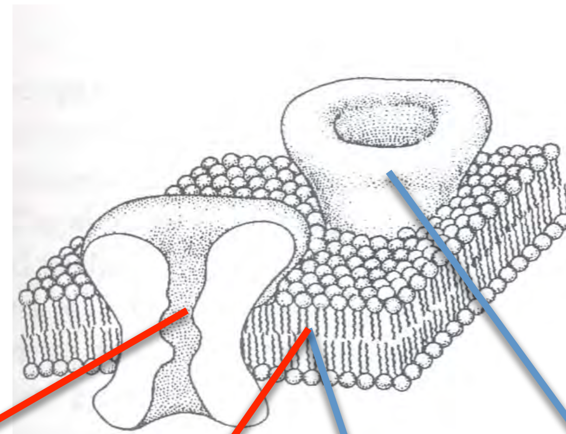
„Ultracold quantum gases offer a unique setting for quantum simulation of interacting many-body systems. The high degree of controllability, the novel detection possibilities and the extreme physical parameter regimes that can be reached in these

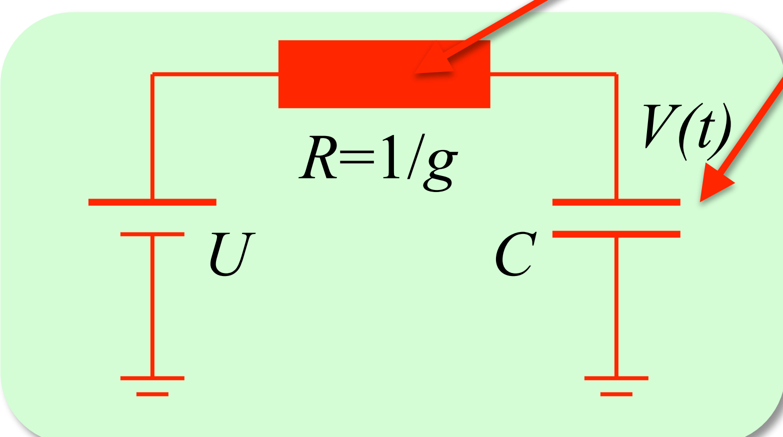
'artificial solids'

provide an exciting complementary set-up compared with natural condensed-matter systems, much in the spirit of Feynman's vision of a quantum simulator"

What is Neuromorphic Computing ?





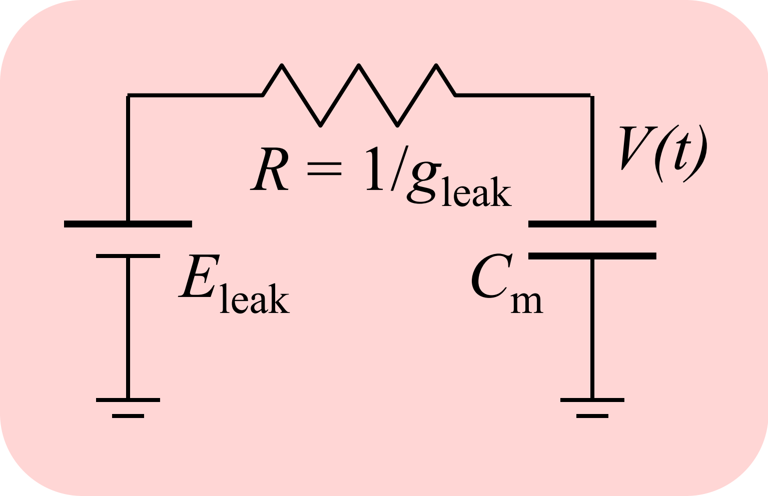


$$C\frac{dV(t)}{dt} = -g\left(V(t) - U\right)$$

A Physical Model rather than a Mathematical Model

Continuous Time Integrating Neural Cell Membrane Model - *Neuromorphic*

$$C_m \frac{dV}{dt} = g_{leak}\left(E_{leak} - V\right)$$



	ΔV [V]	g_{leak} [S]	C_m [F]	$(g\Delta V)/C$ [V/s]
Biology(*)	10^{-2}	10^{-8}	10^{-10}	10^{0}
VLSI	10^{-1}	10^{-6}	10^{-13}	10^{6}

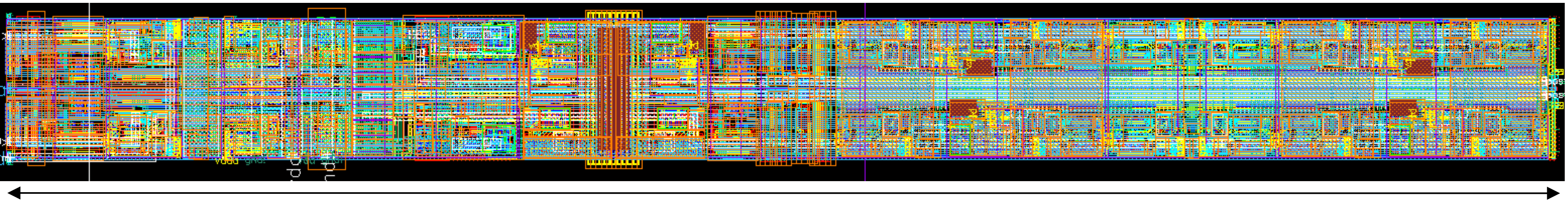
Inherent speed gap:

