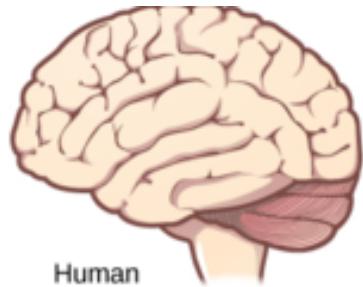


# Cognitive Neuroscience for AI Developers

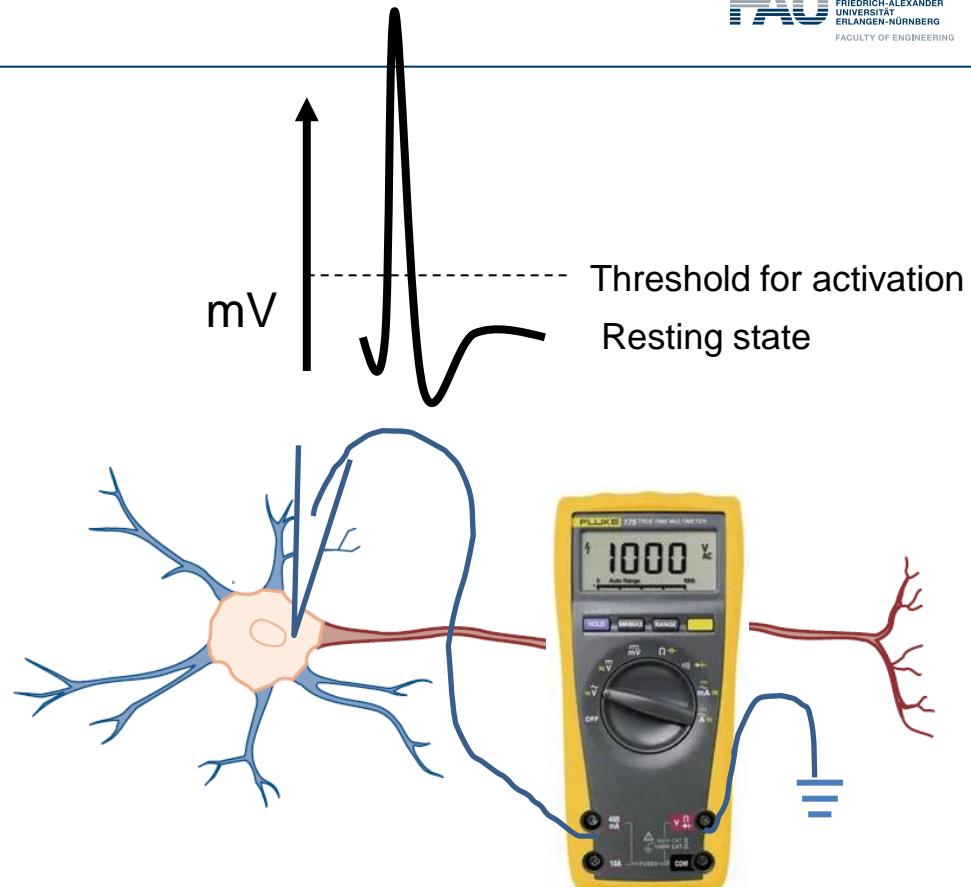
Week 07 – Measuring neural activity and connectivity



# How do we actually know...?

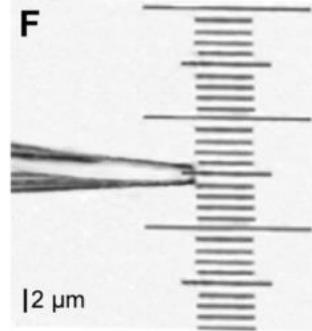
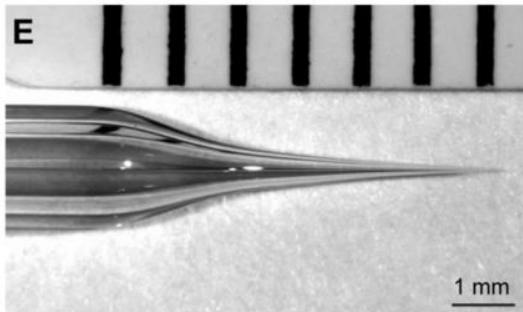
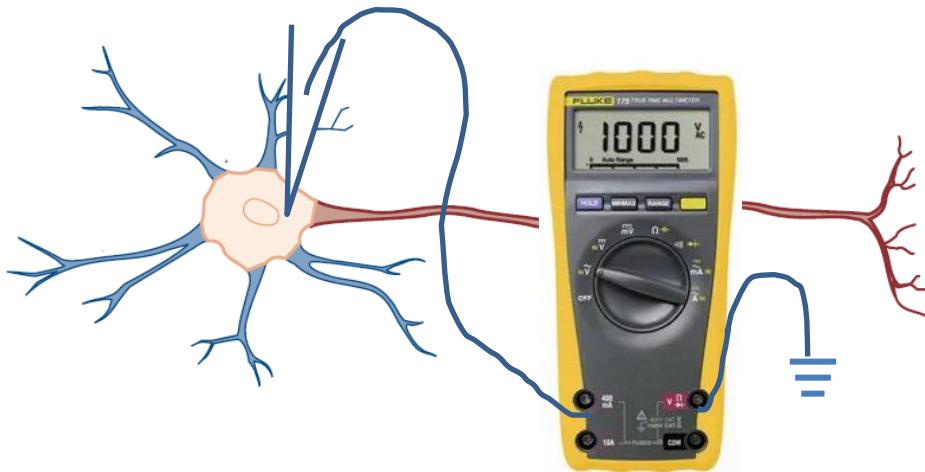


Human

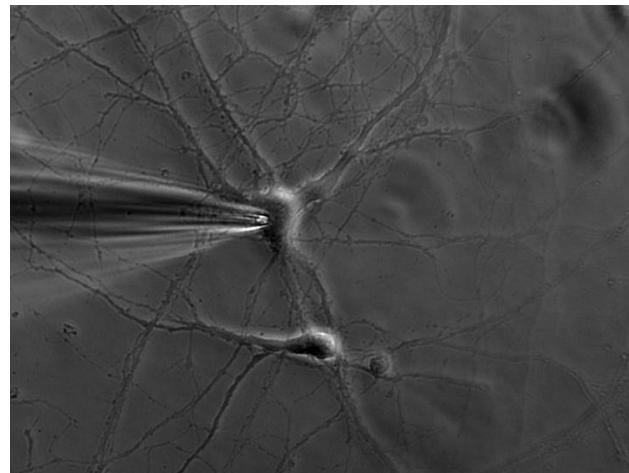


Voltage change → Electrical signal!

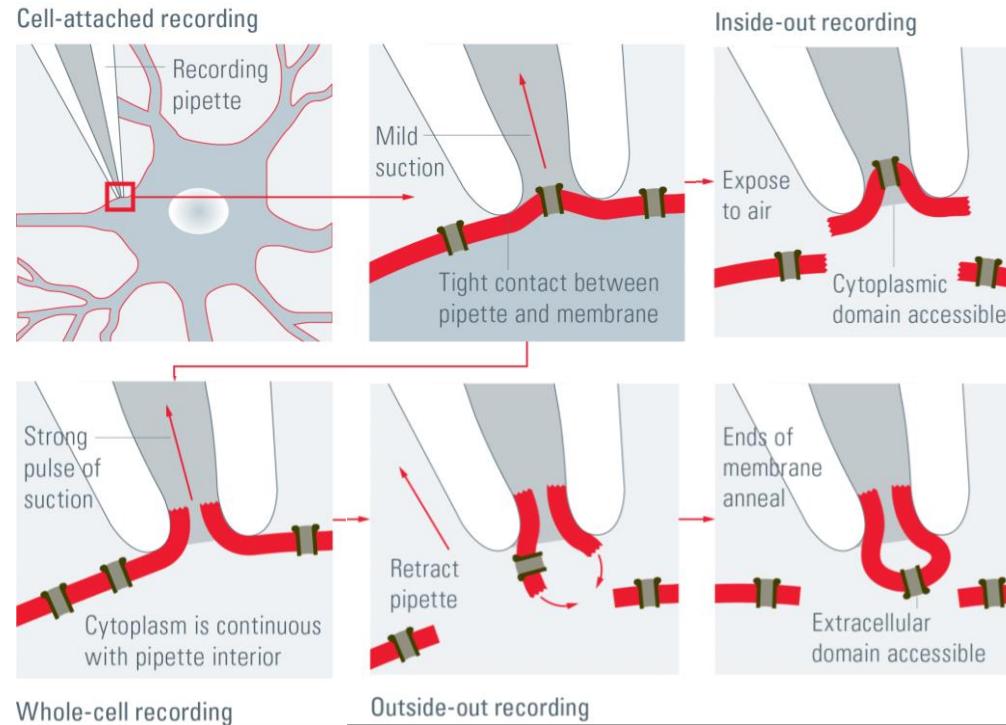
# Measuring a potential across a cell



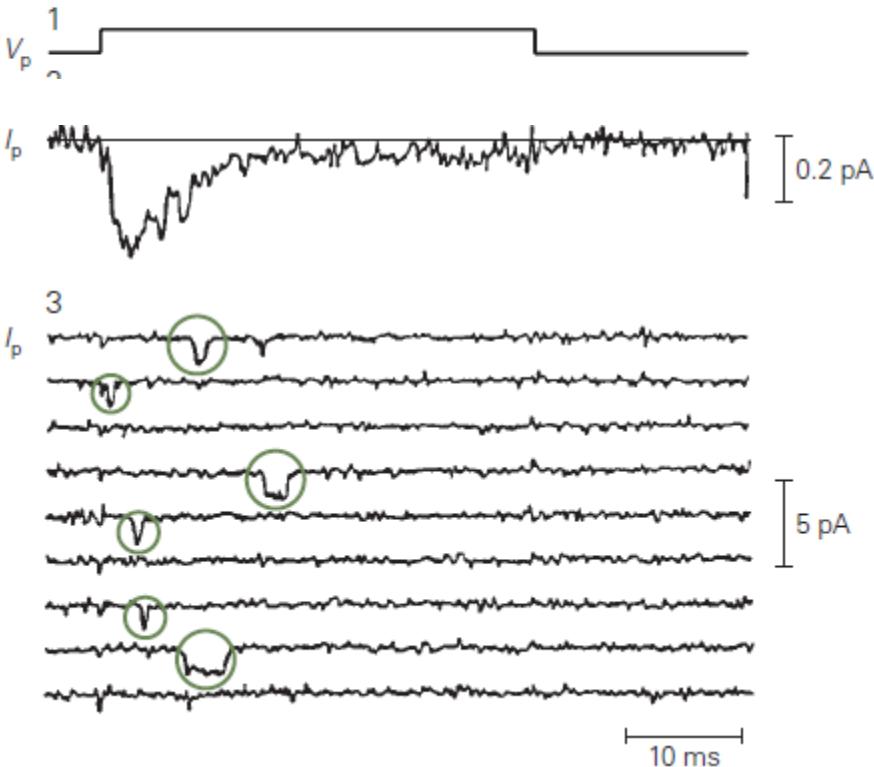
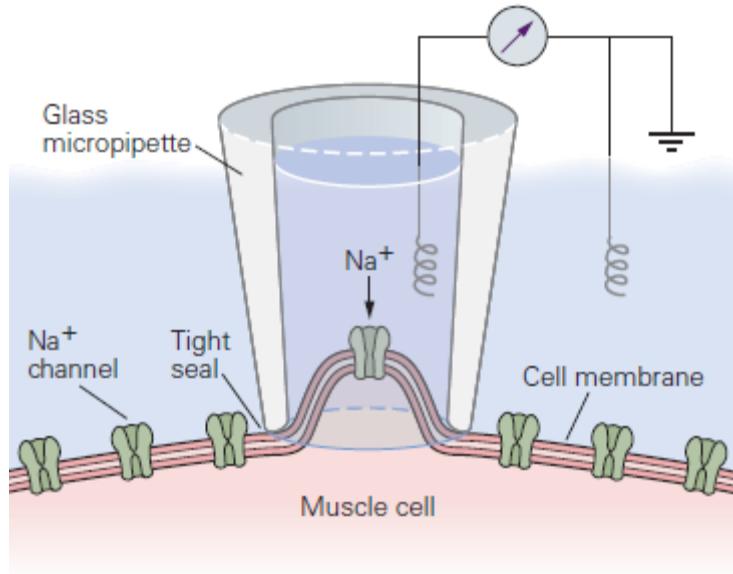
Jouhanneau, Poulet 2019



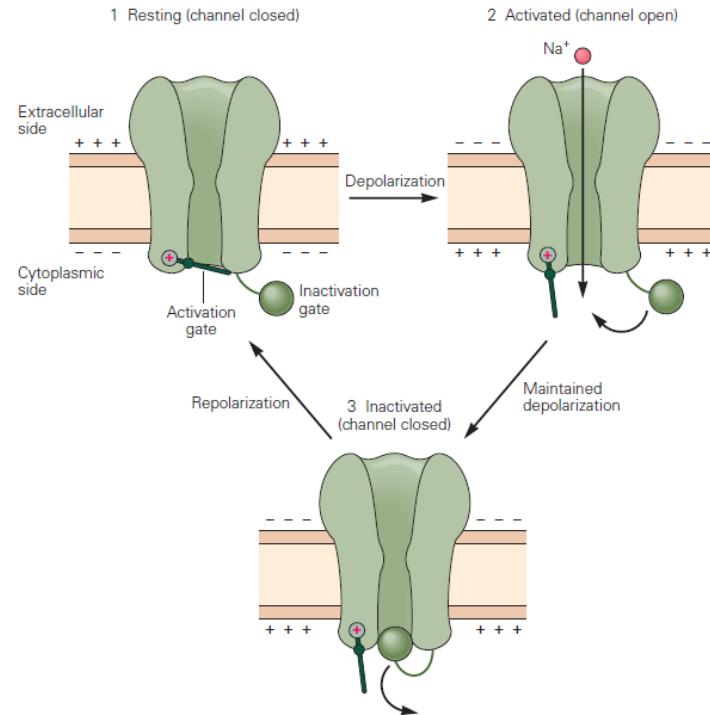
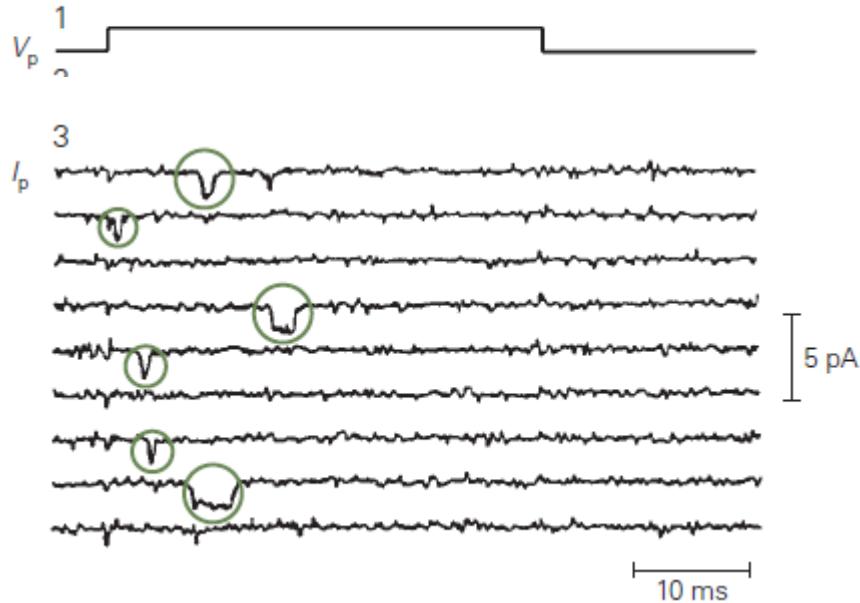
# Accessing the cell



