Exploring Neuronal Networks *In Vivo*

Input / output

x_1

x_2 → output

x_3

Dendrites

Terminal Bulb

Cell Body

Axon

Layer

hidden layer
($n = 15$ neurons)

output layer

input layer
(784 neurons)

0
1
2
3
4
5
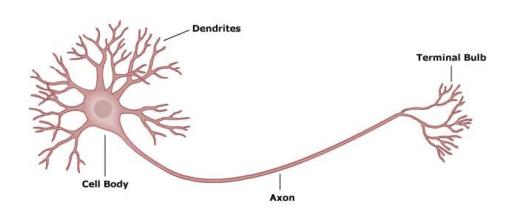6
7
8
9

'Cognition is an emergent property of anatomy'

Let's copy it!

I: Reverse Engineering

Reverse engineering steps
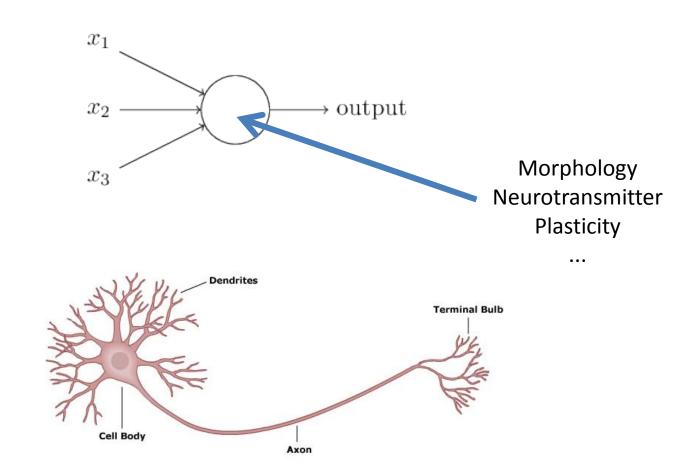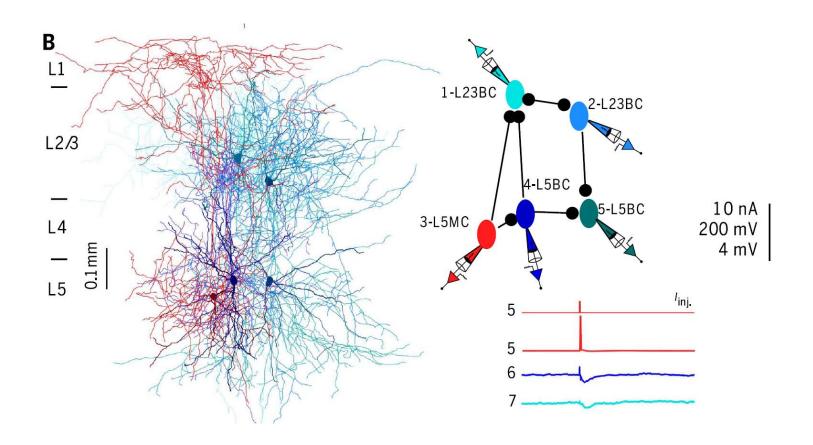
- Assess physiology

Determining transfer function

x_1

x_2 → output

x_3

Morphology
Neurotransmitter
Plasticity
...