10^6 Volt/second

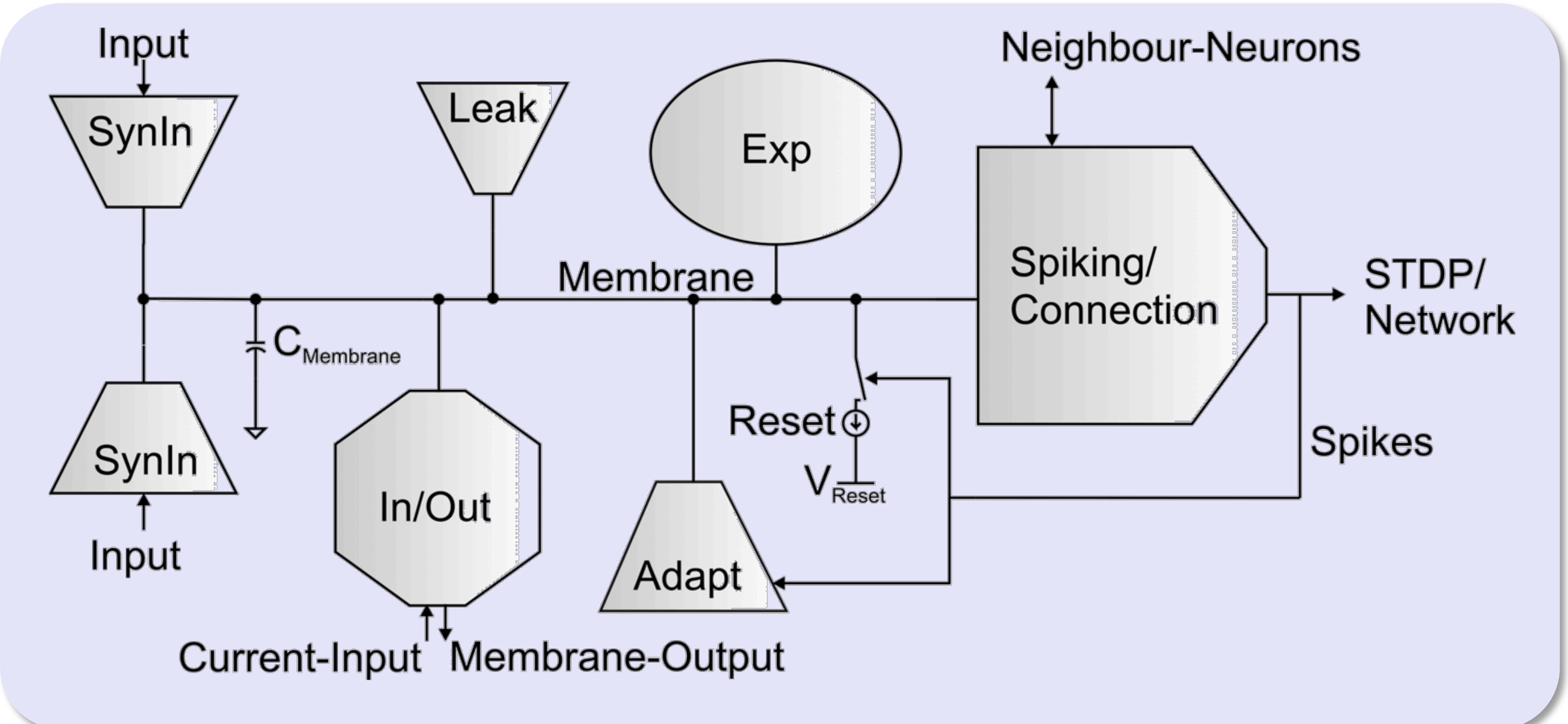
→ accelerated neuron model

(*) Brette/Gerstner, J. Neurophysiology, 2005

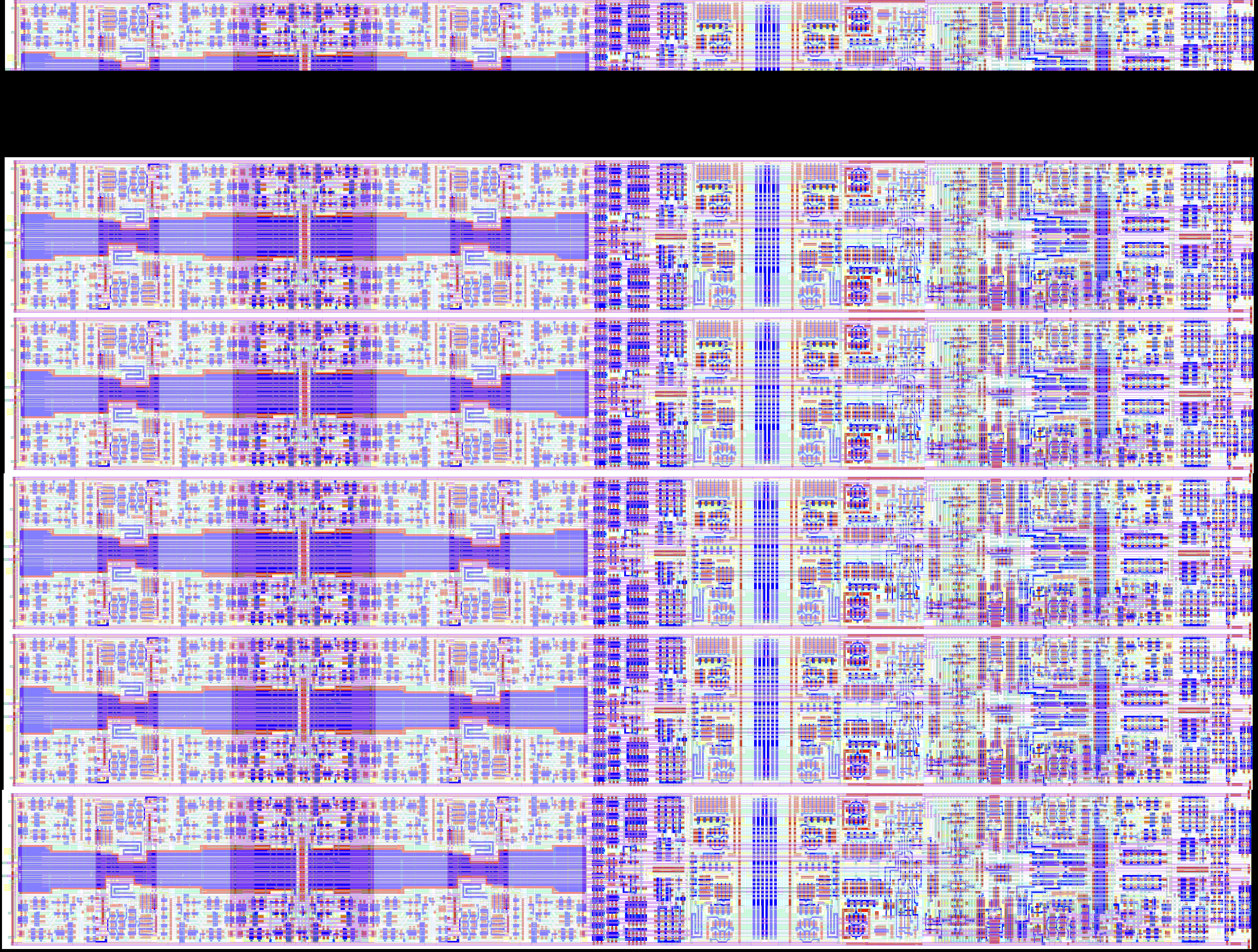
From Mathematics to Electronics

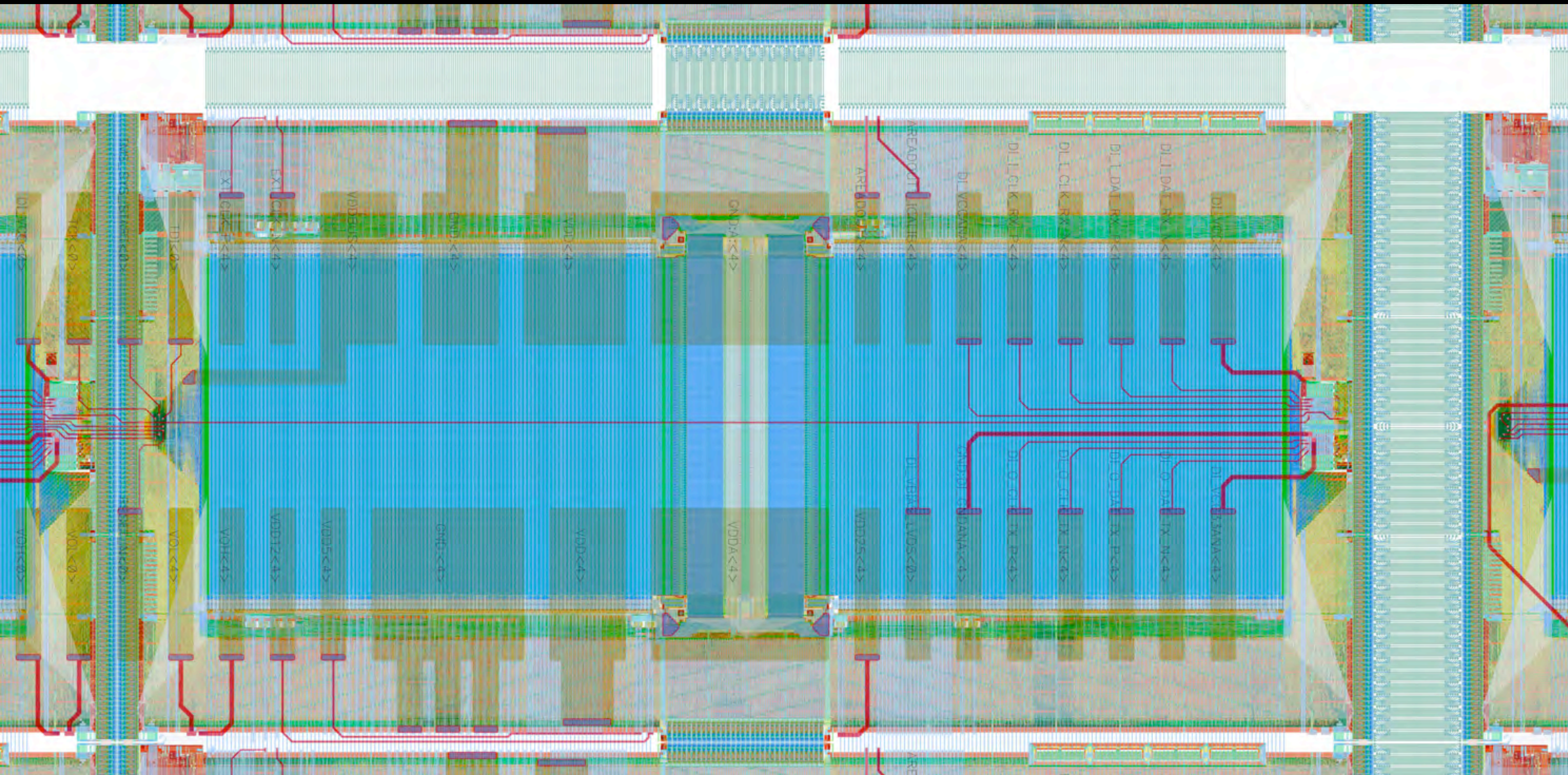


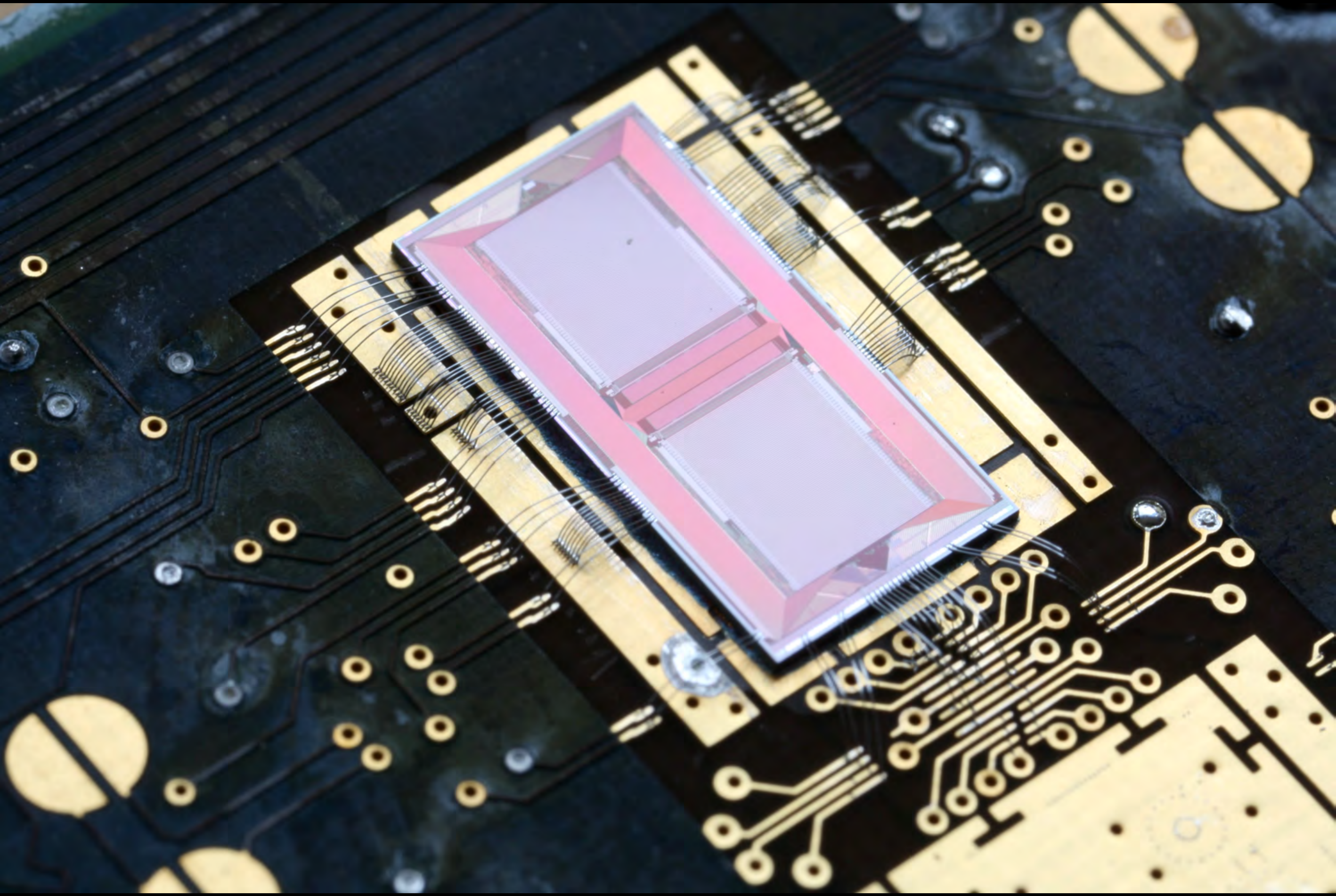
layout drawing of two neurons: 150x20 µm^2