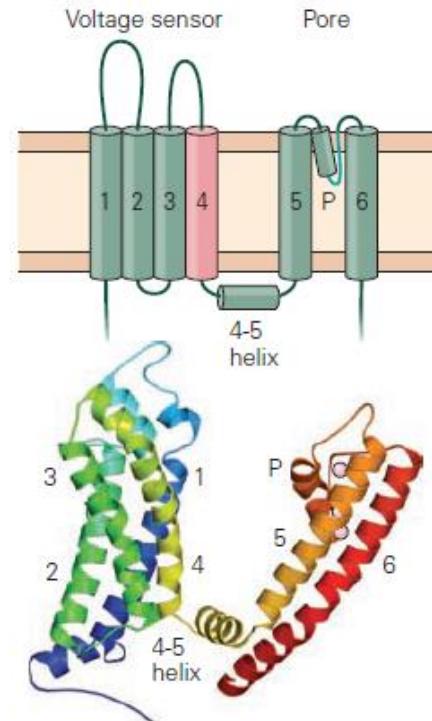
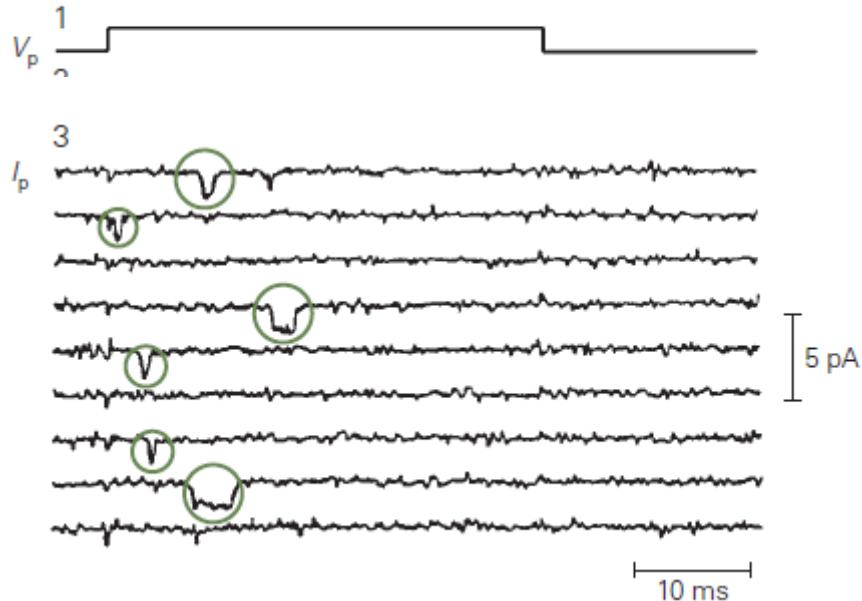
# Measuring a single channel

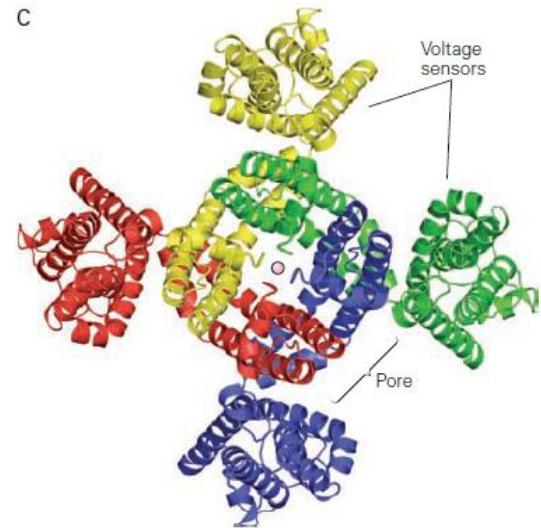
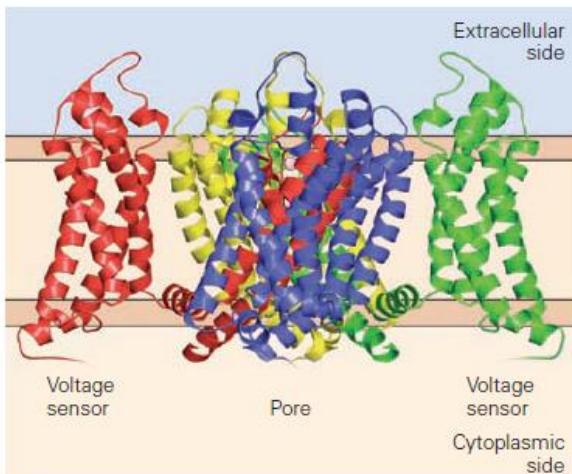
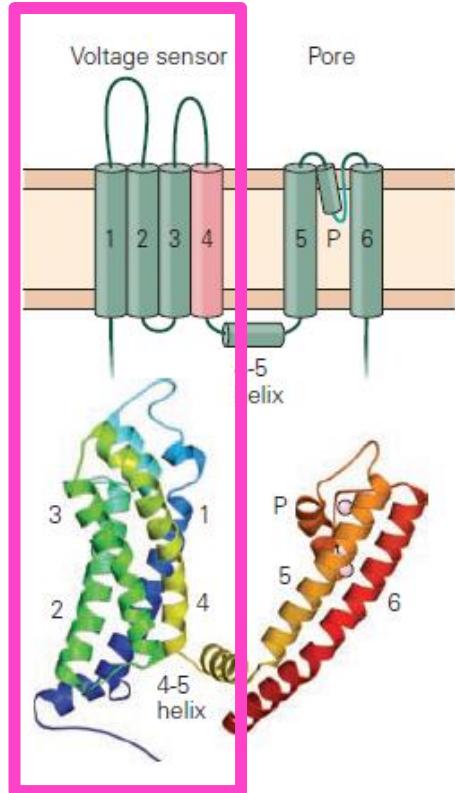


# Ion channels

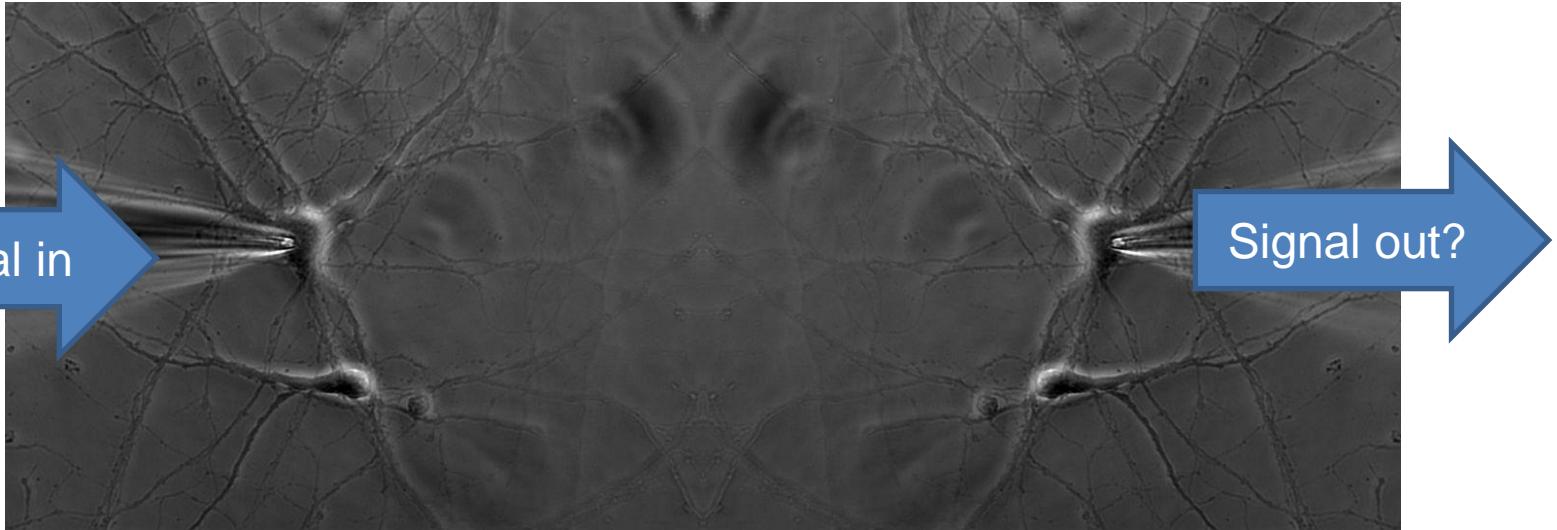


# Sensing voltage





# Measuring single neurons...?



Paired recordings → identification of functional circuitry

# Electrophysiology methods

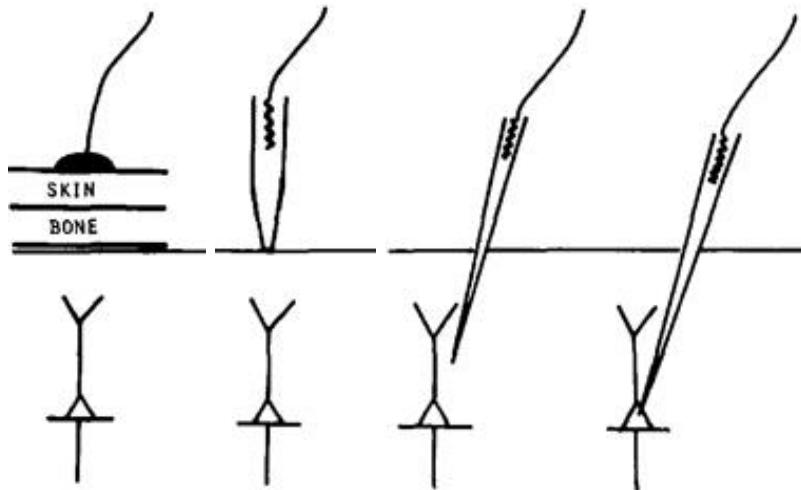
## Localization

EEG

ECoG

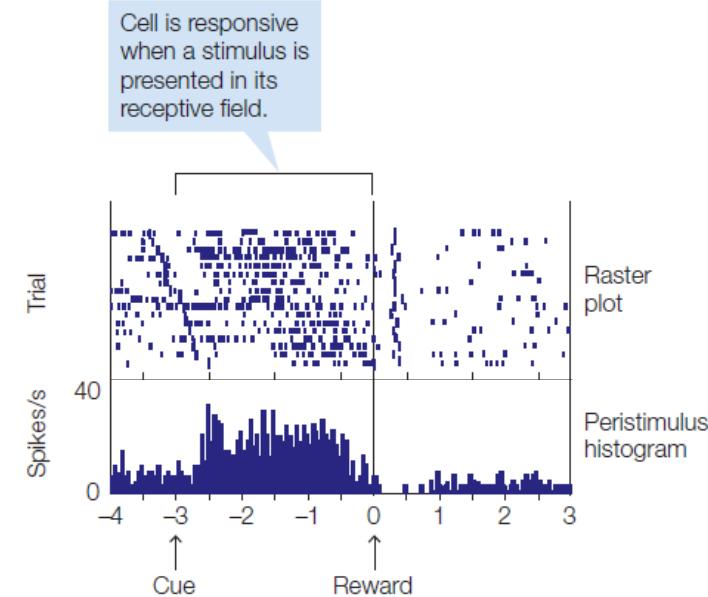
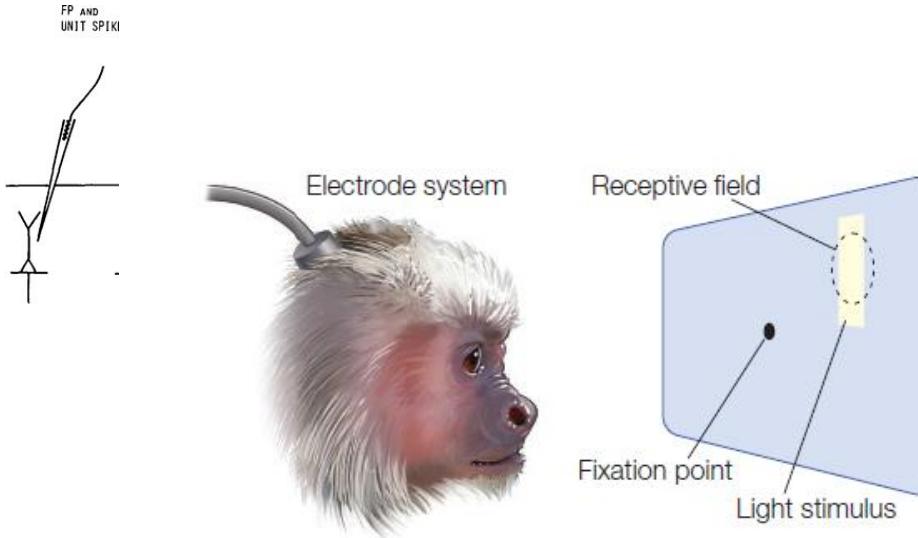
FP AND  
UNIT SPIKES