Dendrites

Terminal Bulb

Cell Body

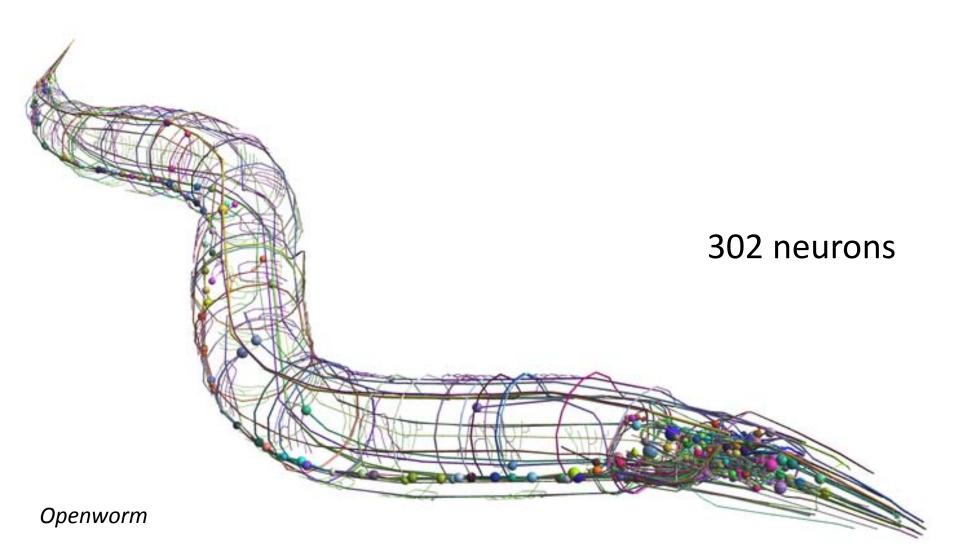Axon

Determining transfer function

Jiang, Science, 2015

Reverse engineering steps

- Assess physiology

- Reproducing circuits neuron by neuron

- Feed it with relevant input

C. Elegans
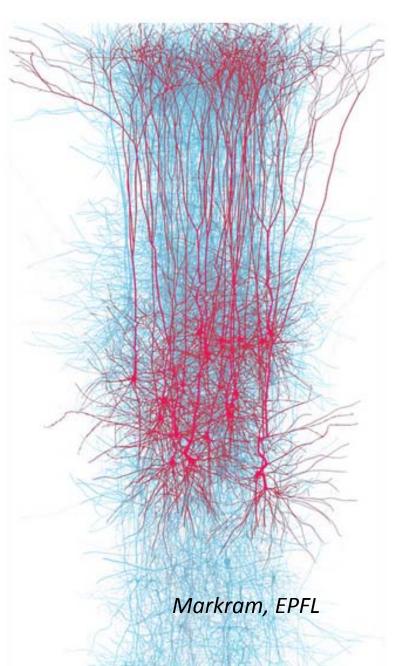

302 neurons

Openworm

C. Elegans

C. Elegans

Enter the worm.

OpenWorm is an open source project dedicated to creating a virtual C. elegans nematode in a computer.

Mammals: the Blue Brain Project

Digital reconstruction

Markram, EPFL

Blue Brain Project Limitations

The project's current reconstructions reproduce [...] a small part of the neocortex of young rats **(about one third of a cubic millimetre of cortical tissue).**
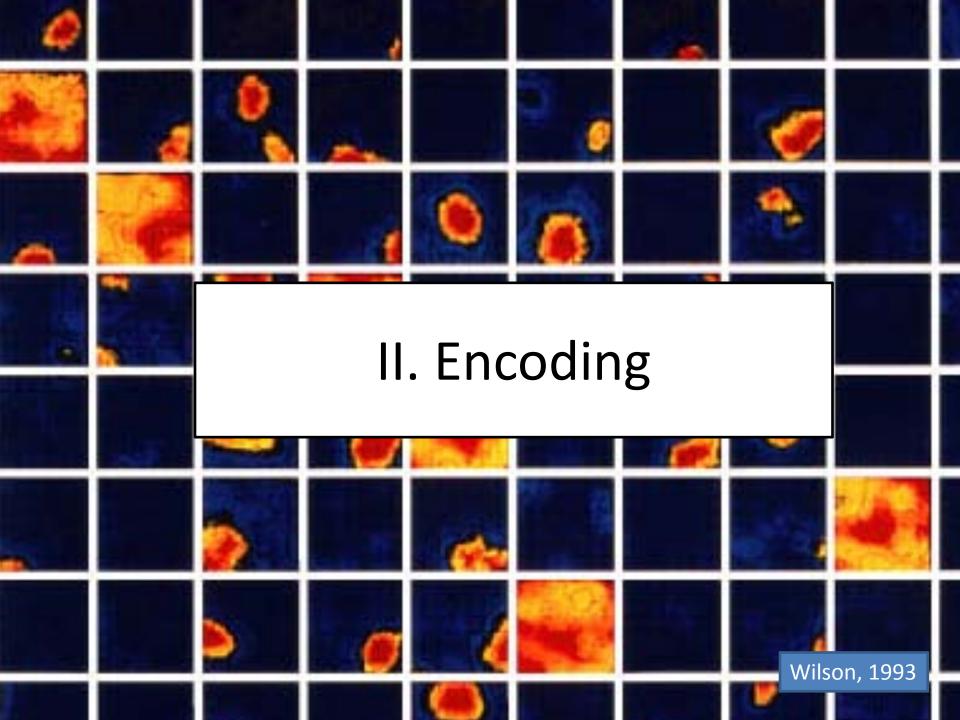
In fact, the BBP's latest reconstruction [...] **representing less than 1% of the synaptic connections in the circuit.**

Markram, EPFL

European Human Brain Project: ~ 1.3 Billion Euros

IBM output

Prospective

We have built a computer that is inspired by the brain. The inputs to and outputs of this computer are *spikes*. Functionally, it transforms a spatio-temporal stream of input spikes into a spatio-temporal stream of output spikes.