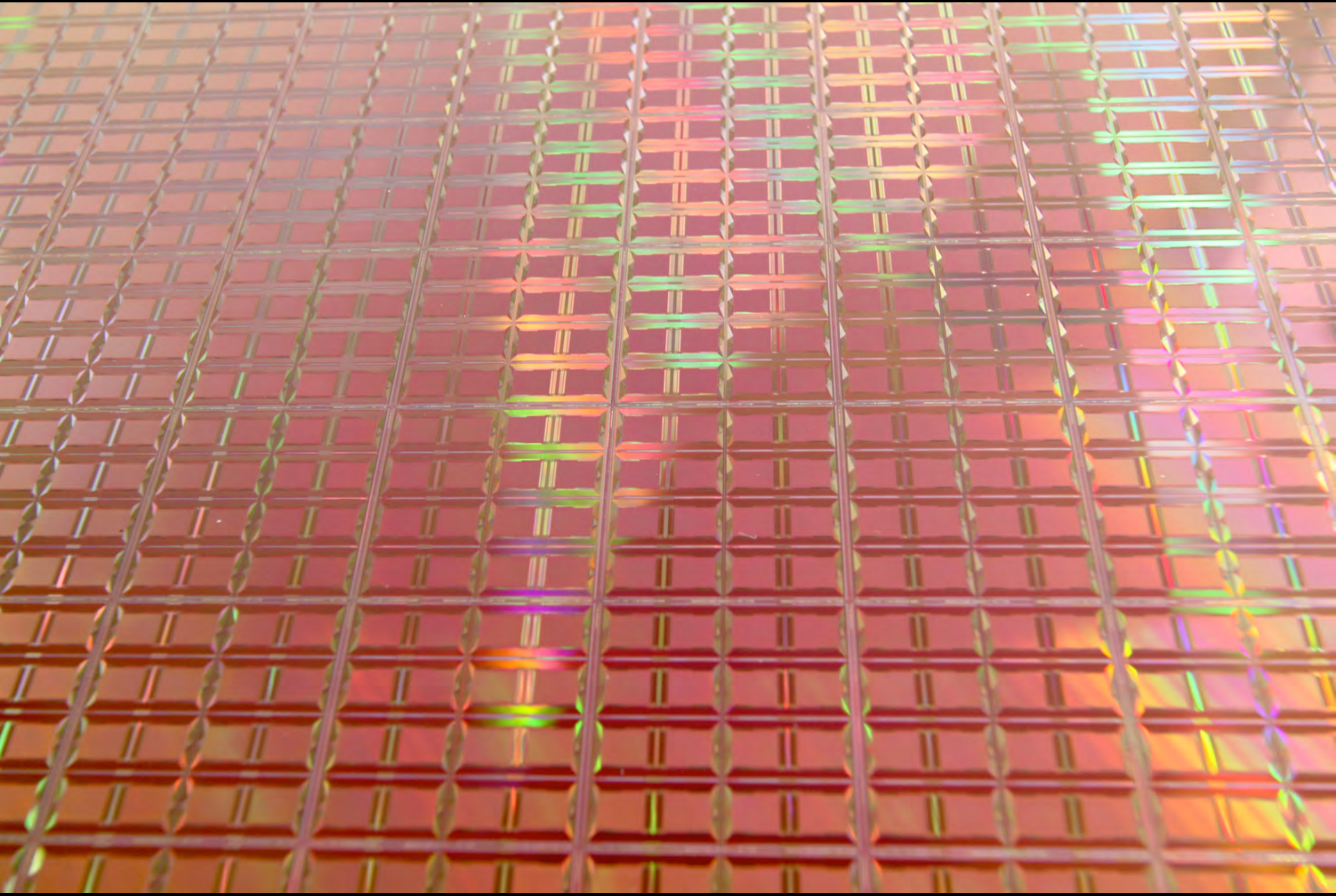


Millner, S., Grübl, A., Meier, K., Schemmel, J., & Schwartz, M. O. (2010). A VLSI implementation of the adaptive exponential integrate-and-fire neuron model. In *Advances in Neural Information Processing Systems* (pp. 1642-1650).