**INTRACELLULAR**

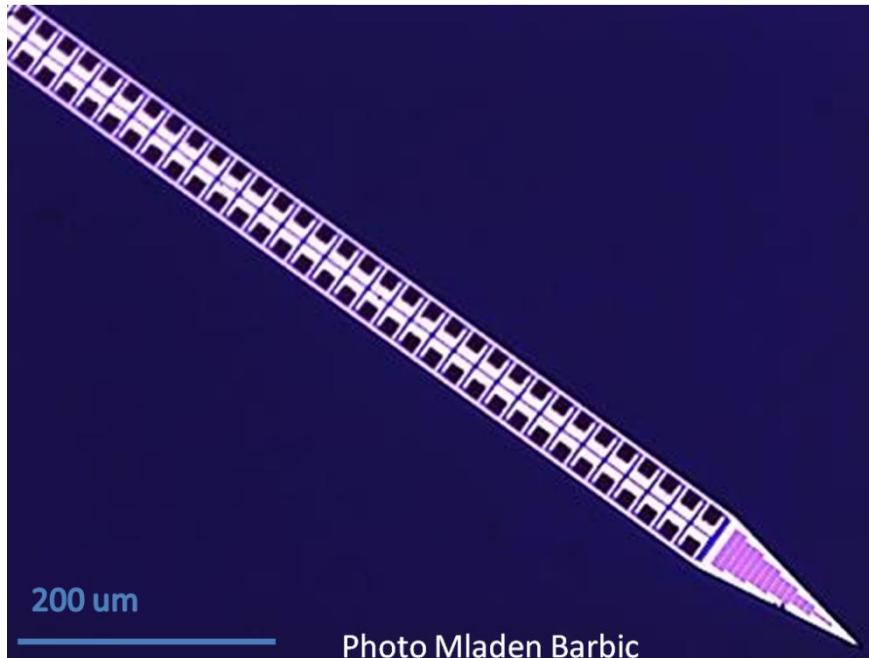


### **invasiveness**

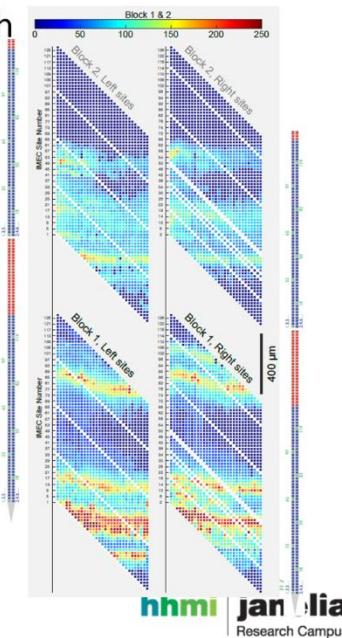
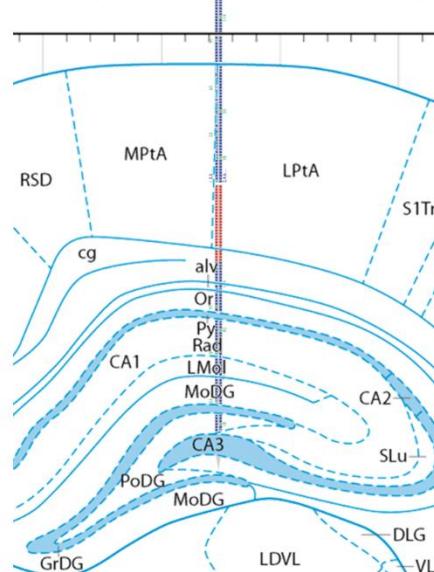
# Local Field Potentials

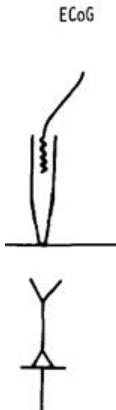


# Multielectrodes

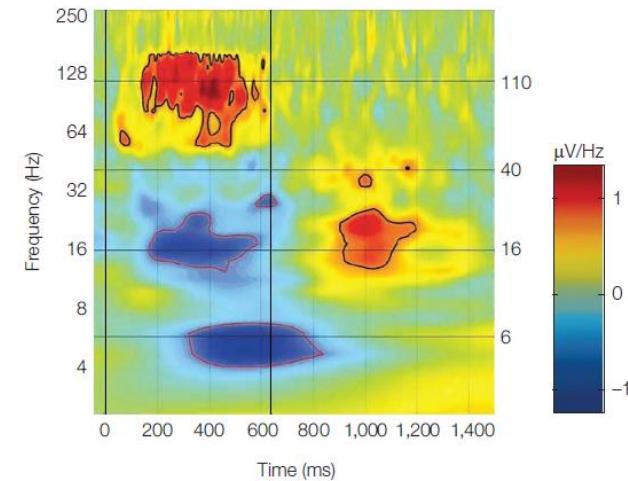
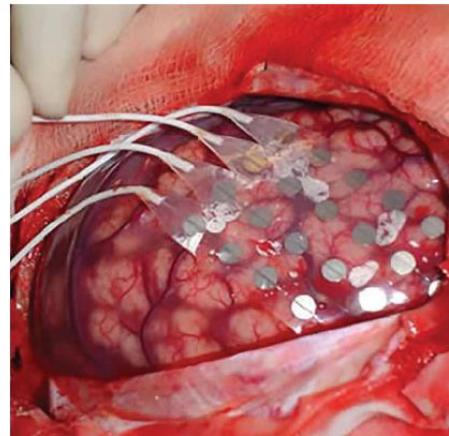


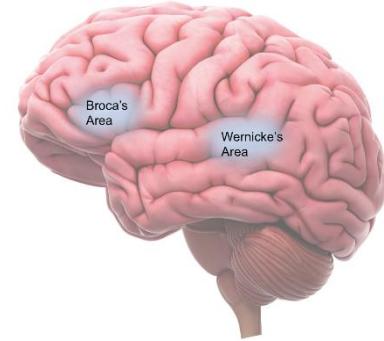
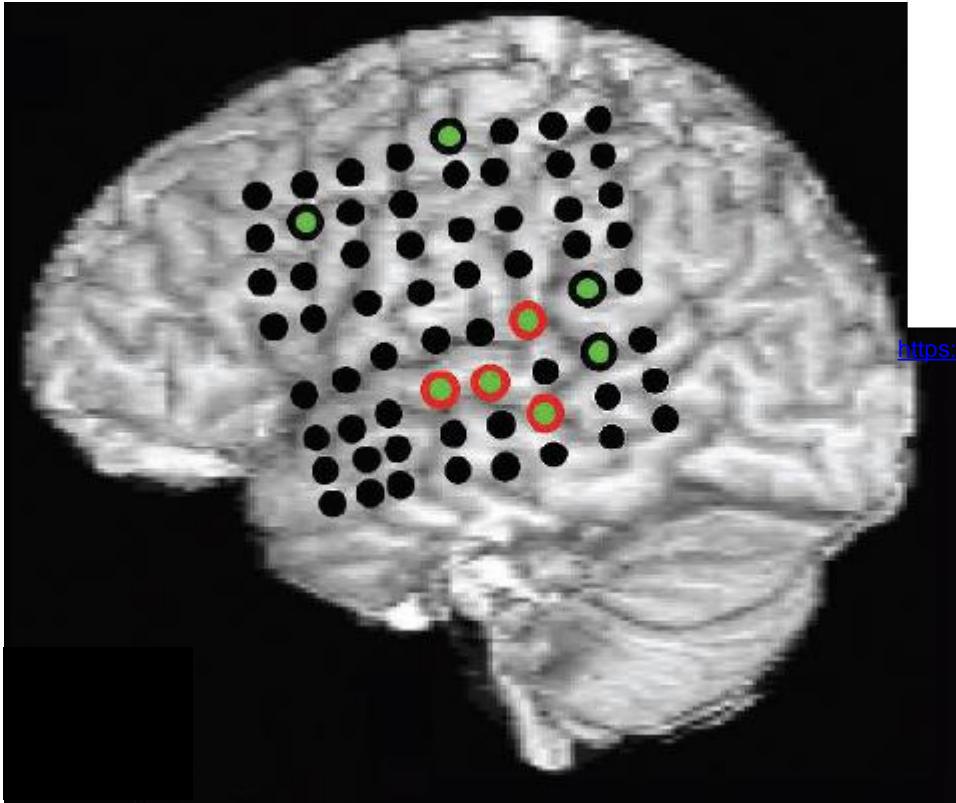
Spike Amplitude vs. Probe Depth





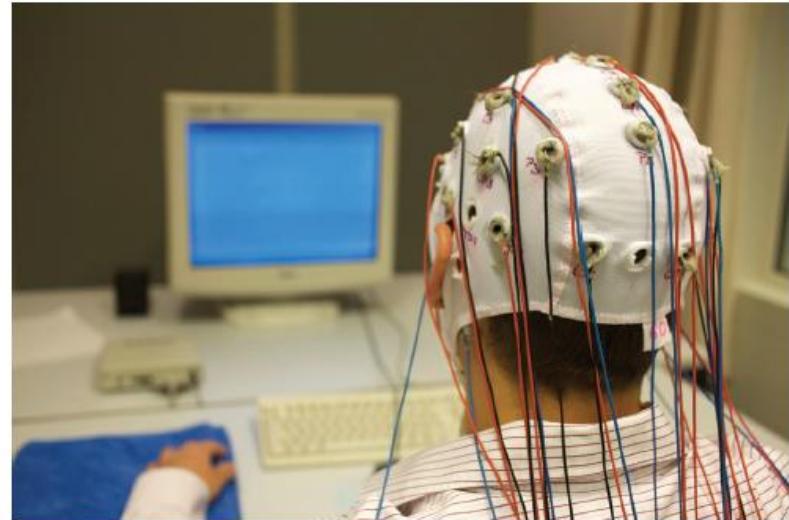
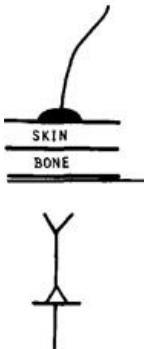
[https://www.eurekalert.org/pub\\_releases/2016-10/uow-ftf102616.php](https://www.eurekalert.org/pub_releases/2016-10/uow-ftf102616.php)





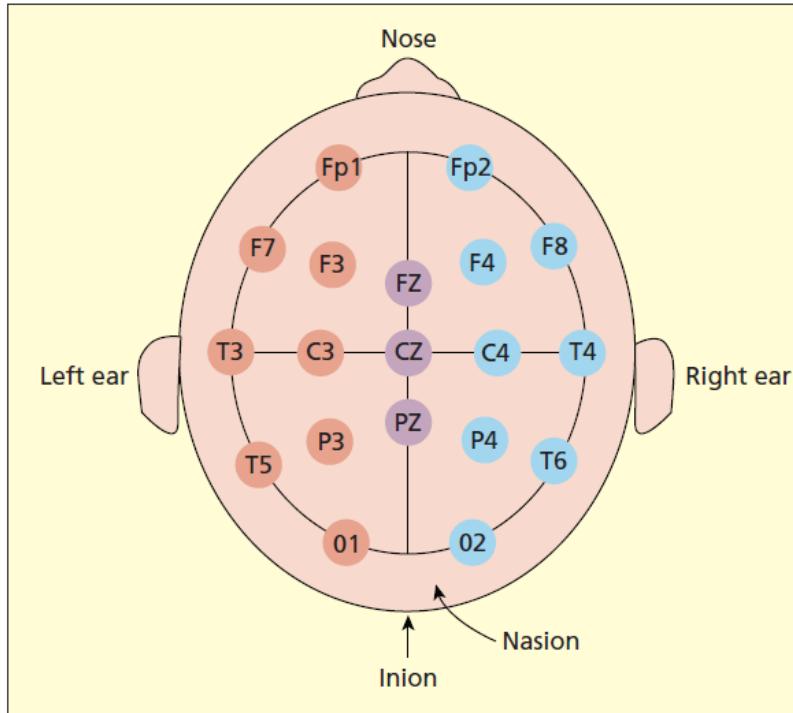
<https://sapienlabs.org/searching-the-brain-for-language/>

EEG

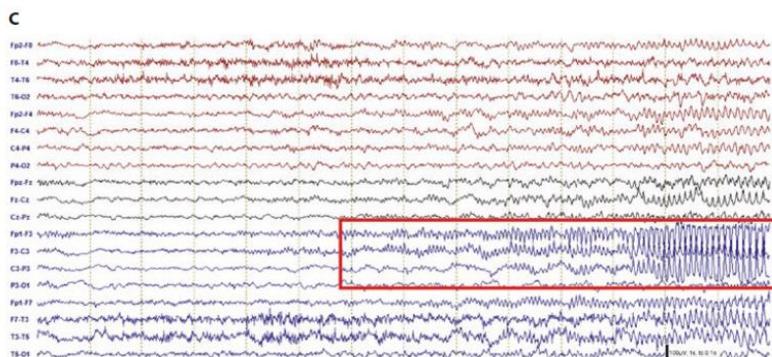
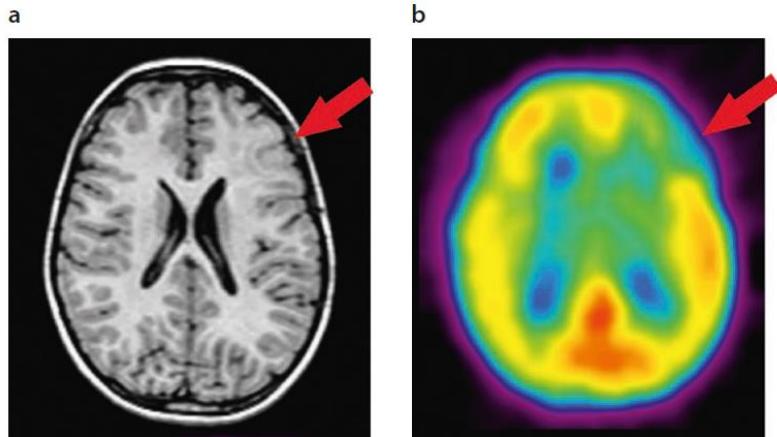
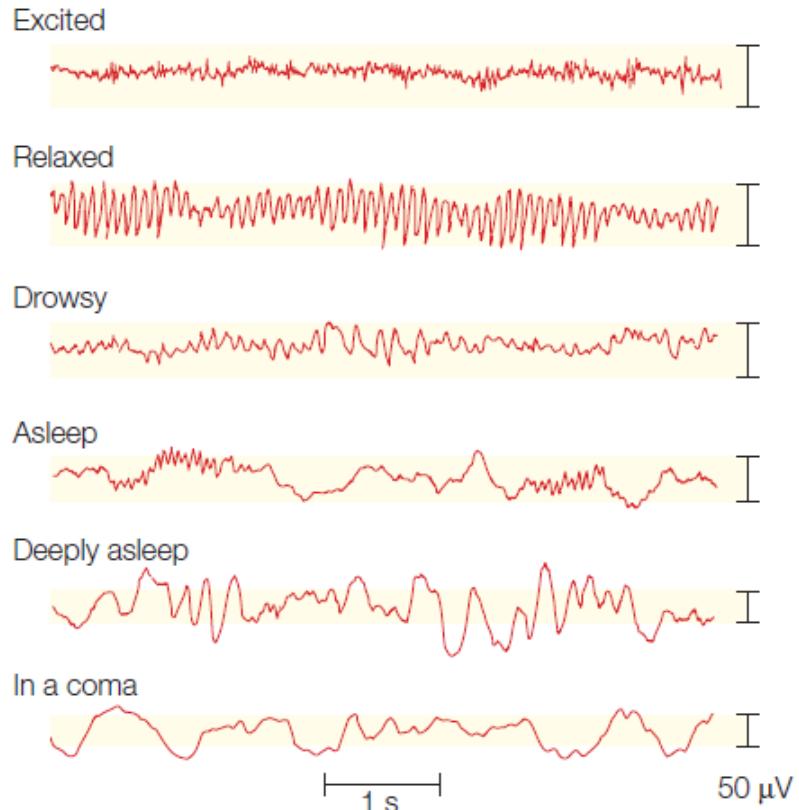