IBM website

II. Encoding

Wilson, 1993

How are neuronal networks representing information?
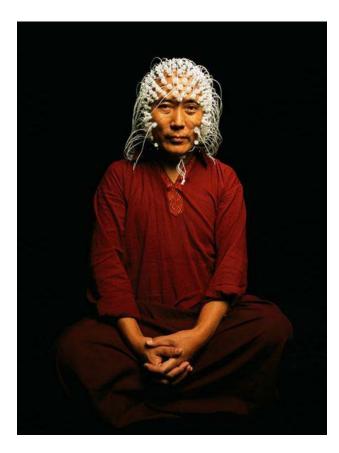
Neuroscientist Toolbox

Monitor neuronal networks
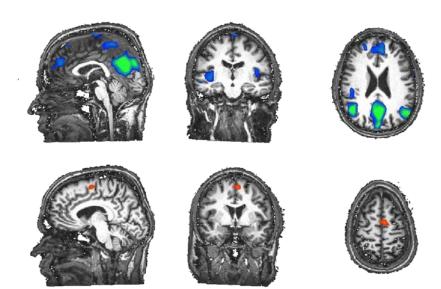
Neuronal scale: in space and time

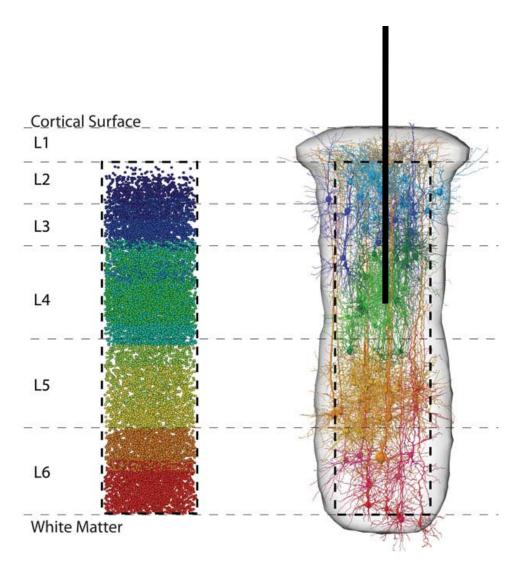**Synchronise complex behavior: in space and time**

Resolution is critical

EEG   MRI
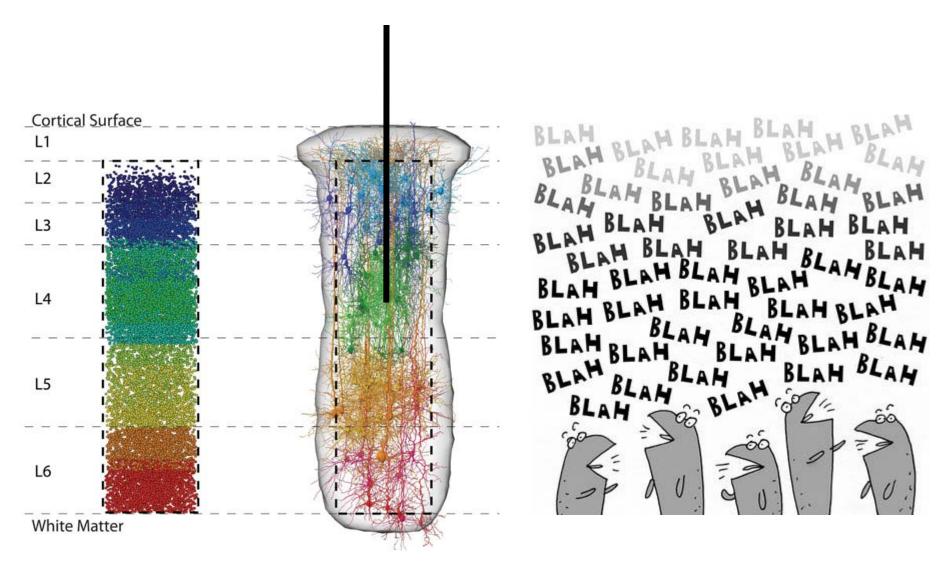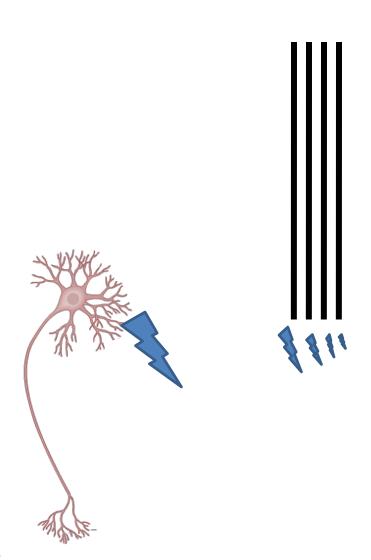

=measure of blood-flow oxygen levels

Electrodes

Cortical Surface
L1
L2
L3
L4
L5
L6
White Matter

We measure Volts! (microVolts)