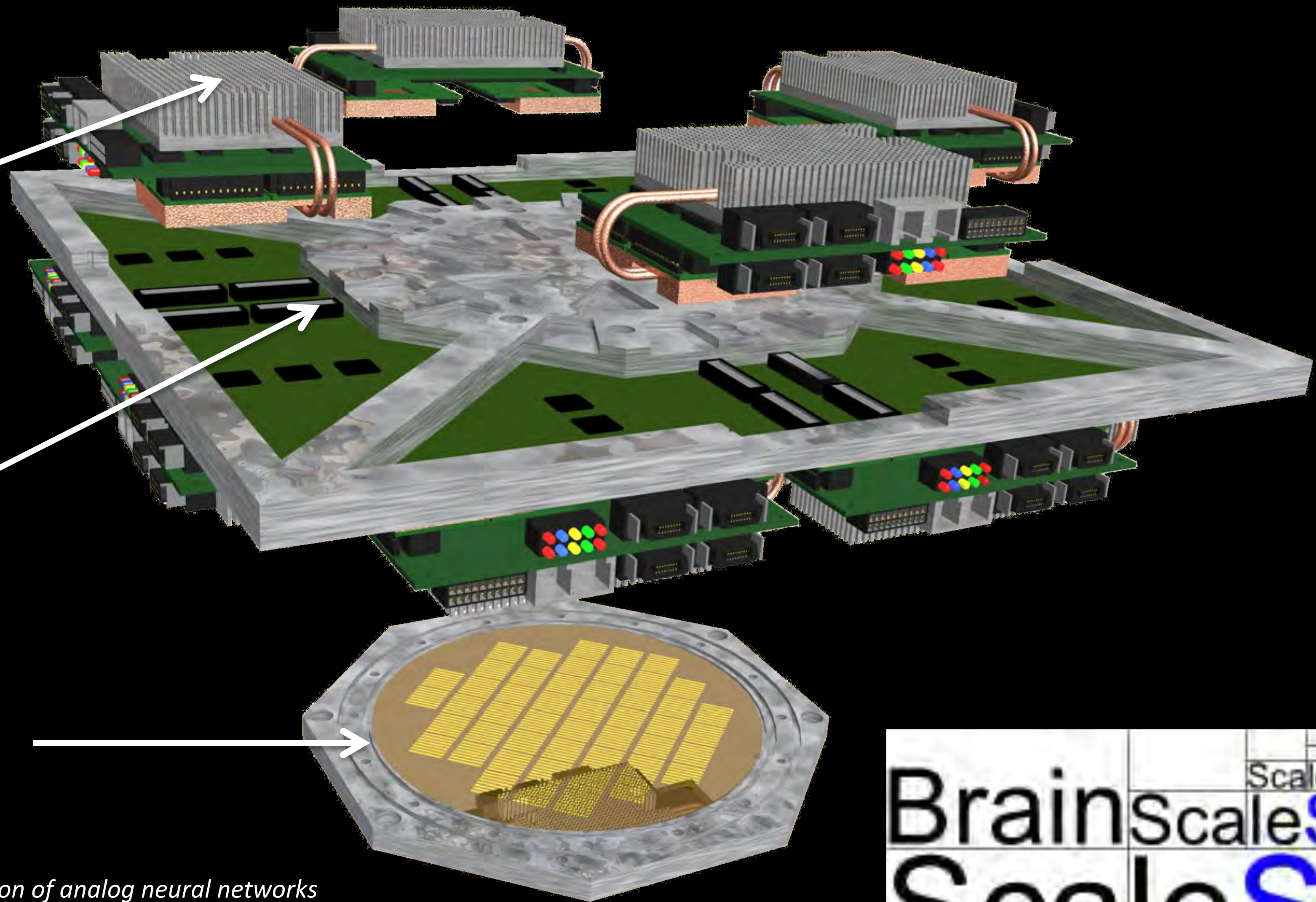






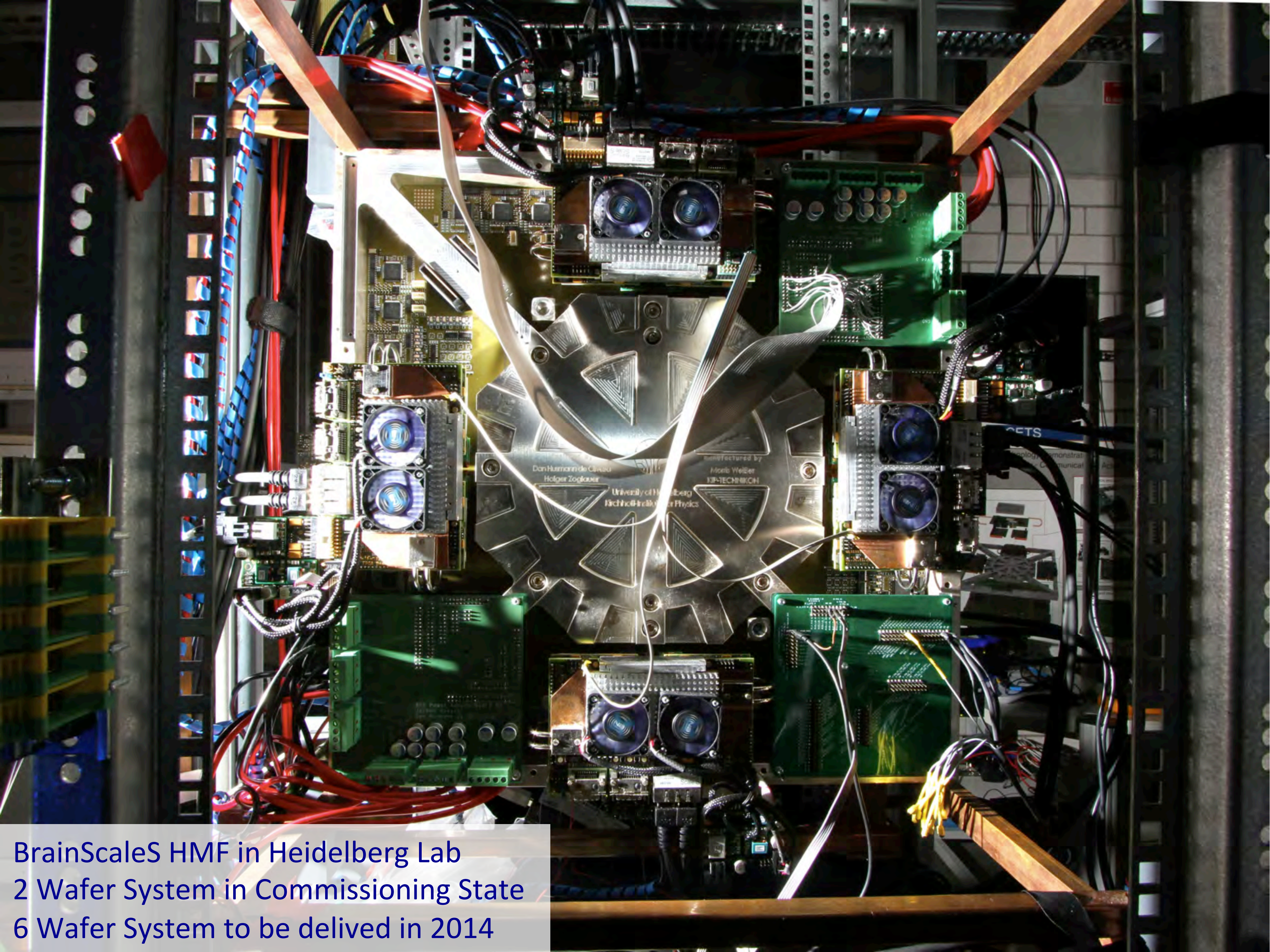


Neural Processing Unit,
up to 200.000 Neurons, 50.000.000 plastic Synapses
Separation of Neural Circuits and Monitoring/Readout/Control



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

BrainScaleS ScaleS



BrainScaleS HMF in Heidelberg Lab
2 Wafer System in Commissioning State
6 Wafer System to be delived in 2014

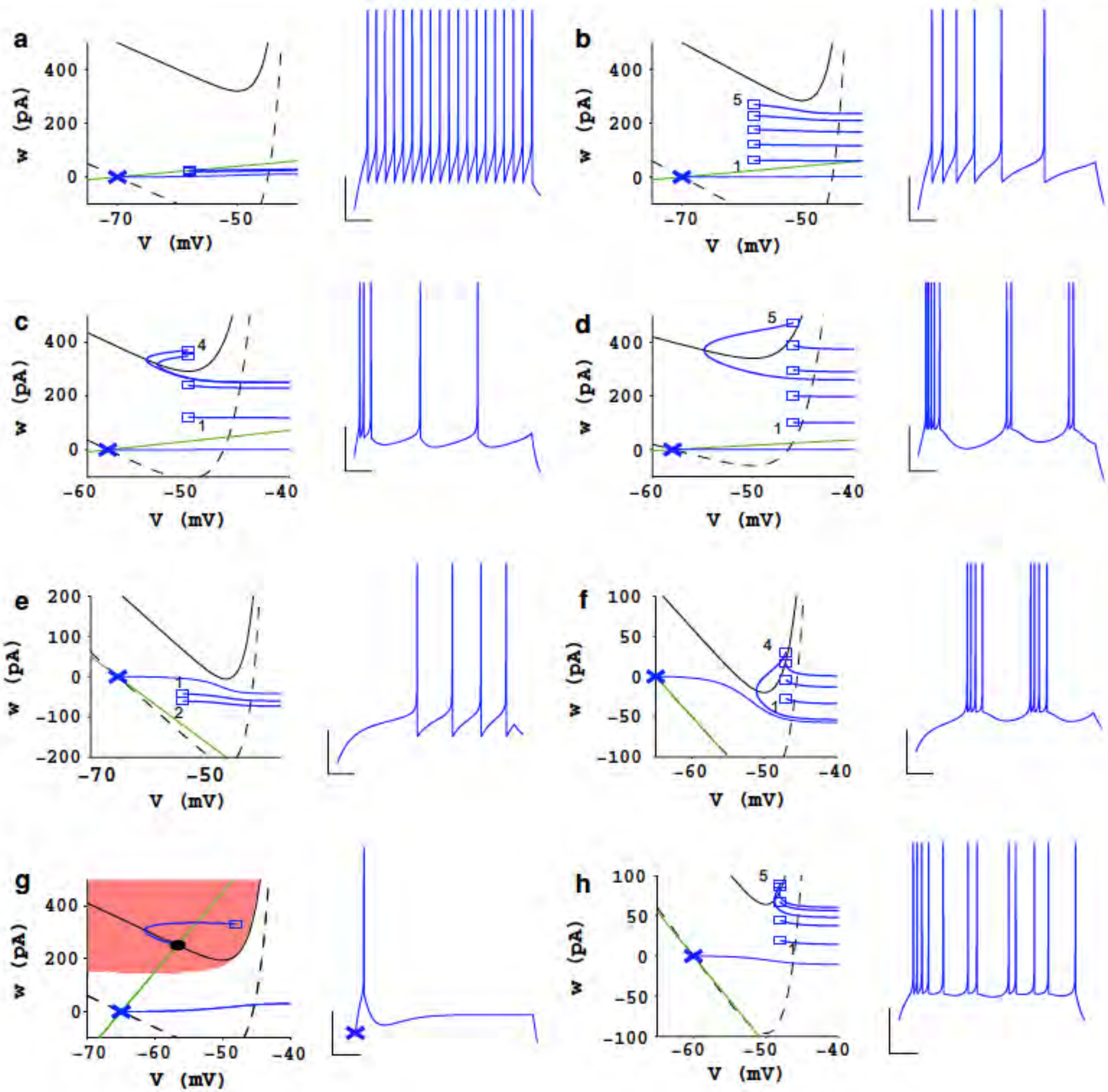
Experiments

I. Basic dynamical properties of isolated cells and circuits
Cell firing patterns, synchronisation, stability, order-chaos

II. Implement and test fundamental, generic concepts and theories
Liquid computing, probabilistic inference, Boltzmann machines

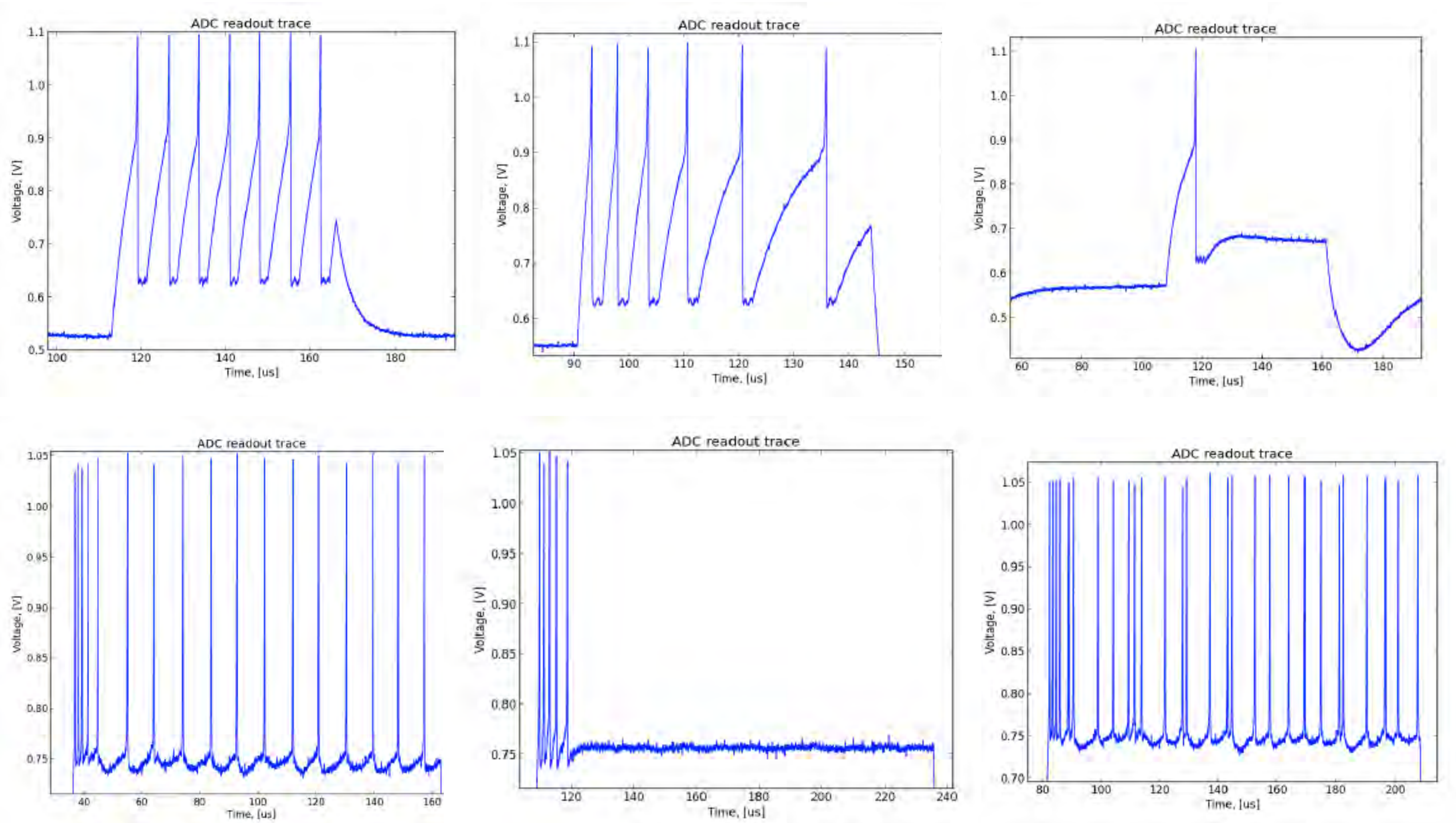
III. Biologically realistic, reverse engineered circuits in closed loops
Small brains, cortical structures, cortical columns, functional units

IV. Generic neuromorphic computing outside neuroscience
Neuromorphic controllers, spatio-temporal pattern detection in data streams, causal relations in big data, approximate computing



Expected single cell firing patterns in the 2D phase-space (w,V)

Naud, R., Marcille, N., Clopath, C., & Gerstner, W. (2008). Firing patterns in the adaptive exponential integrate-and-fire model. *Biological cybernetics*, *99*(4-5), 335-347.