fotografixx/iStock

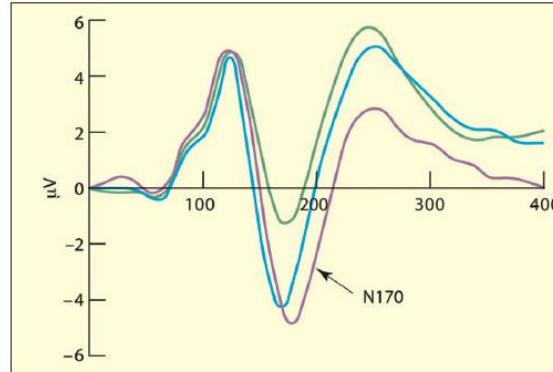
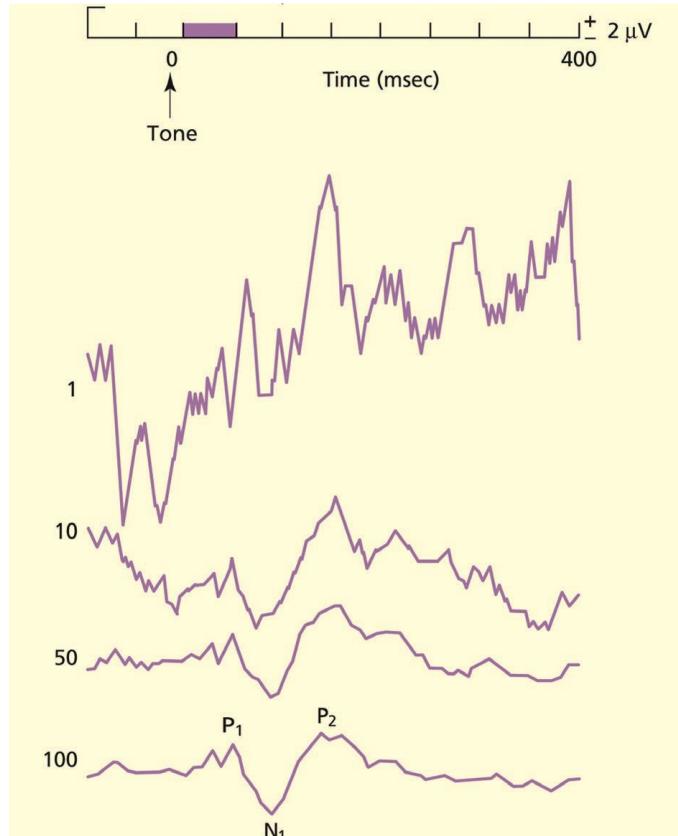
# The 10-20 System



# EEG signals



# Event-related potentials



**FIGURE 3.14:** The N170 is observed for both human faces (purple) and animal faces (blue), but not other objects (green). From Rousselet et al., 2004. With permission of ARVO.

A single recording has a low signal-to-noise ratio.

Averaging over hundreds of trials reveals the tiny signal, as noise is canceling.

Other EEG signals are treated as being non-correlated to the stimulus

→ Serially uncorrelated random variable

→ 0 mean (!) and finite variance

→ No prior distribution is assumed

AVERAGING REMOVES THE NOISE

# Python example

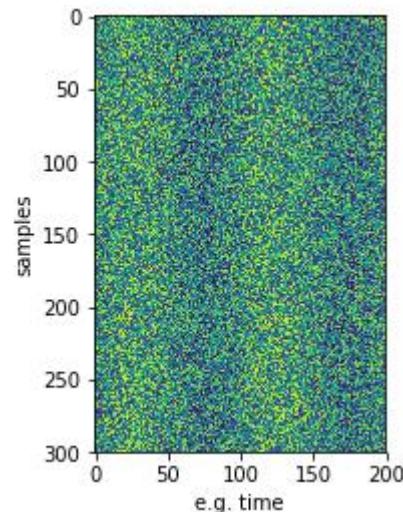
```
In [2]: 1 import numpy as np  
2 import matplotlib.pyplot as plt
```

Generate true signal

```
In [3]: 1 x = np.linspace(0, 4*np.pi, 200)  
2 y = np.sin(x)
```

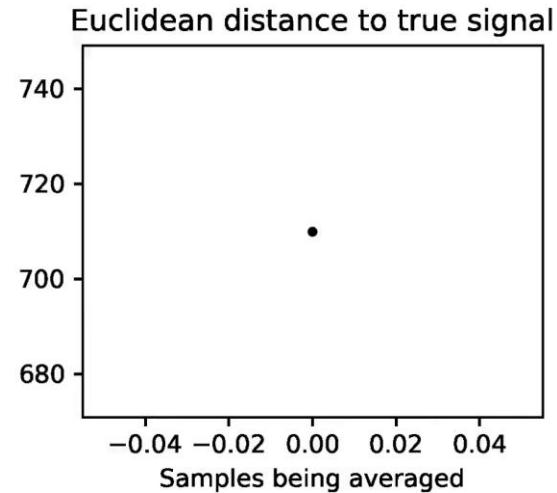
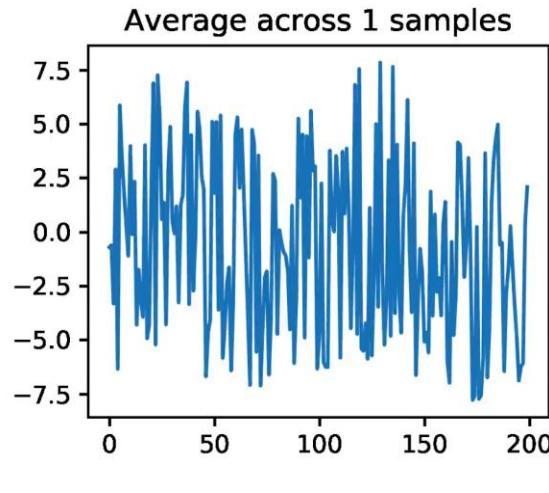
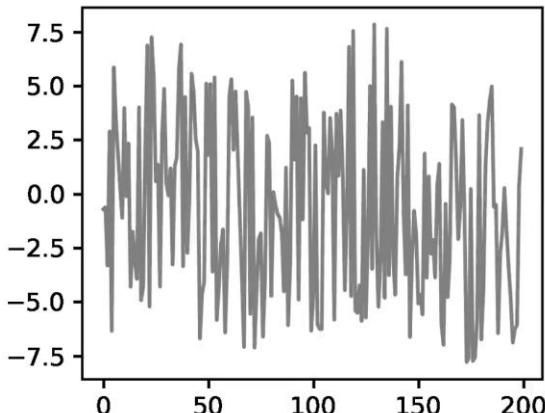
Generate samples from the true signal with added noise.

```
1 s = []  
2 factor=7  
3  
4 for _ in range(300):  
5     s.append(y + np.random.uniform(-factor, factor, y.size))  
6  
7 plt.imshow(s)  
8 plt.ylabel("samples")  
9 plt.xlabel("e.g. time")
```



# Averaging over multiple samples

Sine signal with plenty of white noise (drawn from uniform distribution)



# Noise2Noise and Noise2Void

For the  $L_2$  loss  $L(z, y) = (z - y)^2$ , this minimum is found at the arithmetic mean of the observations:

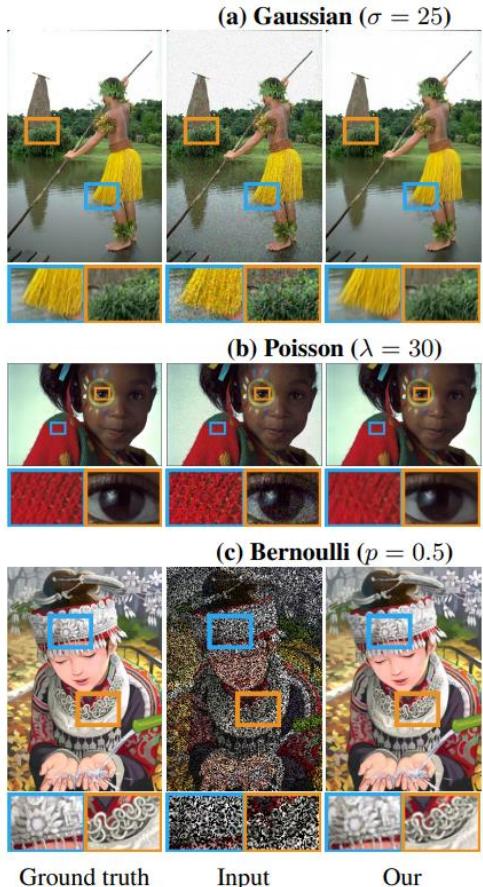
$$z = \mathbb{E}_y\{y\}. \quad (3)$$

The  $L_1$  loss, the sum of absolute deviations  $L(z, y) = |z - y|$ , in turn, has its optimum at the median of the observations.

conditional expected values. *This implies that we can, in principle, corrupt the training targets of a neural network with zero-mean noise without changing what the network learns.* Combining this with the corrupted inputs from Equa-



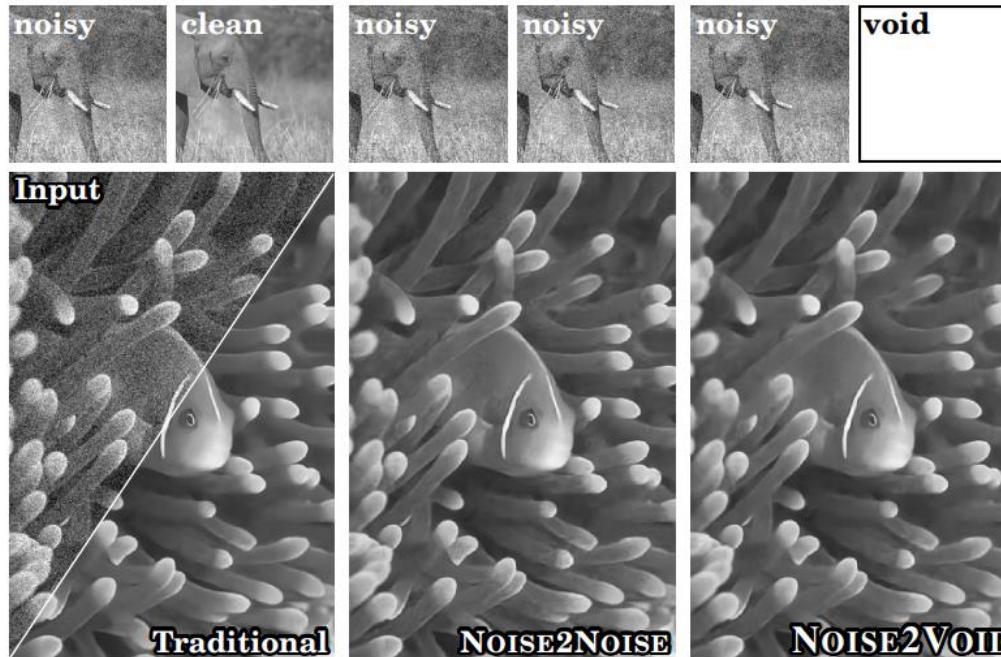
Lehtinen et al., 2018



# Noise2Noise and Noise2Void

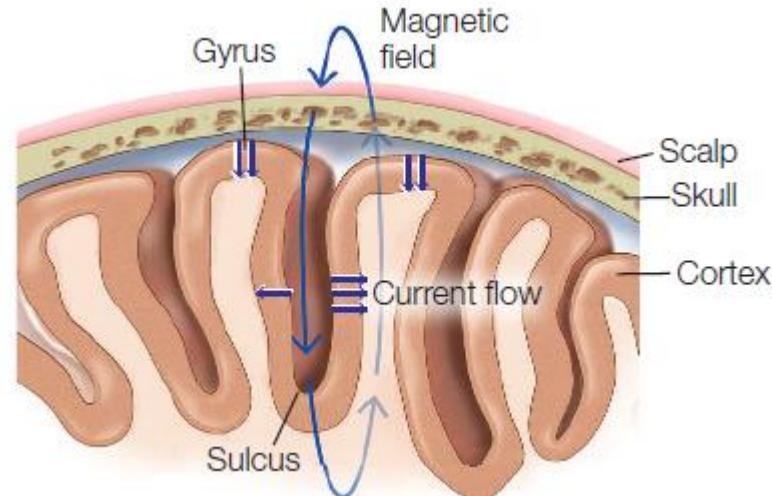
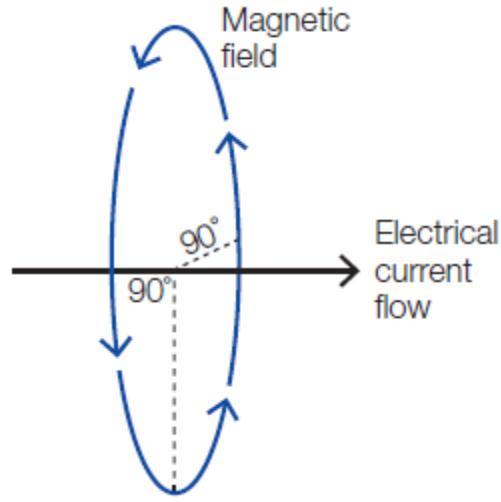