Max Planck Institute

Electrodes

Cortical Surface
L1
L2
L3
L4
L5
L6
White Matter

BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH BLAH
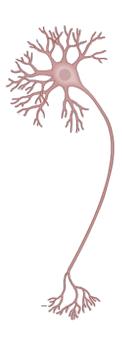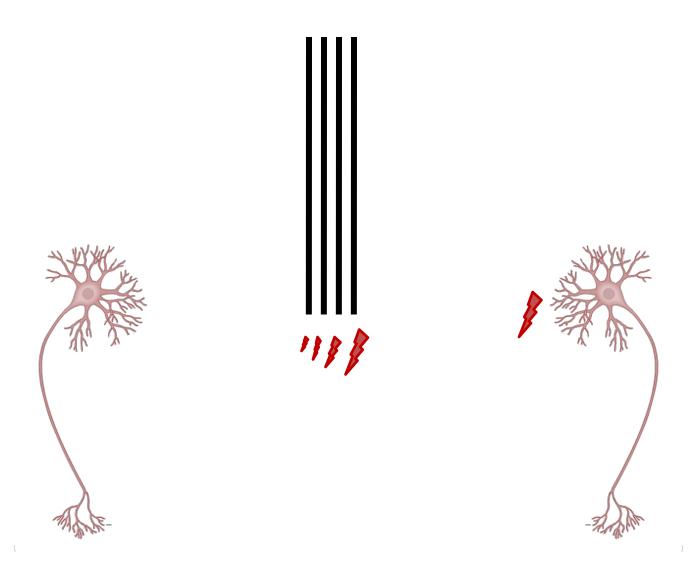
Max Planck Institute

Tetrodes
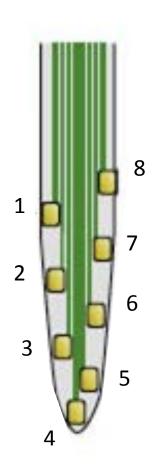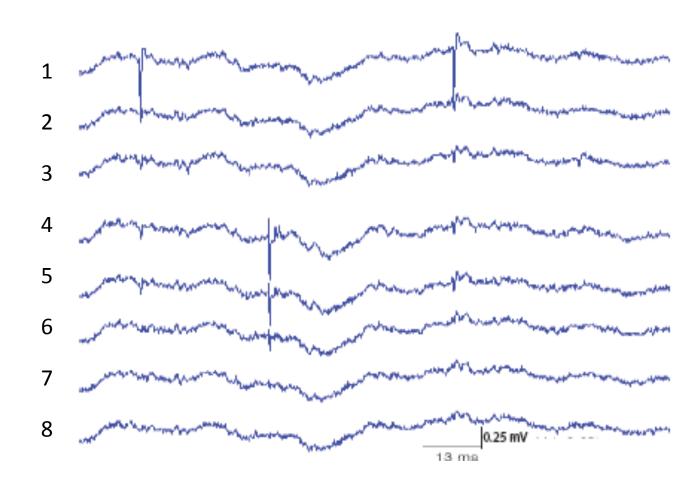
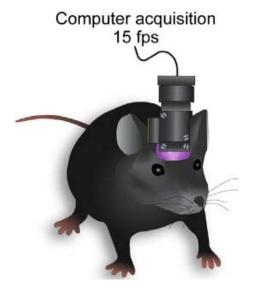# Tetrodes

Silicon probes
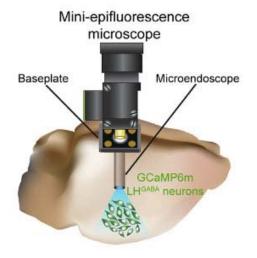
Buzsaki64, NeuroNexus

Calcium-imaging
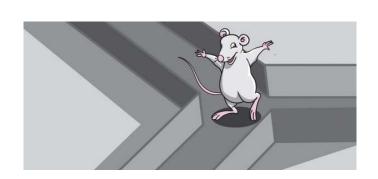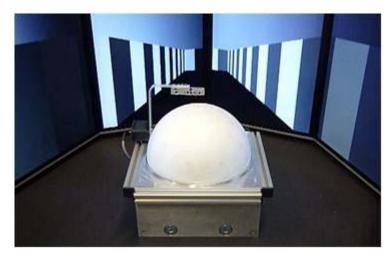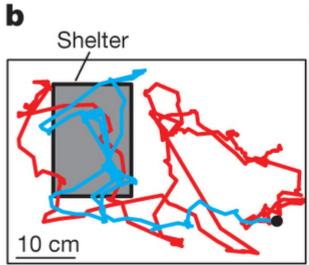
Motor cortex M1 of running mouse
Daniel Huber 2009, Svoboda Lab, JFRC

Behavioral setups

b

Shelter

10 cm

The Task

Kepecs, 2013
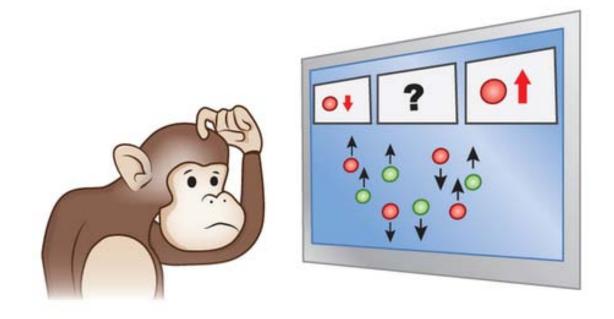
- Extract rules of cognitive processing

  – > What is represented in the brain?
    - Stimulus / Reward / Decision / Self-evaluation / Memories?