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

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.

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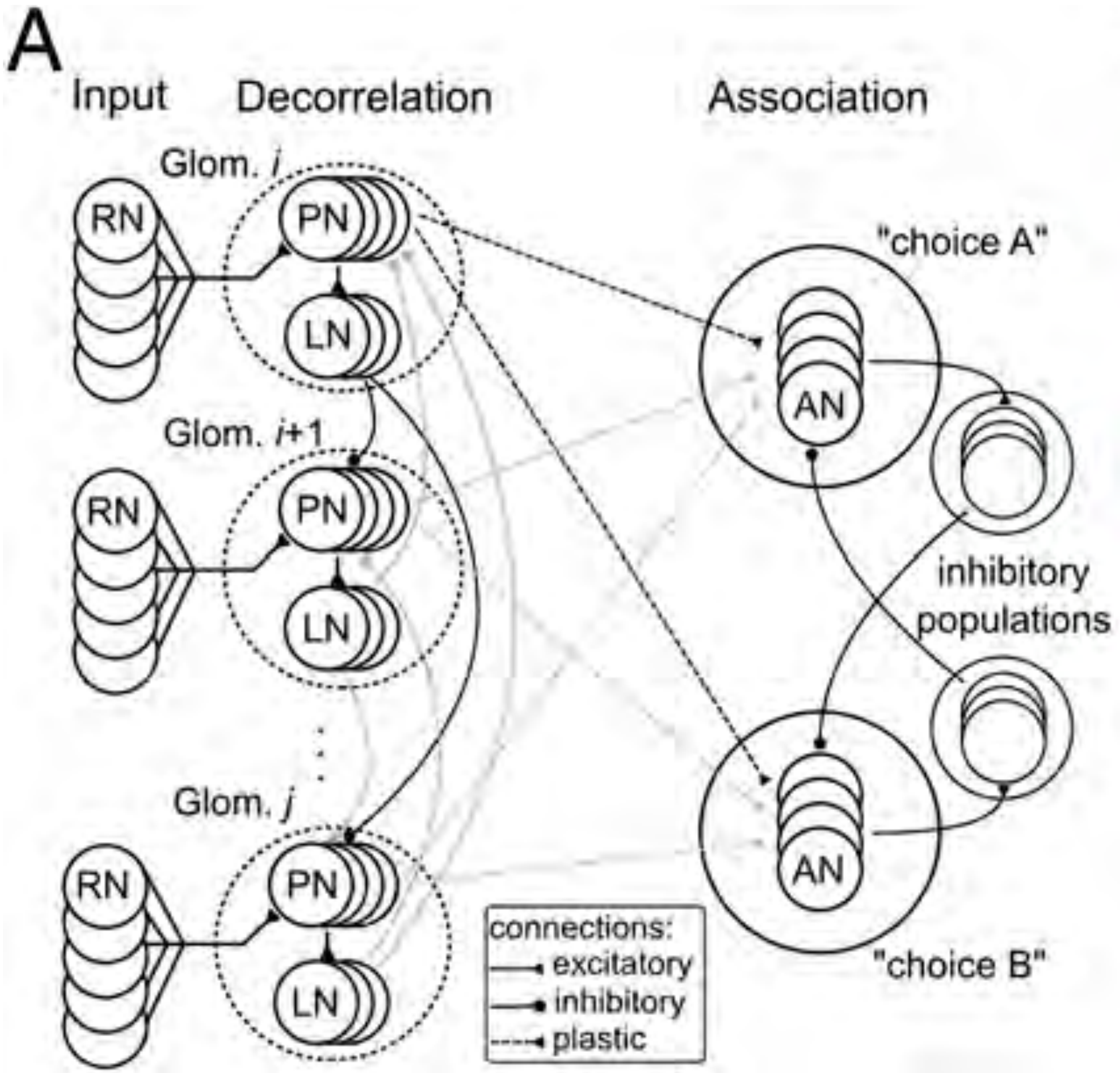


3 Layer Spiking Neuron Network derived from Insect Olfactory System

L I : Receptor Neurons

L II : Decorrelation through lateral inhibition (Glomeruli)

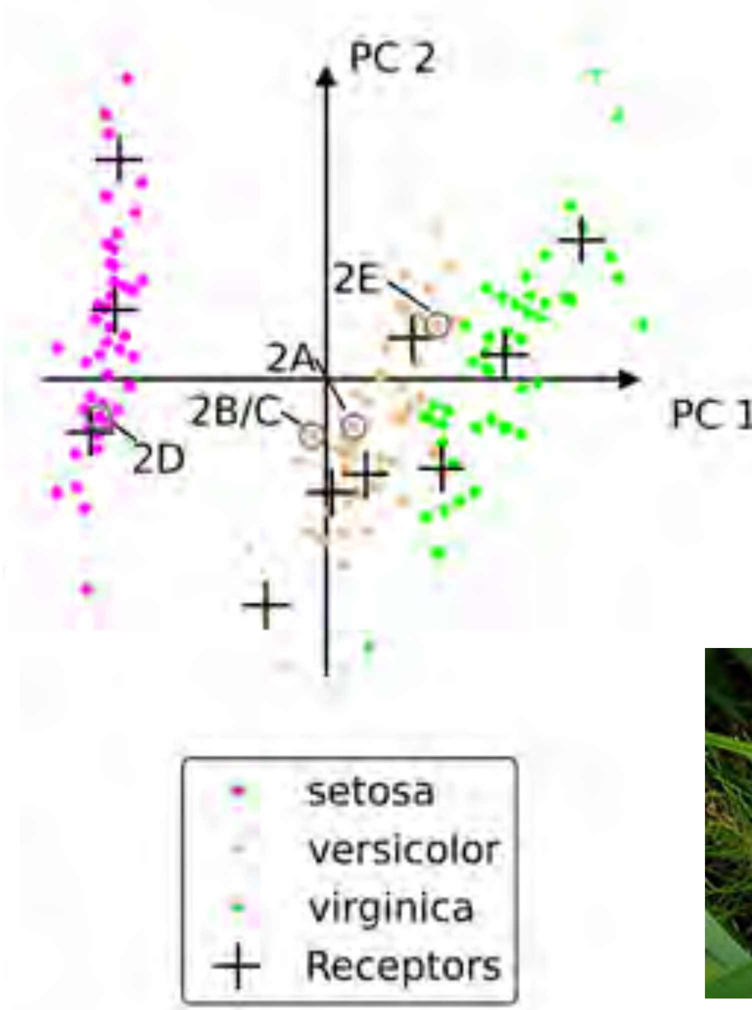
L III : Association (Soft WTA through strong inhibitory populatuions)

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.

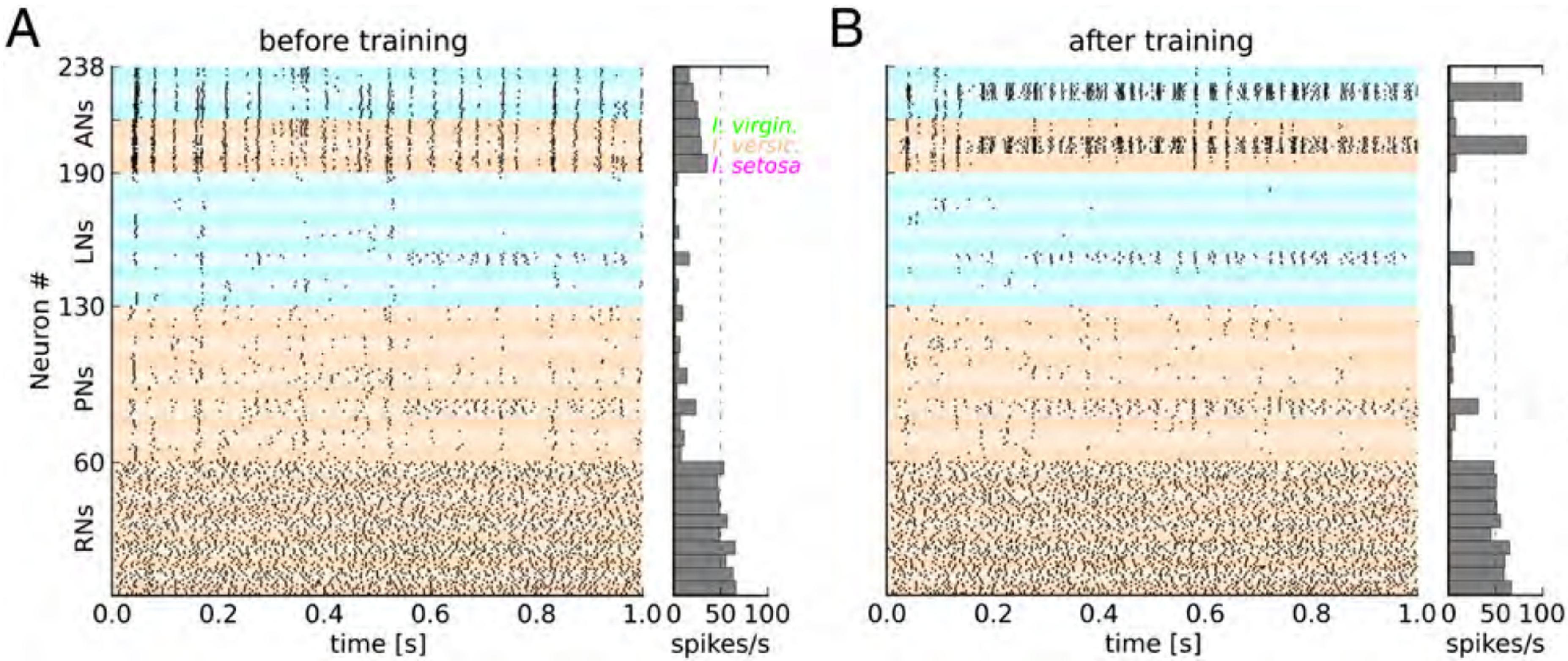
Iris Dataset, First 2 Principal Components