Example training pairs

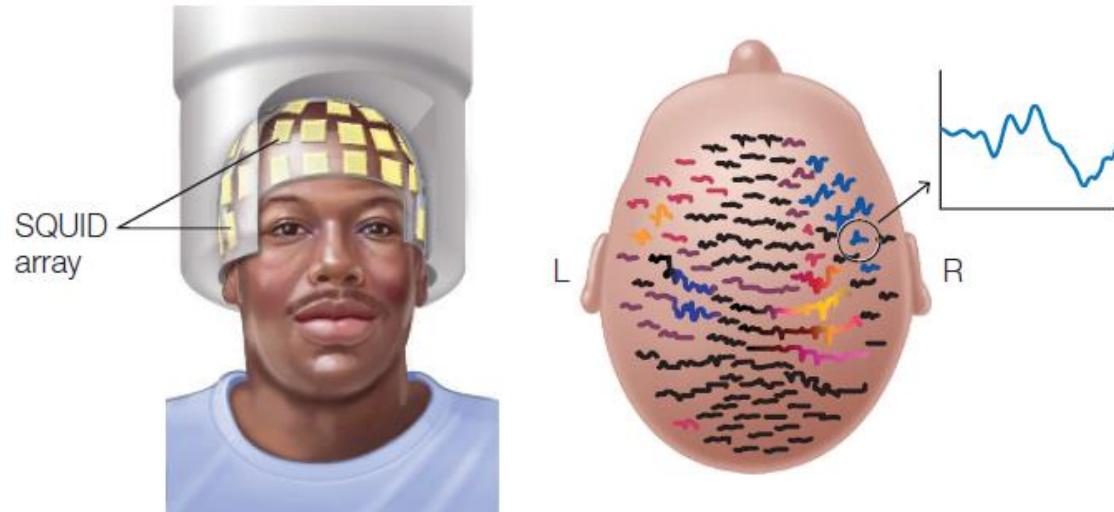


Krull et al., 2019

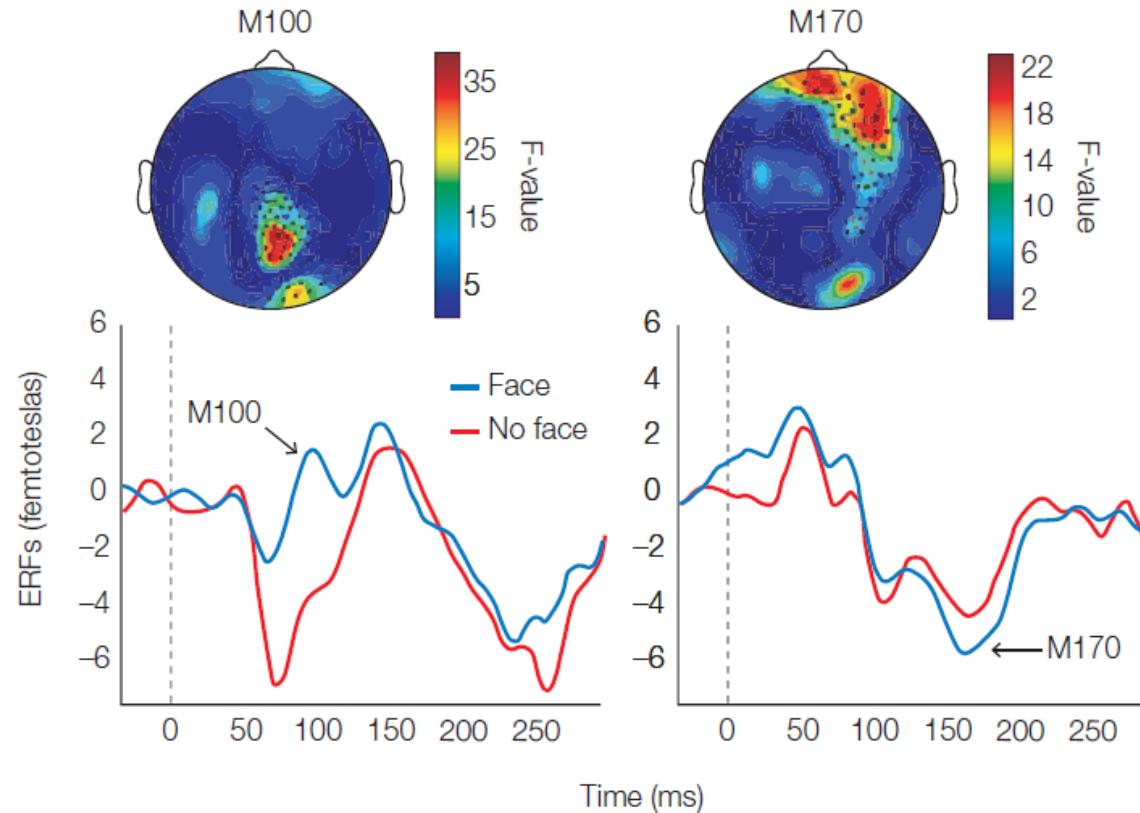
# Magnetoencephalography (MEG)



# MEG recording setting

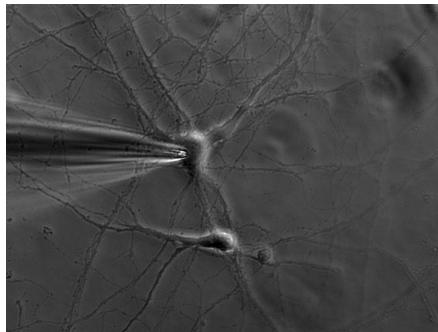
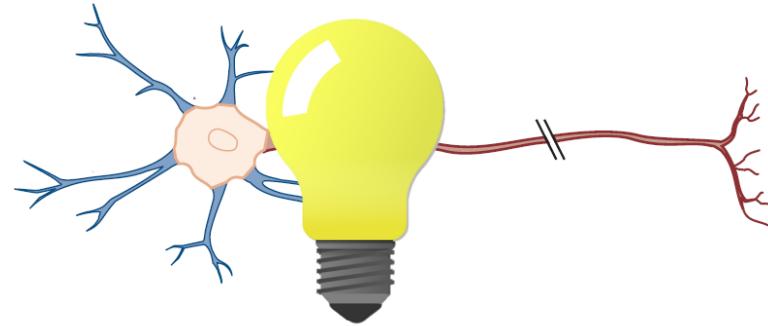
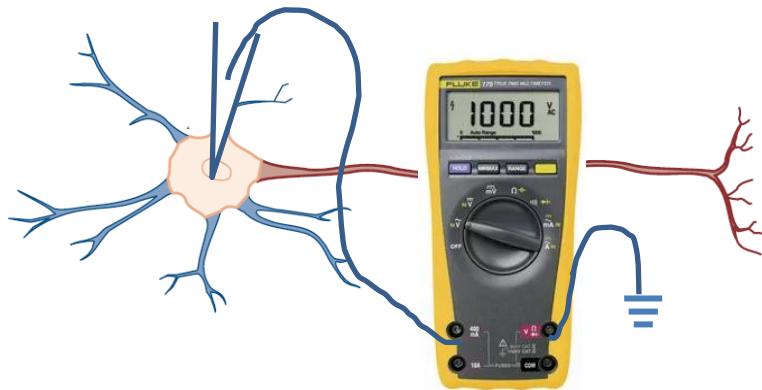


# Topoplots



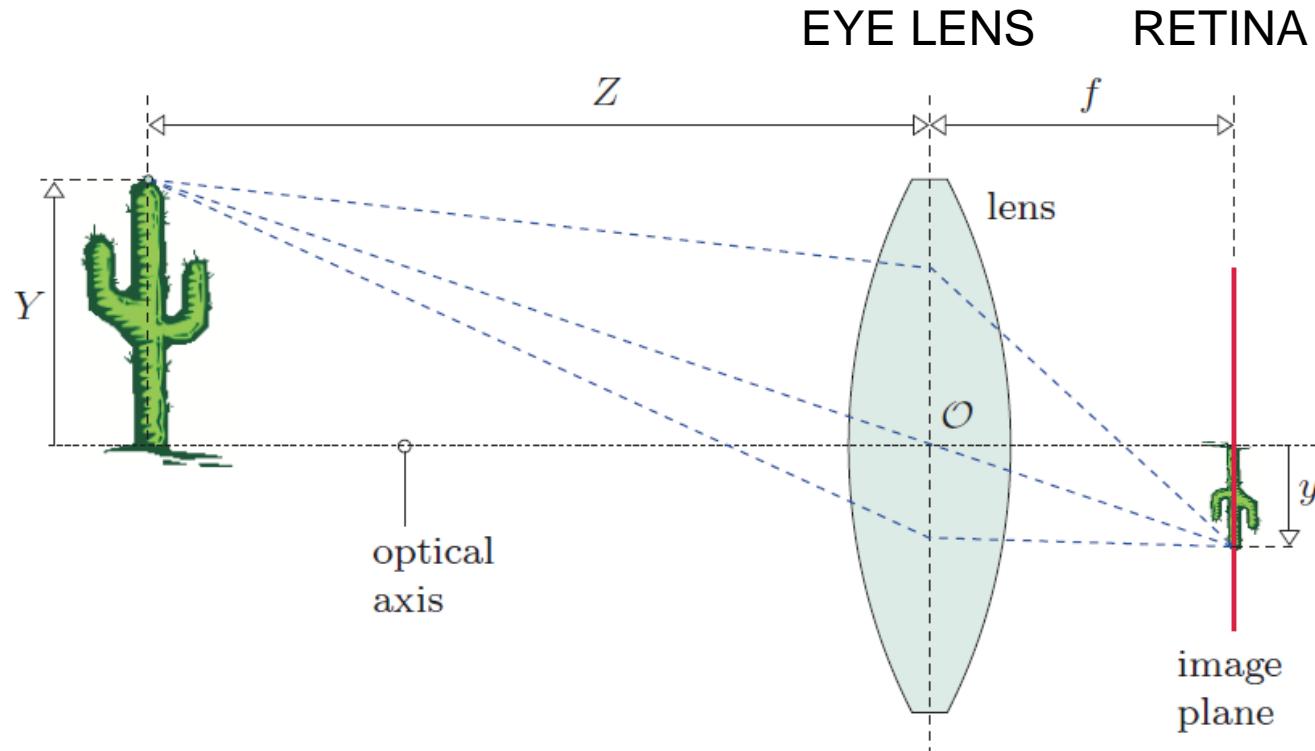
# Optical approaches

# Measuring neural activity

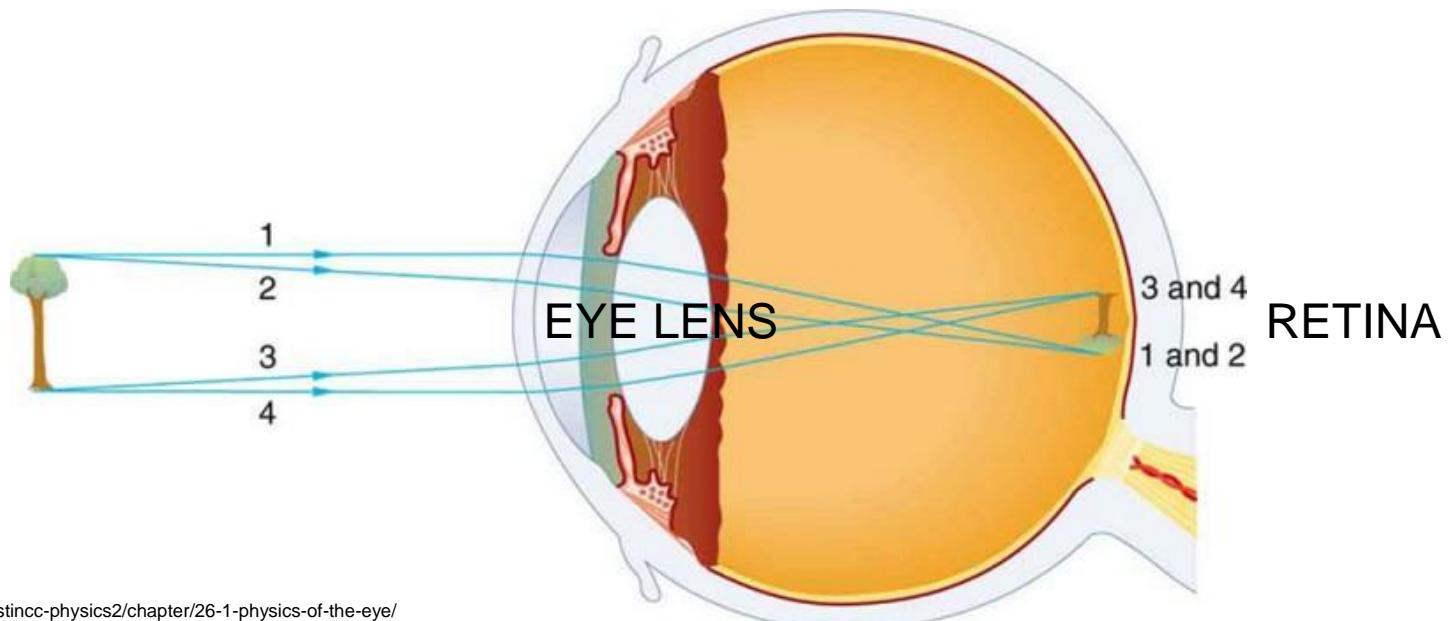
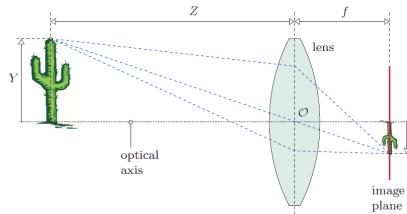


**Optical approaches** to measure  
neural activity

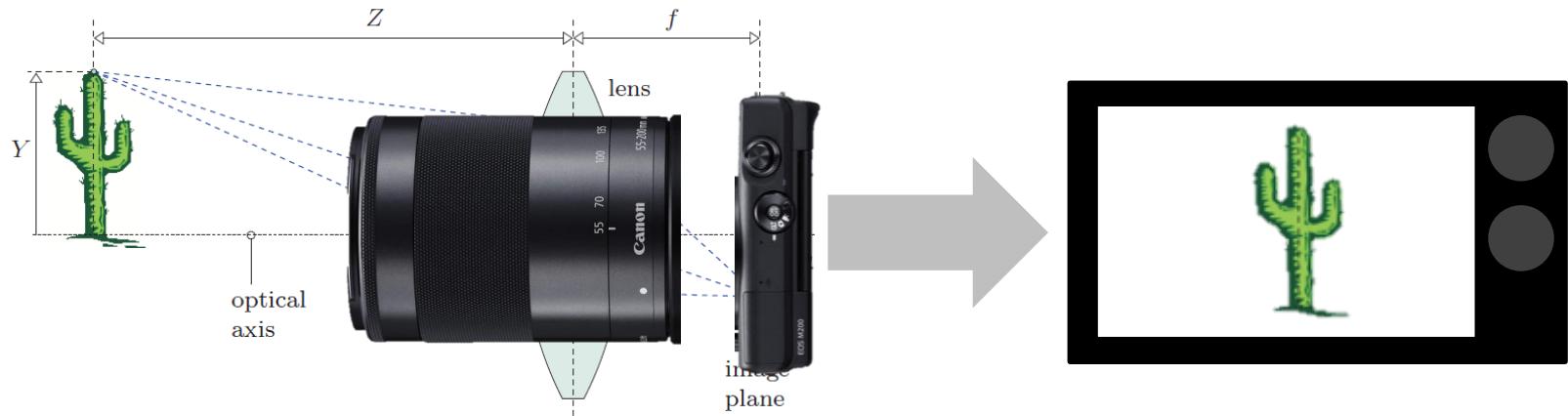
# How does imaging work?