    How is it encoded?

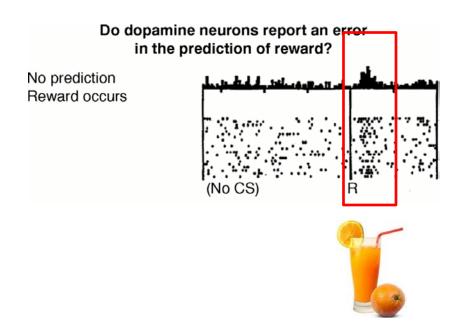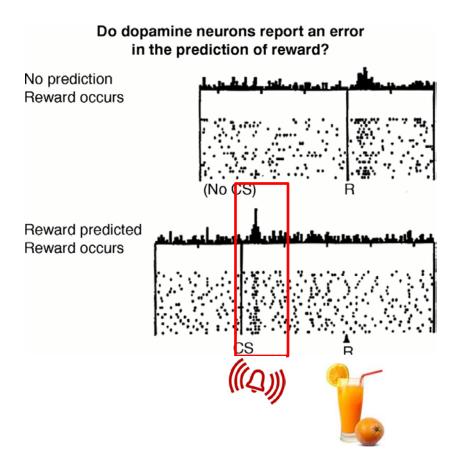 – > What are the dynamics of learning?

Reward prediction

Example for one neuron

Schultz, 1997

Reward prediction

Do dopamine neurons report an error
in the prediction of reward?

No prediction
Reward occurs

(No CS)

R

Schultz, 1997

Reward prediction

Do dopamine neurons report an error in the prediction of reward?

No prediction
Reward occurs

(No CS)   R

Reward predicted
Reward occurs

CS   R

Schultz, 1997

Reward prediction

Do dopamine neurons report an error
in the prediction of reward?

No prediction
Reward occurs

(No CS)   R

Reward predicted
Reward occurs

CS   R

Reward predicted
No reward occurs

-1   1   2 s
(No R)

Schultz, 1997

Reward prediction

Do dopamine neurons report an error in the prediction of reward?

No prediction
Reward occurs

(No CS)   R

Reward predicted
Reward occurs

CS   R

Reward predicted
No reward occurs

-1   1   2 s
(No R)

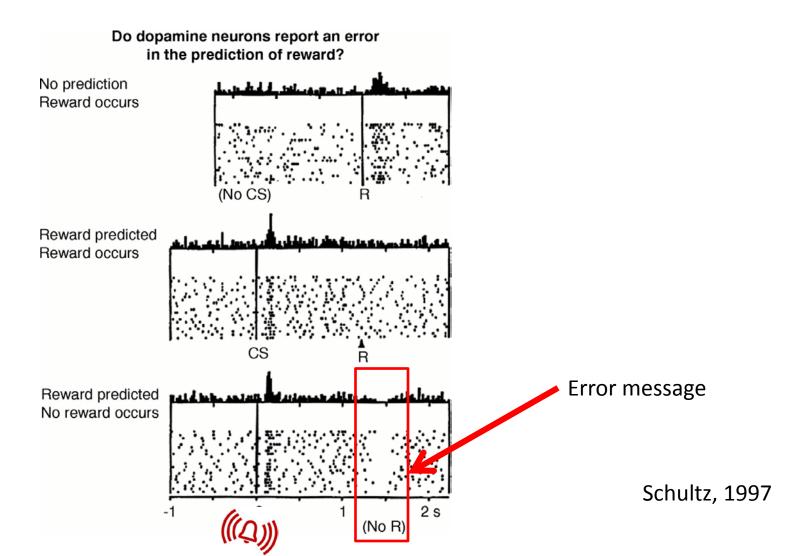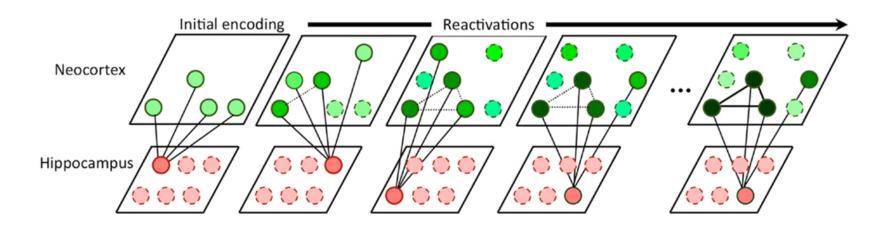Error message