Placement of „Virtual Receptors (VR)“

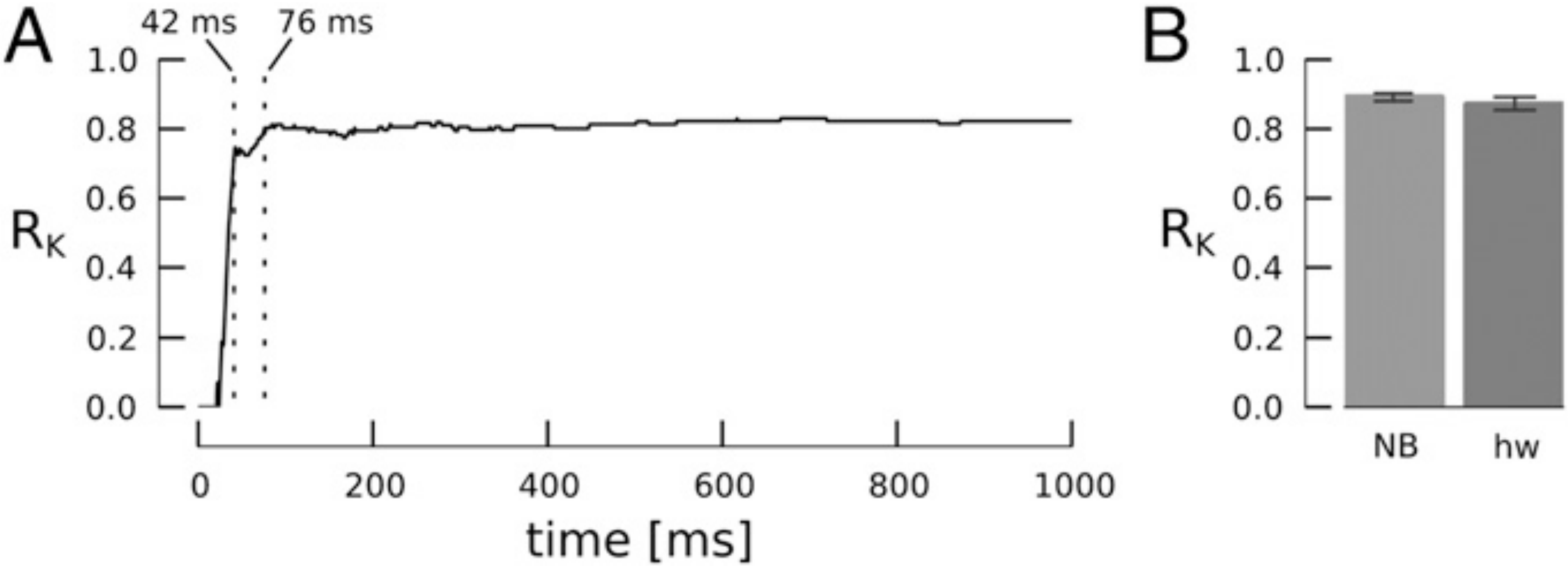
Schmuker, Michael, Thomas Pfeil, and Martin Paul Nawrot. "A neuromorphic network for generic multivariate data classification." *Proceedings of the National Academy of Sciences* (2014): 201303053.

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



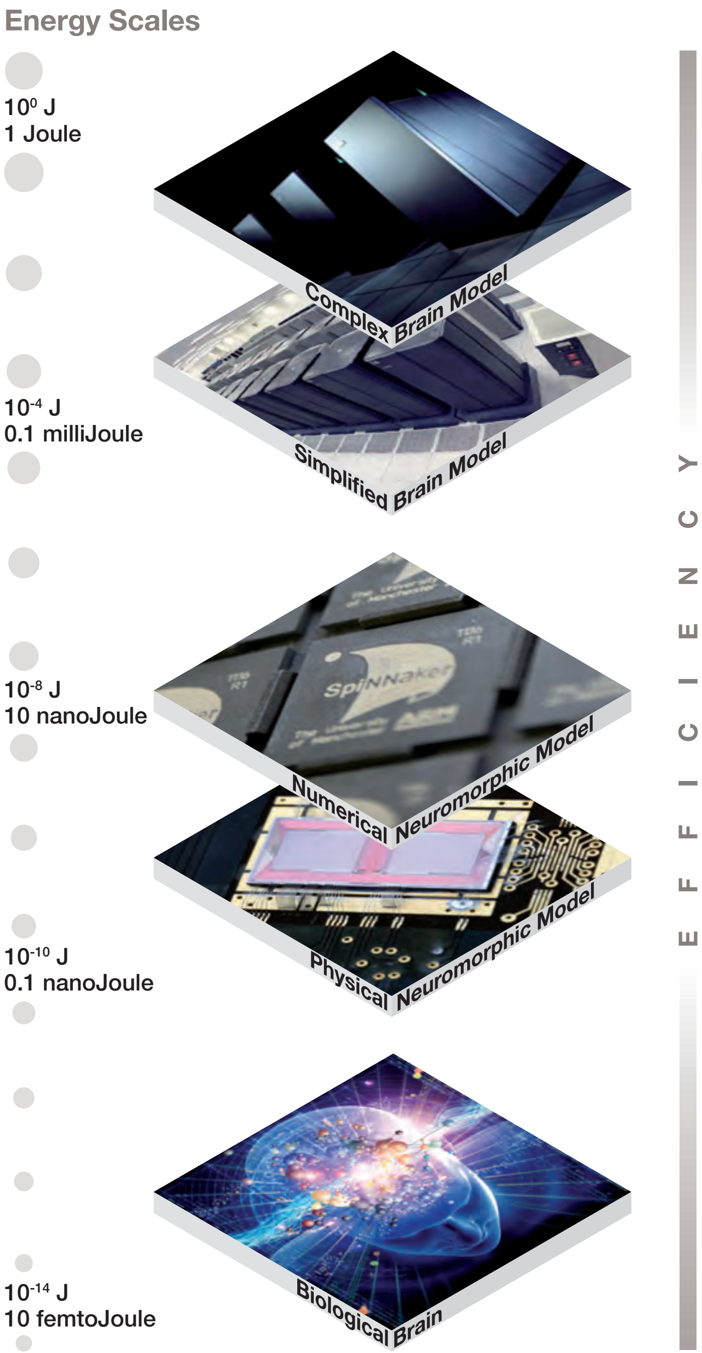
Boring ?

Probably .....

What is (are) the Holy Grail(s) of Neuromorphic Computing ?

- Using faulty, diverse Devices
- Real-World Applications outside Biology
- Use Learning and Plasticity
- Energy efficiency

  Simulation Speed



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

TimeScales	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

2011 EDITION : EMERGING RESEARCH DEVICES, Chapter 5.3

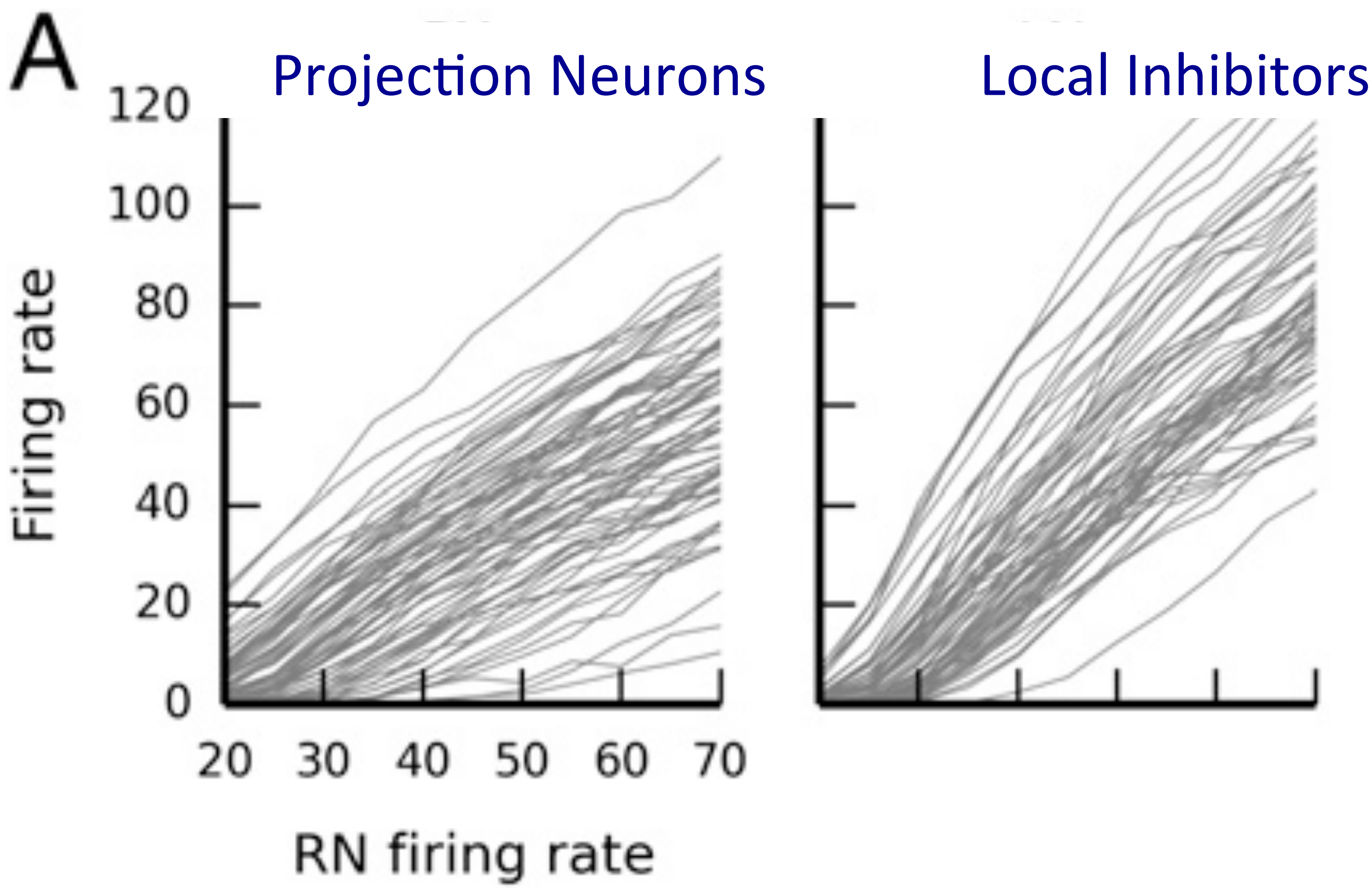
The appeal of neuromorphic architectures lies in