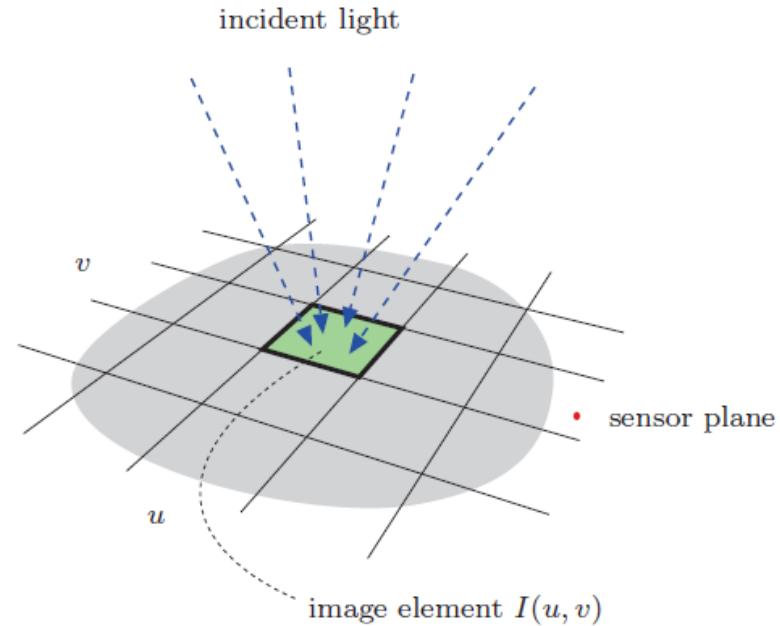
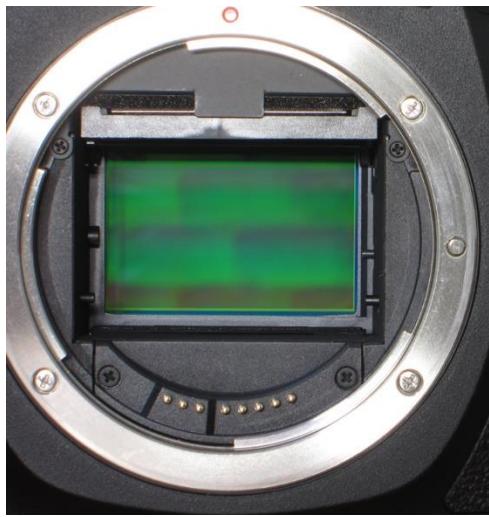


# How does imaging work?

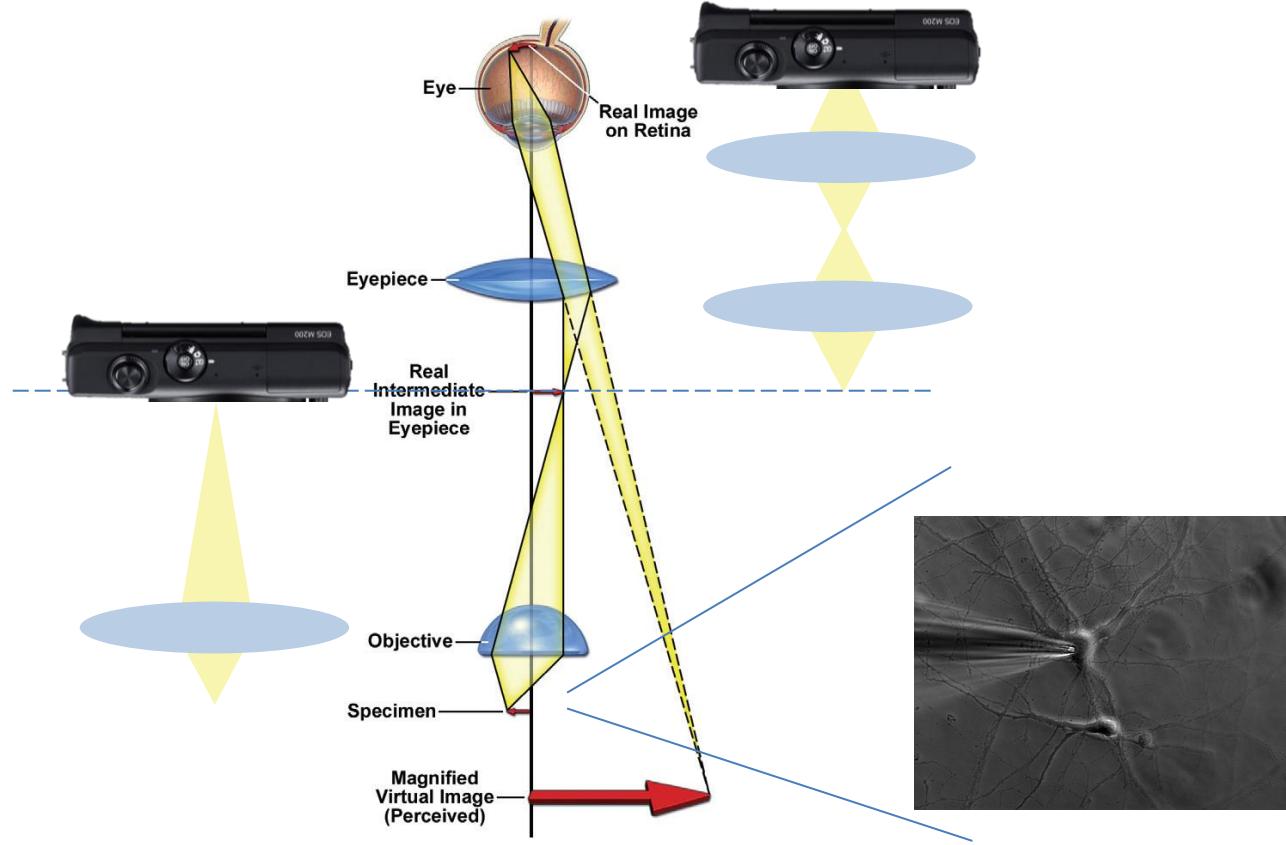


# How does imaging work?

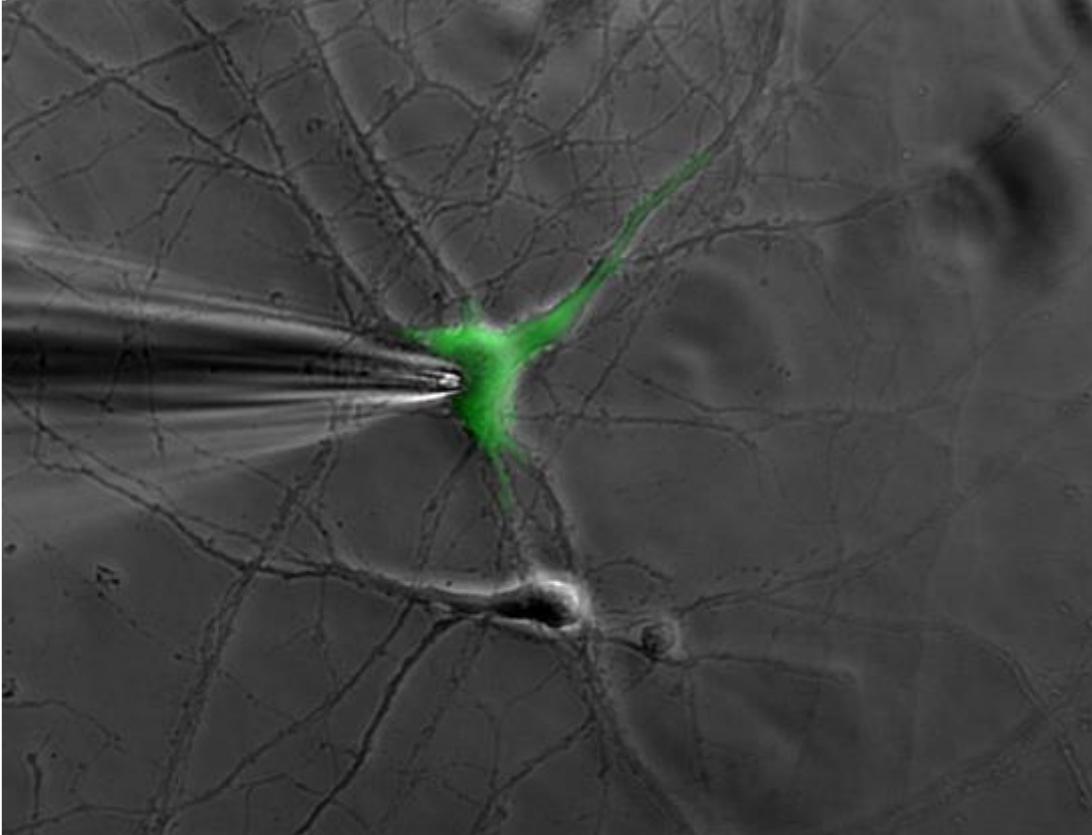




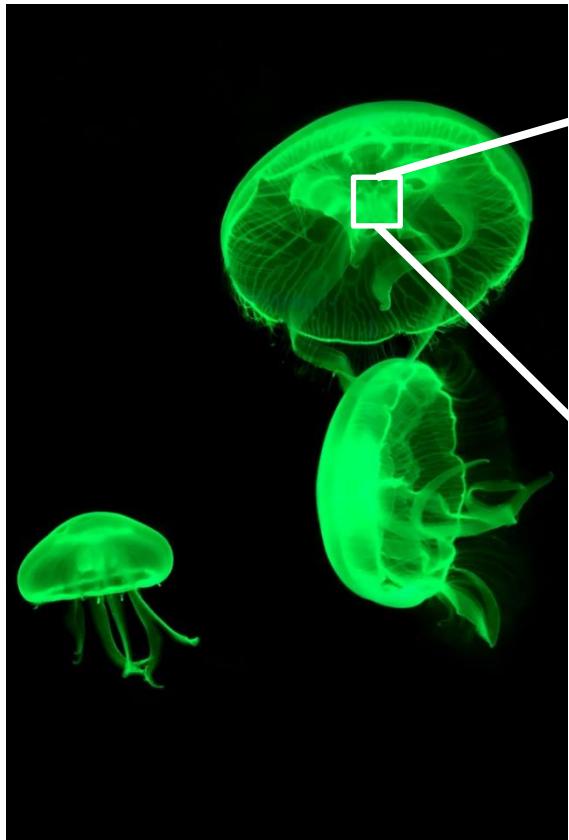
# A basic microscopy setup



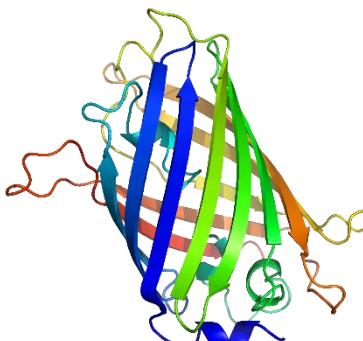
# Making cells shine



# Glowing jellyfish



## Green fluorescent protein (GFP)



The Nobel Prize in Chemistry 2008



© The Nobel Foundation. Photo: U. Montan  
**Osamu Shimomura**  
Prize share: 1/3



© The Nobel Foundation. Photo: U. Montan  
**Martin Chalfie**  
Prize share: 1/3



© The Nobel Foundation. Photo: U. Montan  
**Roger Y. Tsien**  
Prize share: 1/3

The Nobel Prize in Chemistry 2008 was awarded jointly to Osamu Shimomura, Martin Chalfie and Roger Y. Tsien "for the discovery and development of the green fluorescent protein, GFP."

# A protein that fluoresces

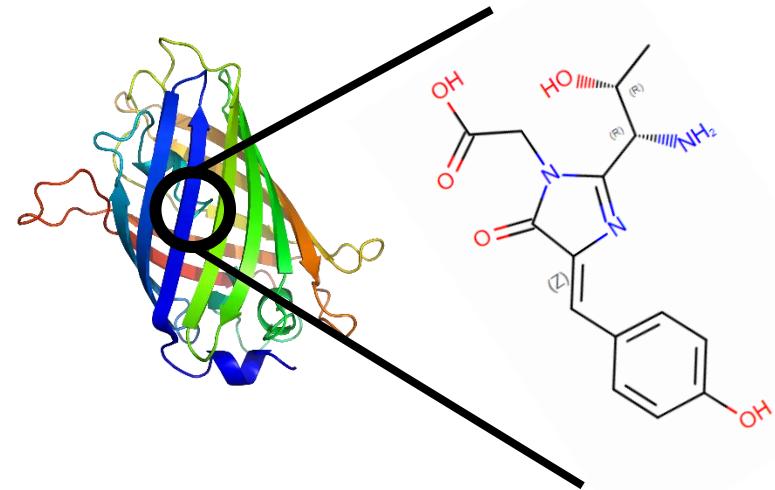
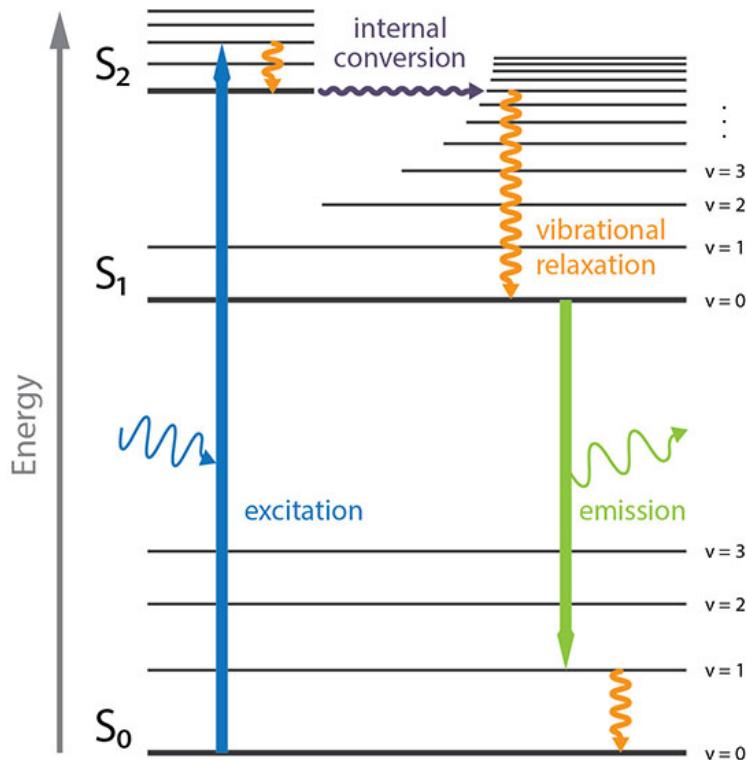
Bacteria expressing GFP



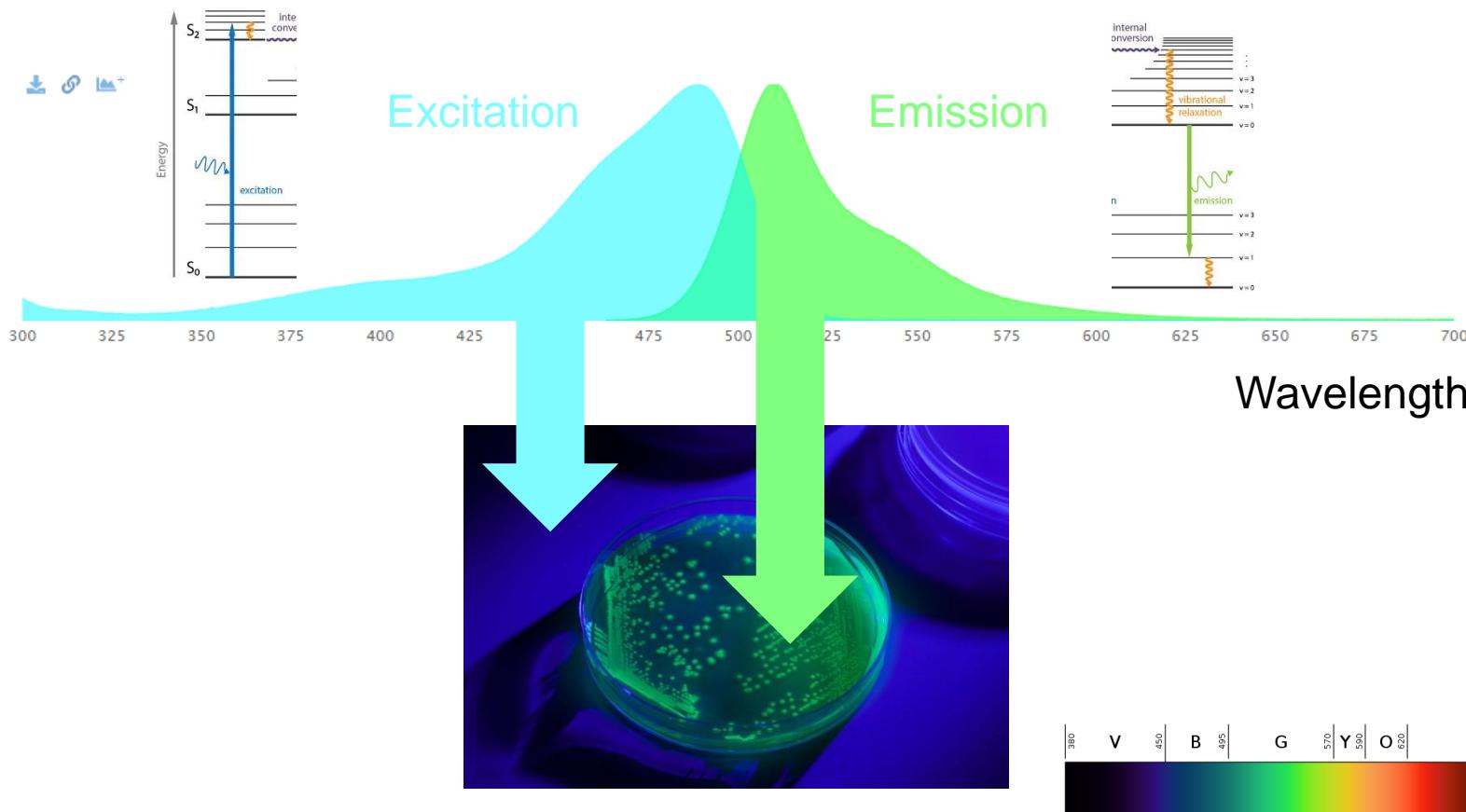
What is fluorescence?