Schultz, 1997

Topics of interest

- Cognitive flexibility

- Decision-making (gambling task)

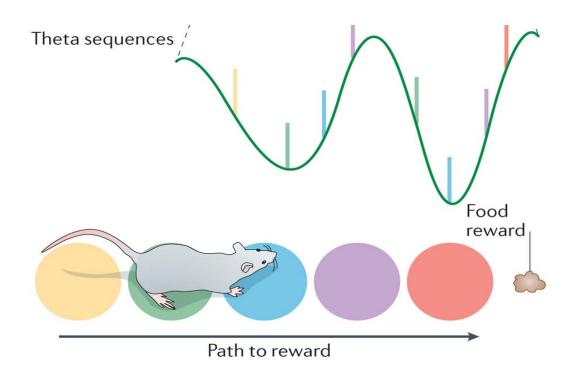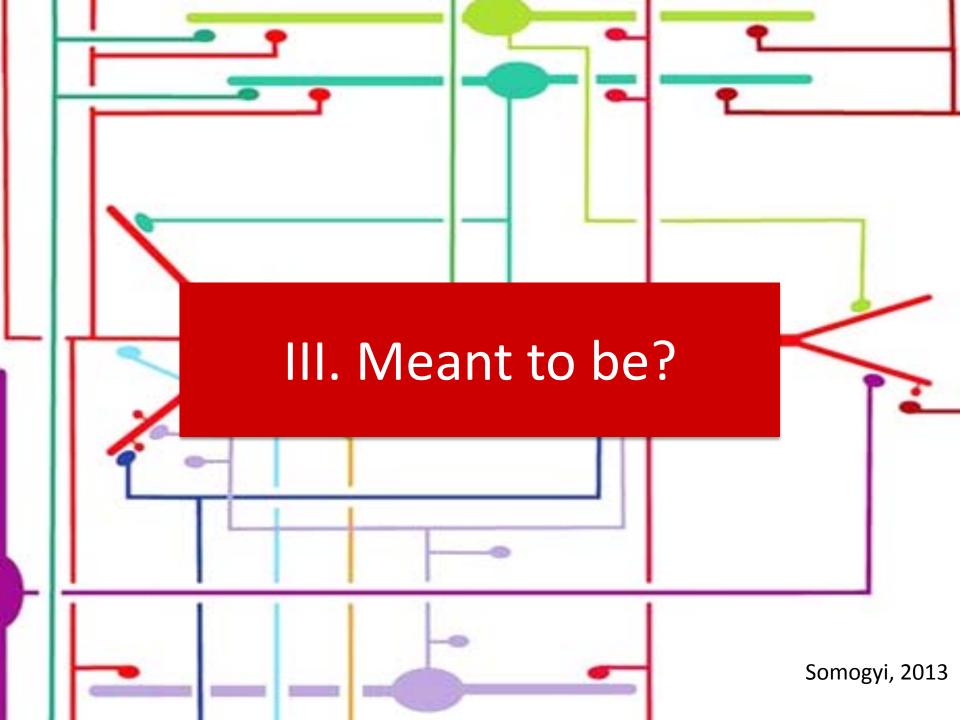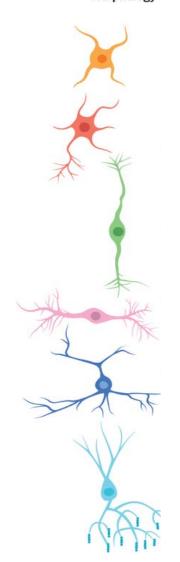- Spatial navigation
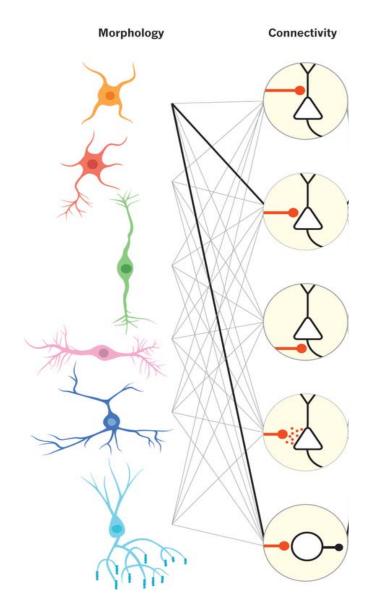
- Meta-cognition (confidence)

At a network level

Yassa, 2013

Dynamic properties

Theta sequences

Food reward

Path to reward

Nature Reviews | Neuroscience

Colgin, 2016

III. Meant to be?

Somogyi, 2013

How about the neuronal types?

Morphology

Kepecs, 2014

How about the neuronal types?