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.

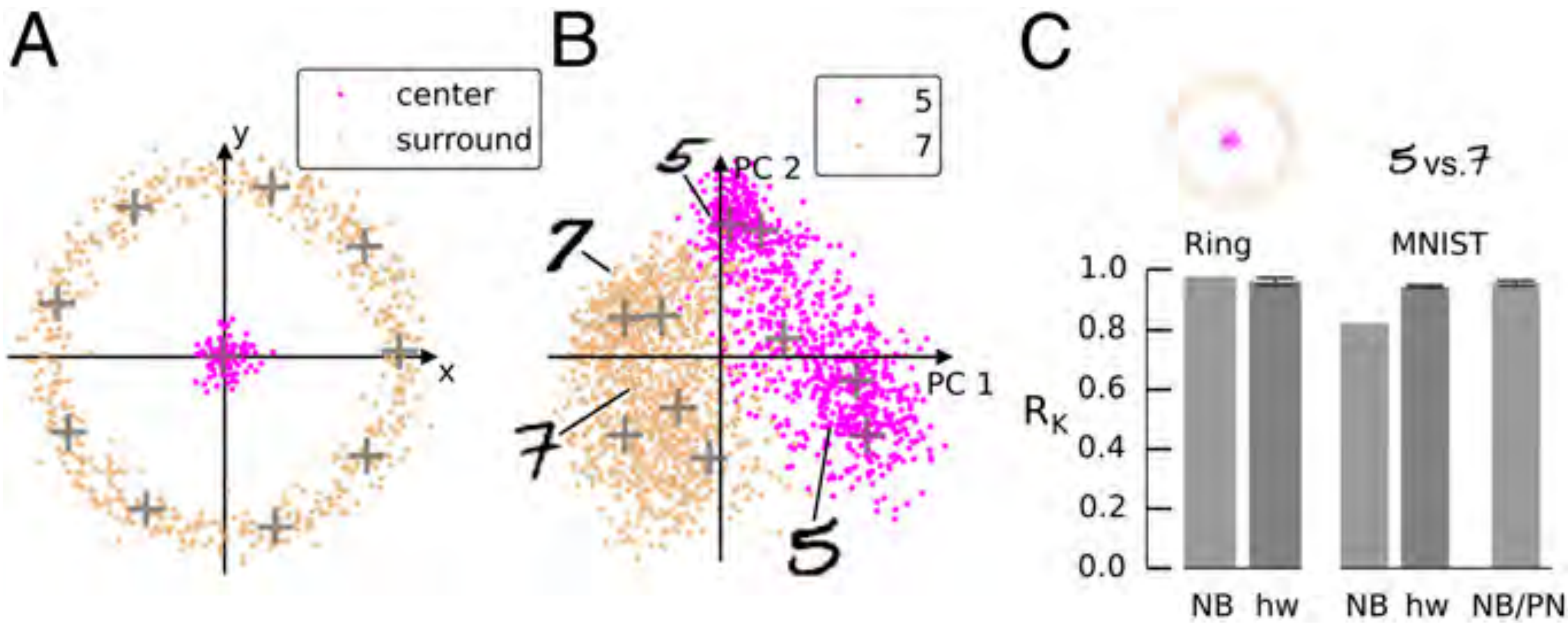
Therefore, at the level of human-like computing tasks, neuromorphic machines have the potential to be superior to von Neumann machines.

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.

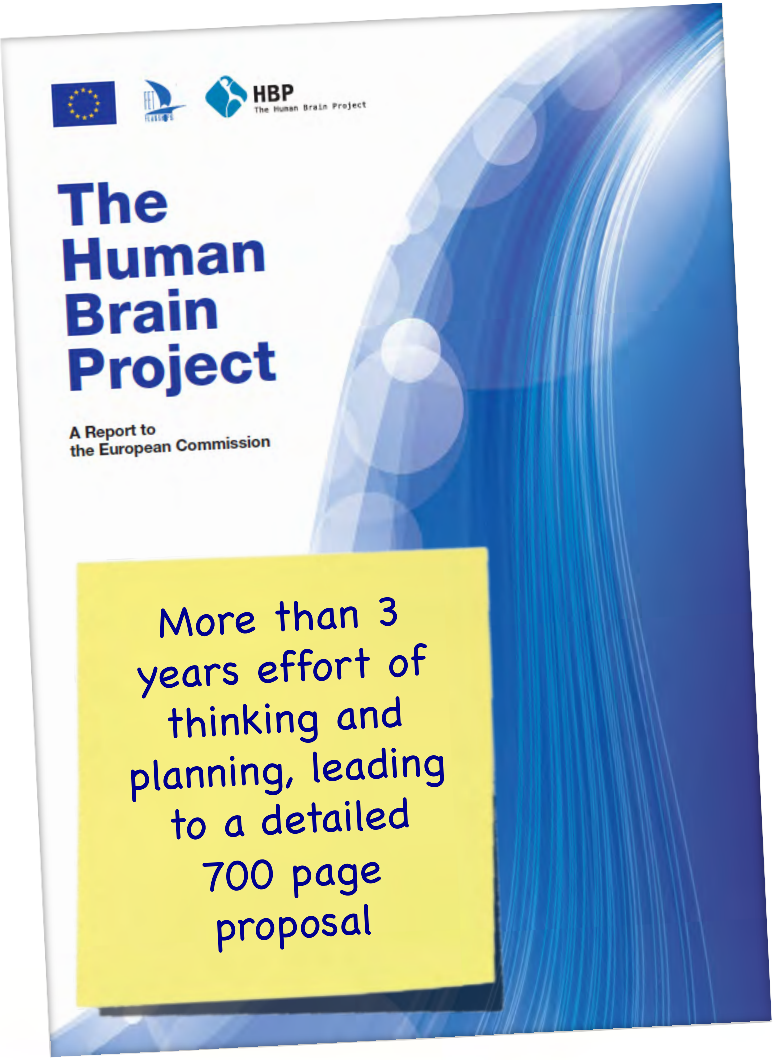
Generic Data Mining with a biologically derived Neuromorphic System



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.

Human Brain Project

The Human Brain Project



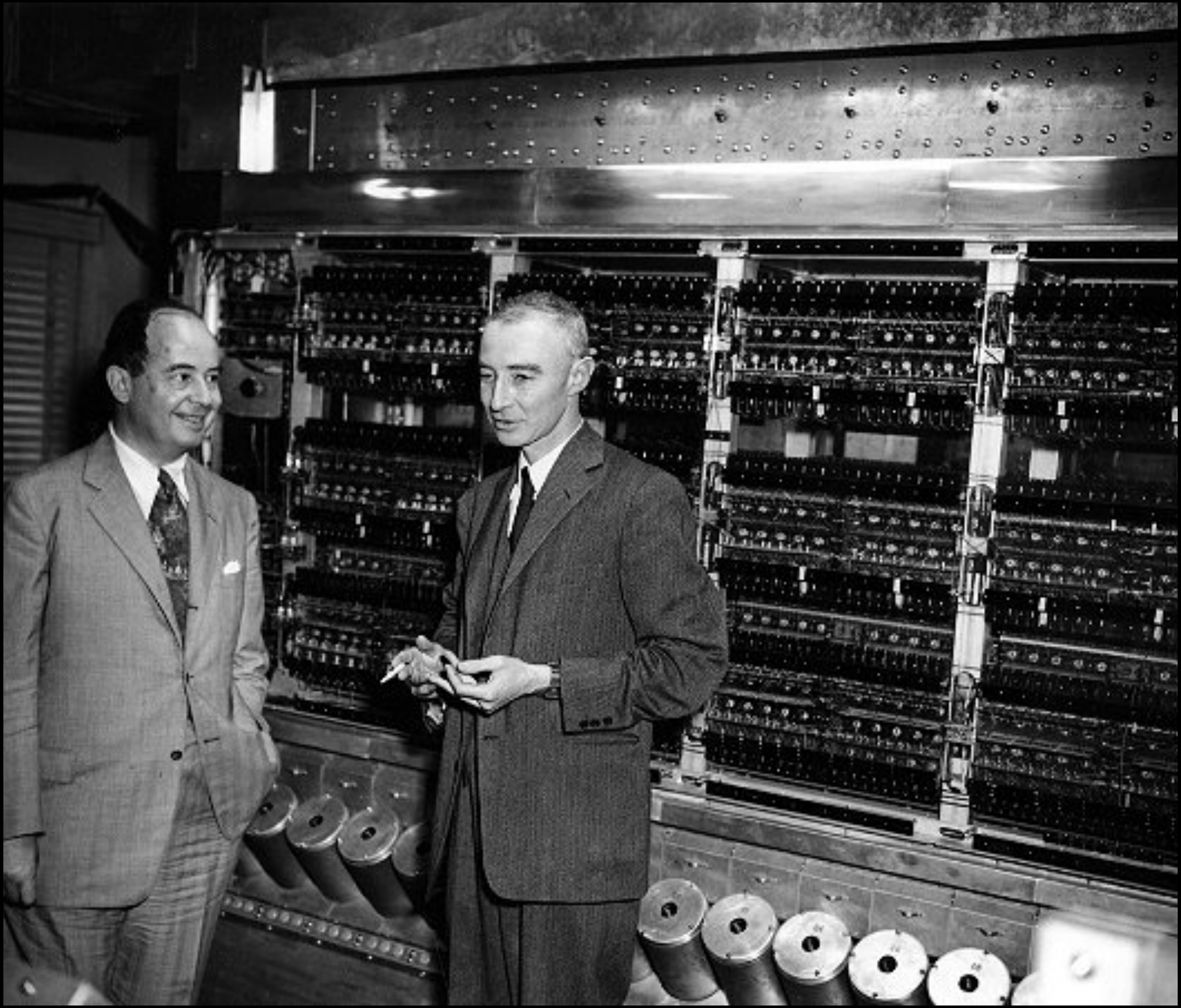
A coordinated effort to understand, improve and exploit the brain