Why is it useful?

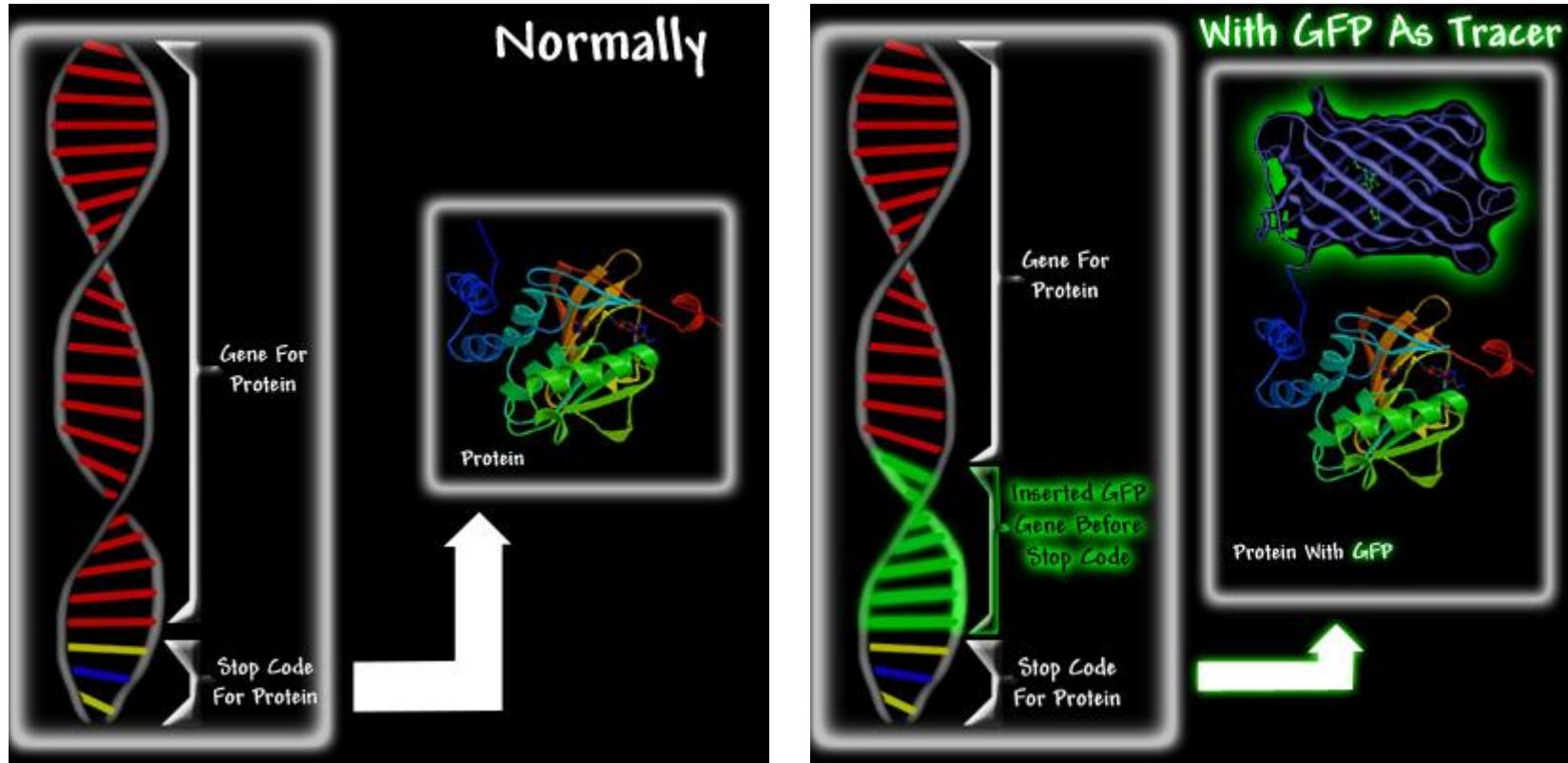
# Fluorescence in essence



# Spectral properties of GFP

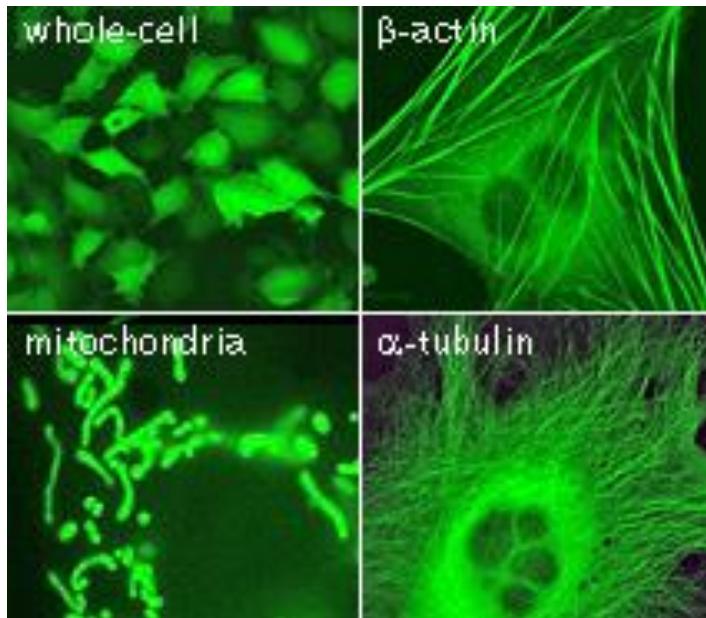


# Why is it useful

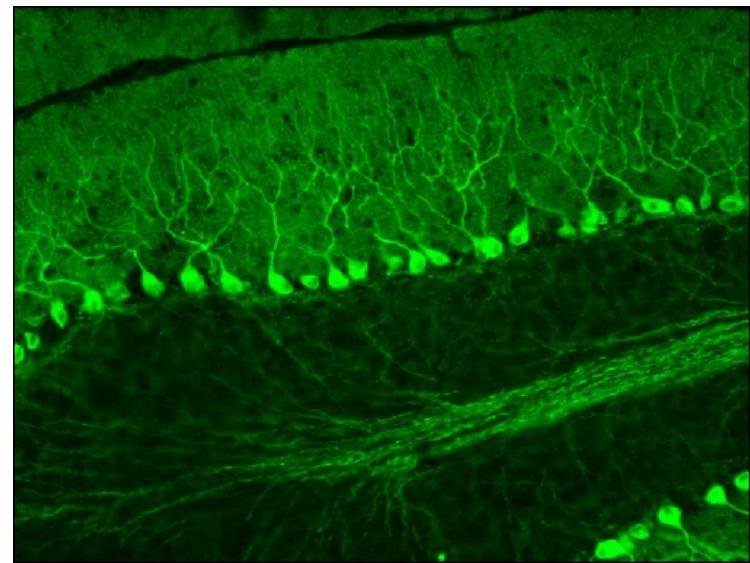


# GFP tagging

GFP allows the visualization of cell structures,  
when CELLS ARE ALIVE!

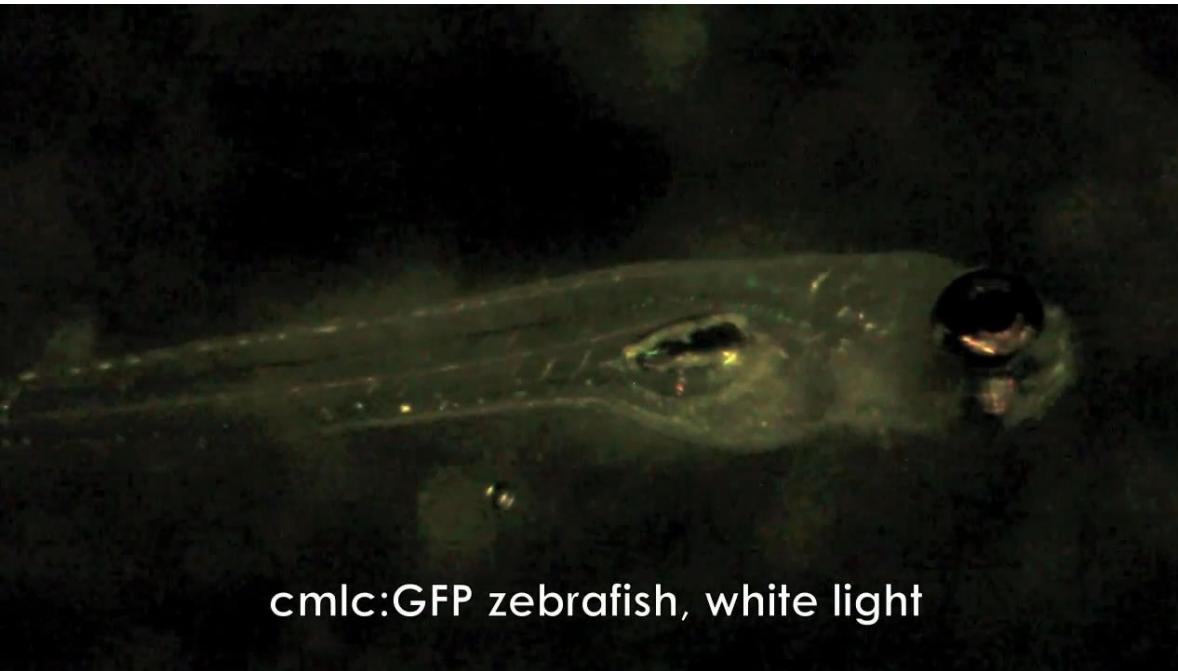


<https://www.biocat.com/proteomics/green-fluorescent-proteins-gfp-s>



[https://www2.tmicg.or.jp/Mn\\_B/English/GFP\\_in\\_Purkinje\\_cell.html](https://www2.tmicg.or.jp/Mn_B/English/GFP_in_Purkinje_cell.html)

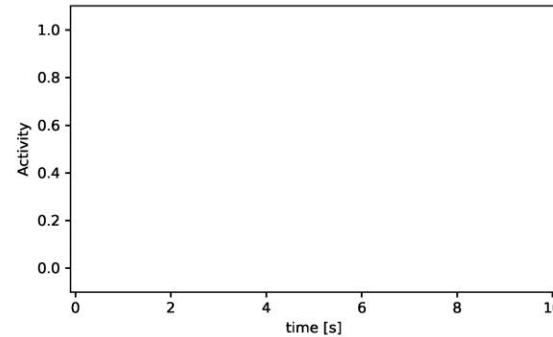
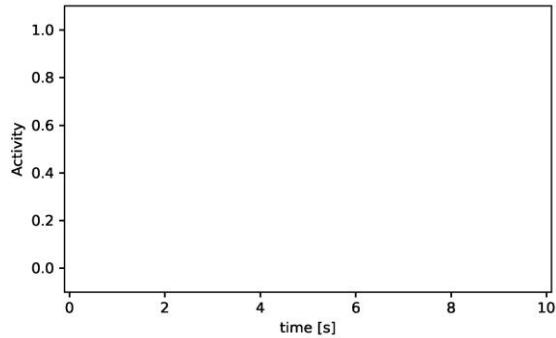
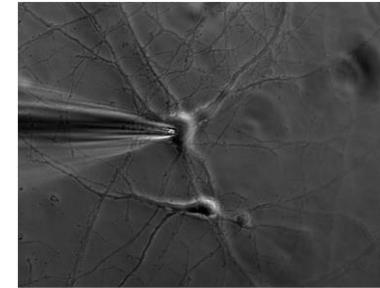
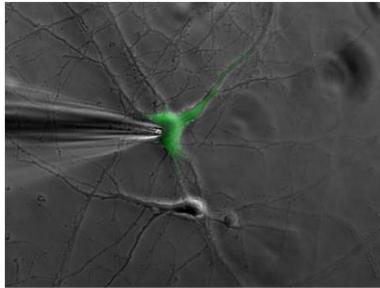
Larval zebrafish (ca. 5 days old)



cmlc:GFP zebrafish, white light

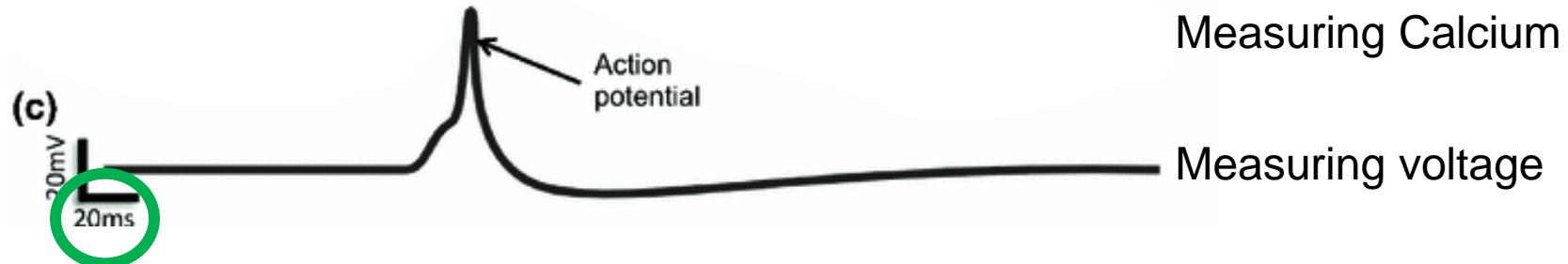
© Nightsea, <https://www.youtube.com/watch?v=fYMOEN7ANM>

# How to track neural activity?

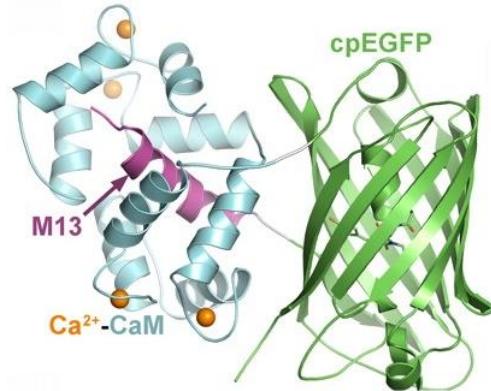


Activity-dependent fluorescence!