Morphology

Connectivity

Kepecs, 2014

How about the neuronal types?

Morphology   Connectivity   Intrinsic properties

Kepecs, 2014

How about the neuronal types?
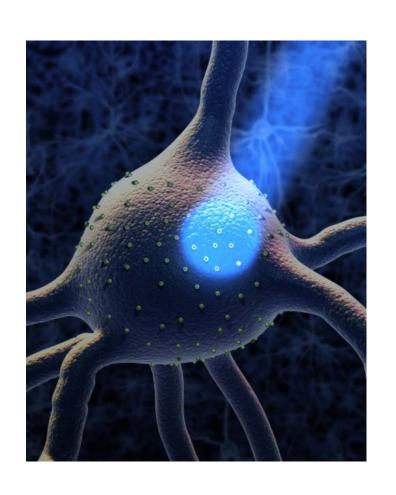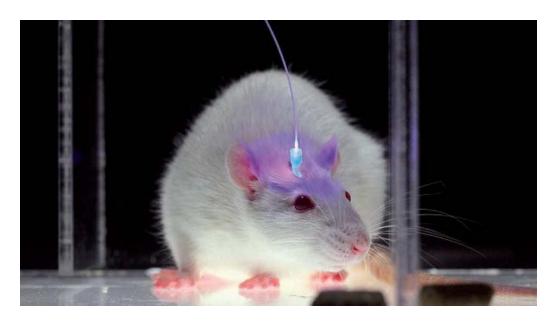

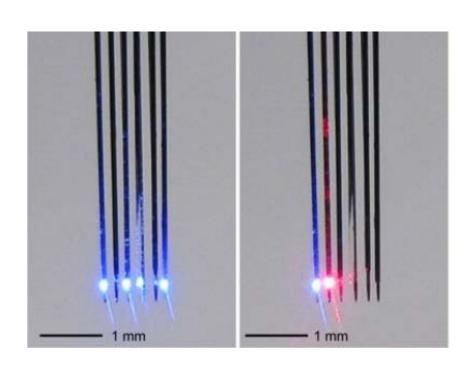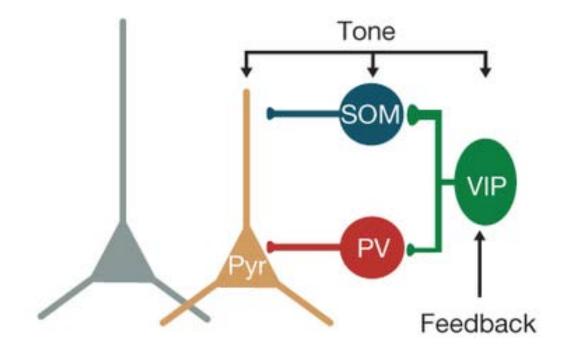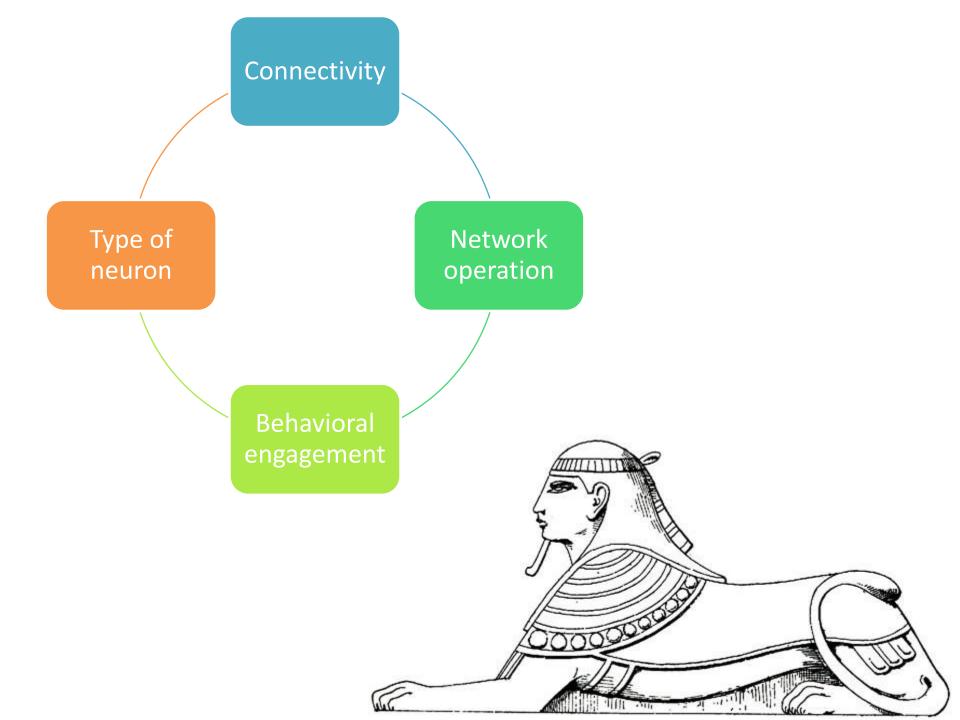Kepecs, 2014
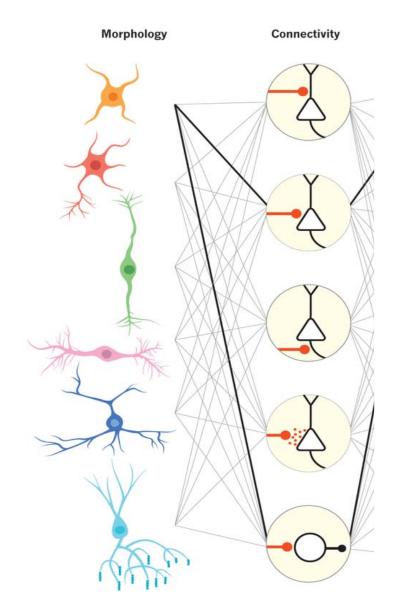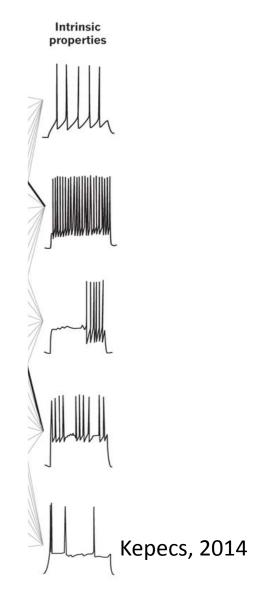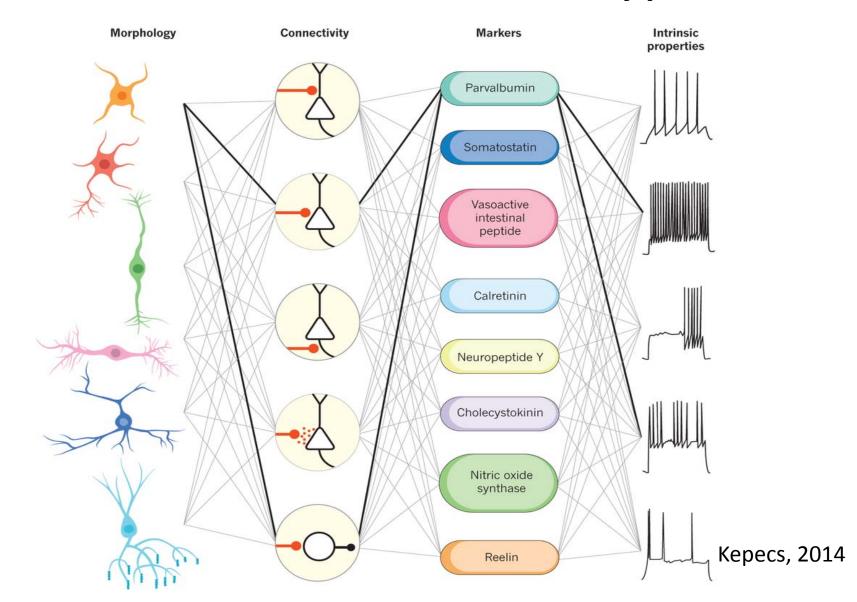
Optogenetics