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



Robert Oppenheimer and John von Neumann
Institute for Advanced Study, Princeton, 1952

HBP : Two complementary neuromorphic computing concepts

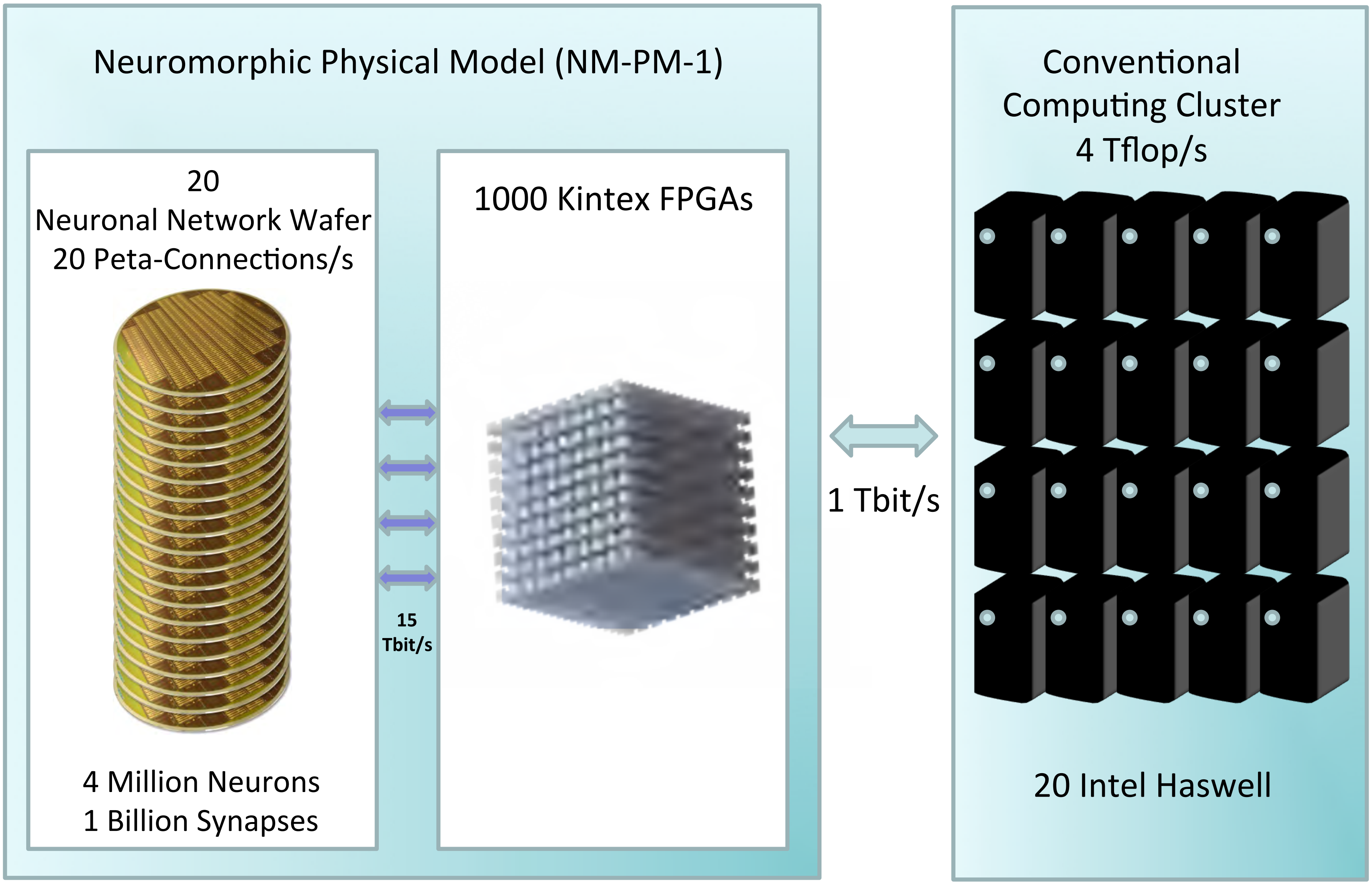
MANY-CORE DIGITAL PROCESSOR SYSTEM

Many clocked digital ARM processors – address-based, small packet, asynchronous low density communication – effectively running at biological real-time

PHYSICAL MODEL MIXED SIGNAL SYSTEM

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

The Physical Model Machine

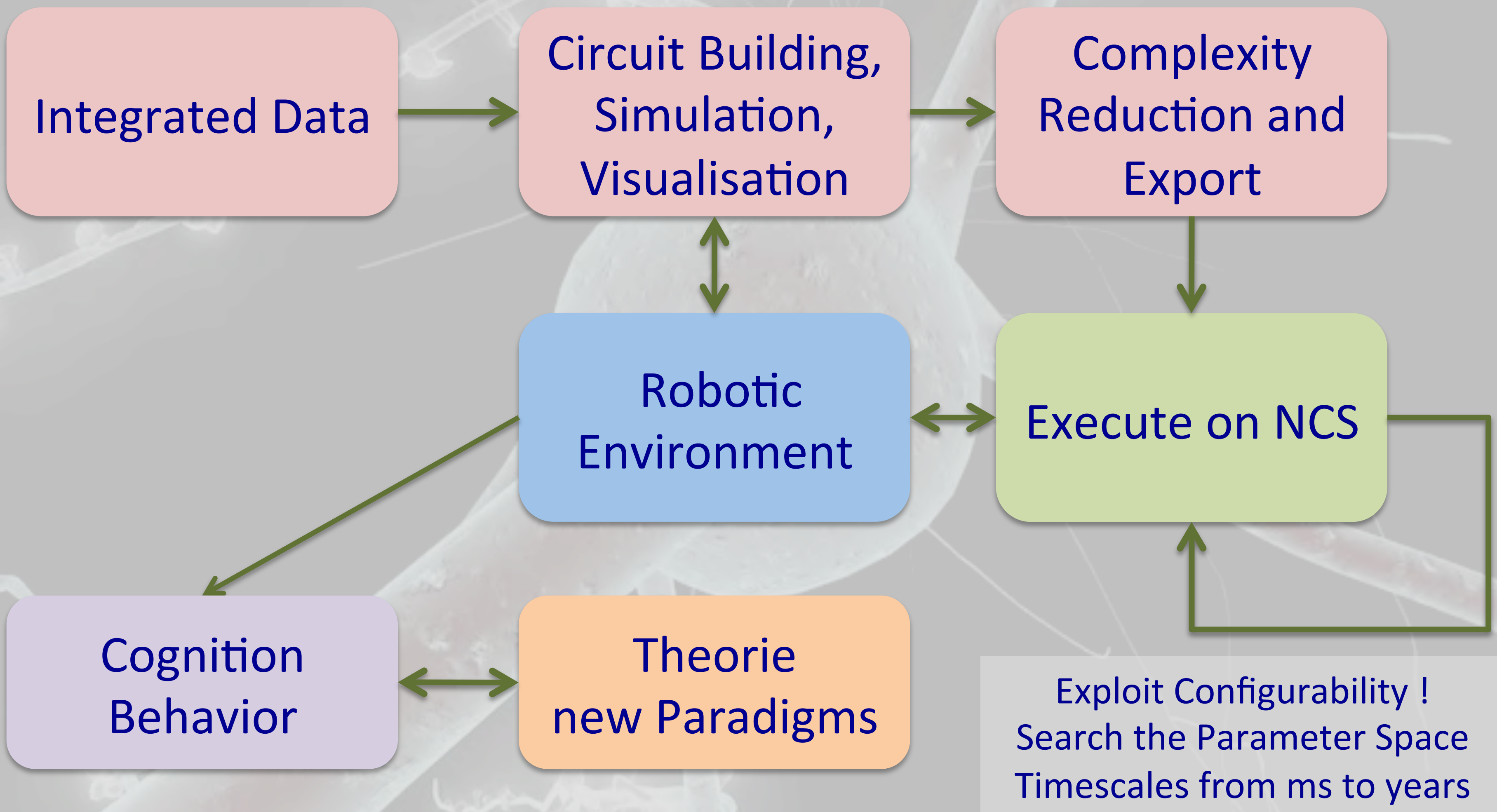



50kW
HBP NM-PM-1
Scaling up : 20 Wafers, 4 Million
Neurons, 1 Billion Synapses
by October 2015

HBP
The Human Brain Project

Workflow : An Example

„Reducing Complexity – How far can we go ?“



BRAIN-DERIVED COMPUTING

- Consistent concept for a novel 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


7D_0113712-06.06.2013-09_18 UHEI Group