Optogenetic tagging

Control information flow

Répertoire of neurons 'Fit to function'

Pi, 2013

Building Bridges

Convolutional networks for fast, energy-efficient neuromorphic computing

Steven K. Esser[a,1], Paul A. Merolla[a], John V. Arthur[a], Andrew S. Cassidy[a], Rathinakumar Appuswamy[a], Alexander Andreopoulos[a], David J. Berg[a], Jeffrey L. McKinstry[a], Timothy Melano[a], Davis R. Barch[a], Carmelo di Nolfo[a], Pallab Datta[a], Arnon Amir[a], Brian Taba[a], Myron D. Flickner[a], and Dharmendra S. Modha[a]

Author Affiliations ⌃

Abstract | Full Text | Authors & Info | Figures | SI | Metrics | Related Content | PDF | PDF + SI

Significance

Brain-inspired computing seeks to develop new technologies that solve real-world problems while remaining grounded in the physical requirements of energy, speed, and size. Meeting these challenges requires high-performing algorithms that are capable of running on efficient hardware. Here, we adapt deep convolutional neural networks, which are today's state-of-the-art approach for machine perception in many domains, to perform classification tasks on neuromorphic hardware, which is today's most efficient platform for running neural networks. Using our approach, we demonstrate near state-of-the-art accuracy on eight datasets, while running at between 1,200 and 2,600 frames/s and using between 25 and 275 mW.

Thank you ;)

sabria.lagoun@meduniwien.ac.at