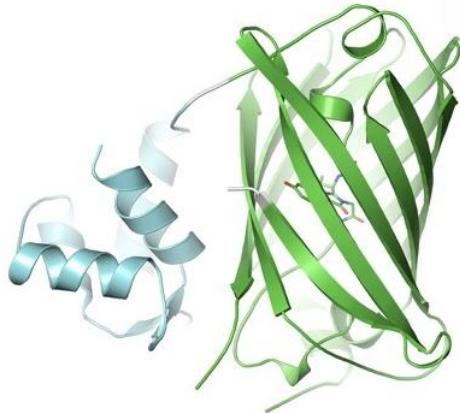
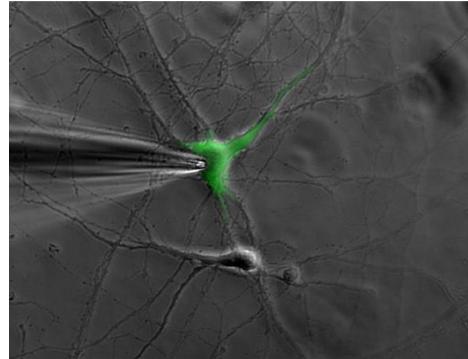
# Activity dependent fluorescence



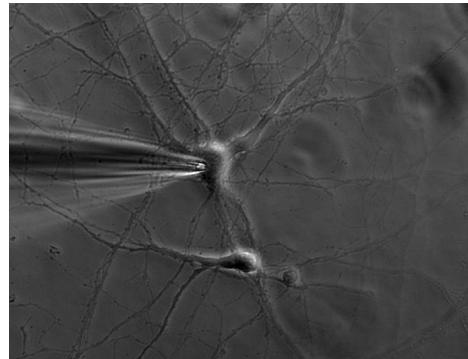
# Calcium imaging



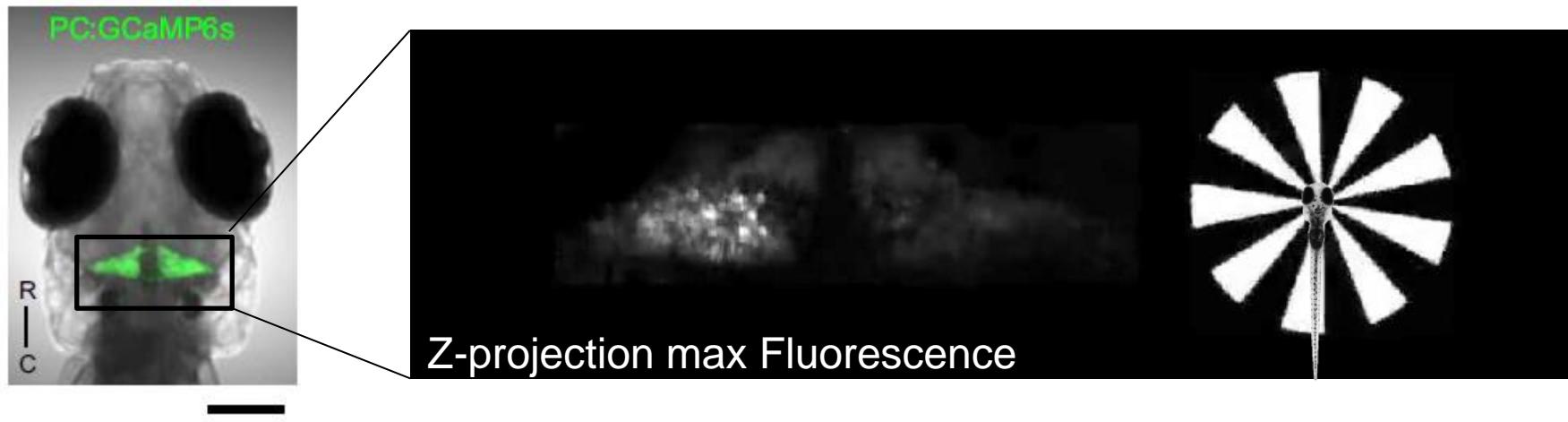
with  $\text{Ca}^{2+}$



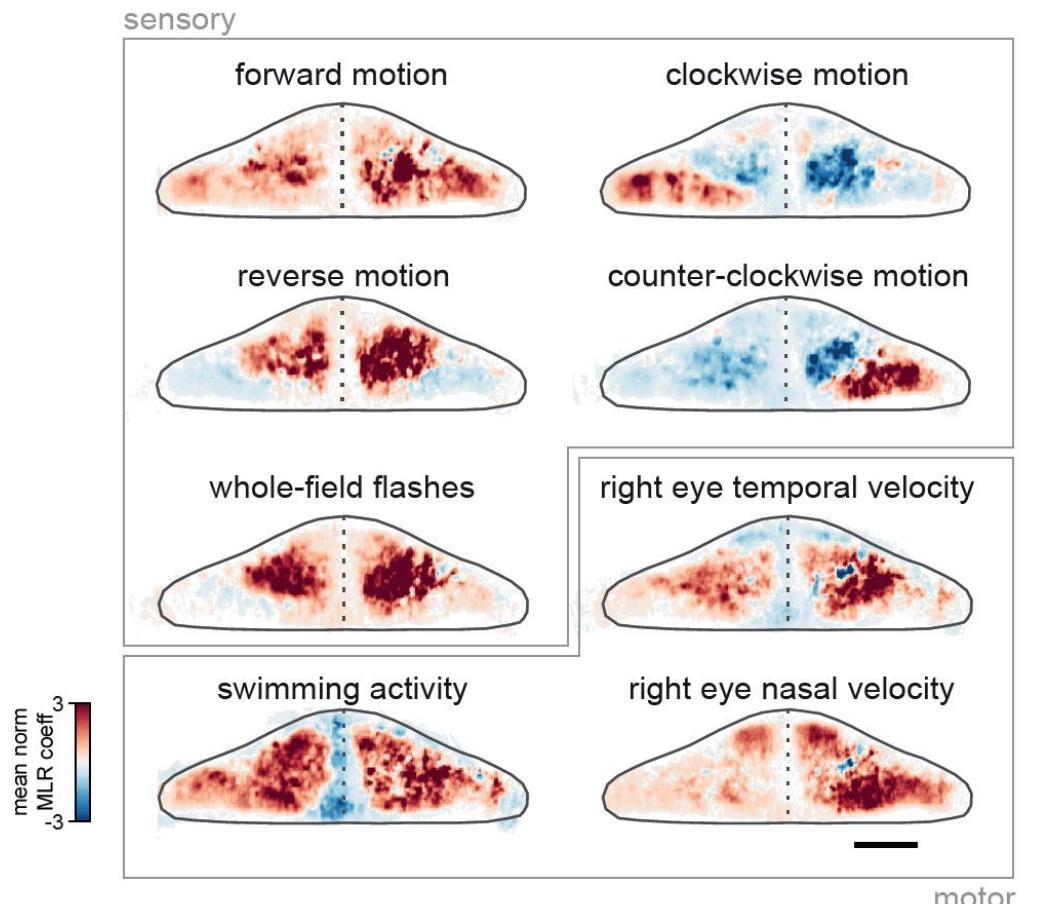
w/o  $\text{Ca}^{2+}$



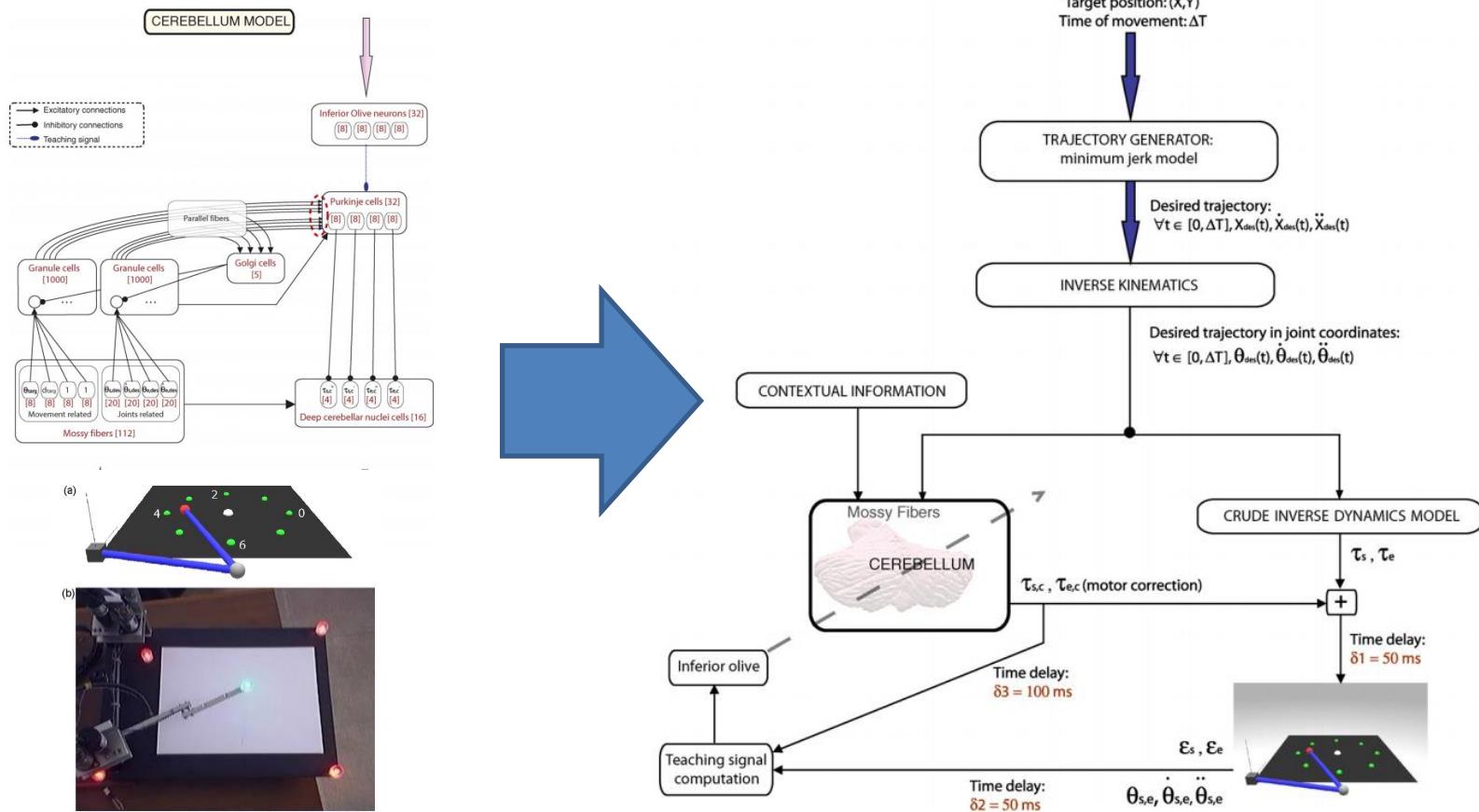
# Imaging Purkinje cells in larval zebrafish



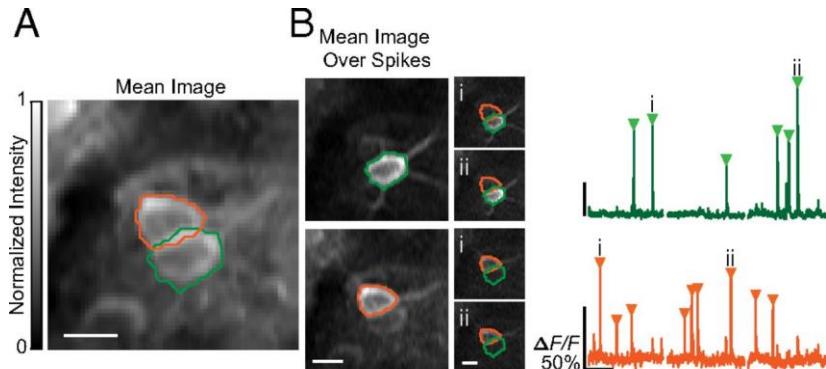
# Calcium imaging reveals activity dependent on sensory stimuli



# Why is this important to AI Developers?



# Application of AI in life sciences



## CalciumGAN: A Generative Adversarial Network Model for Synthesising Realistic Calcium Imaging Data of Neuronal Populations

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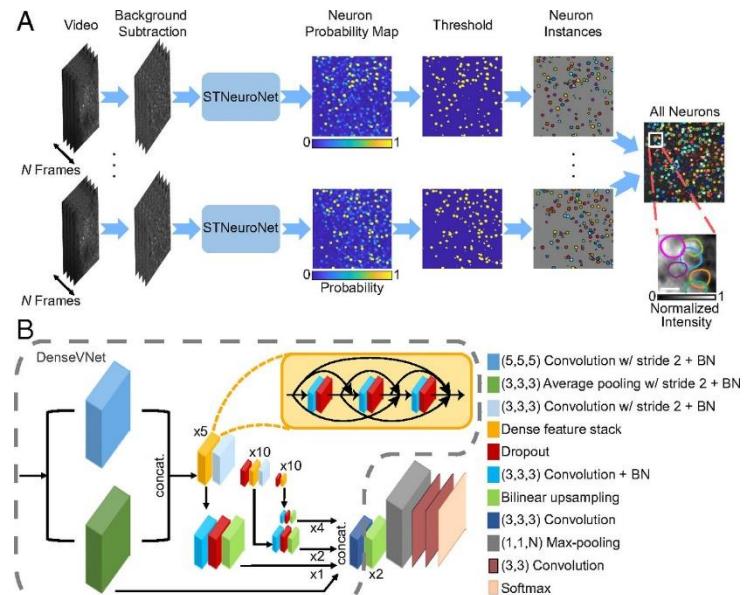
<sup>2</sup>Centre for Discovery Brain Sciences, University of Edinburgh

<sup>3</sup>Simons Initiative for the Developing Brain, University of Edinburgh

## Fast and robust active neuron segmentation in two-photon calcium imaging using spatiotemporal deep learning

• Somayeh Soltanian-Zadeh, Kaan Sahingur, Sarah Blau, Yiyang Gong, and Sina Farsiu  
+ See all authors and affiliations

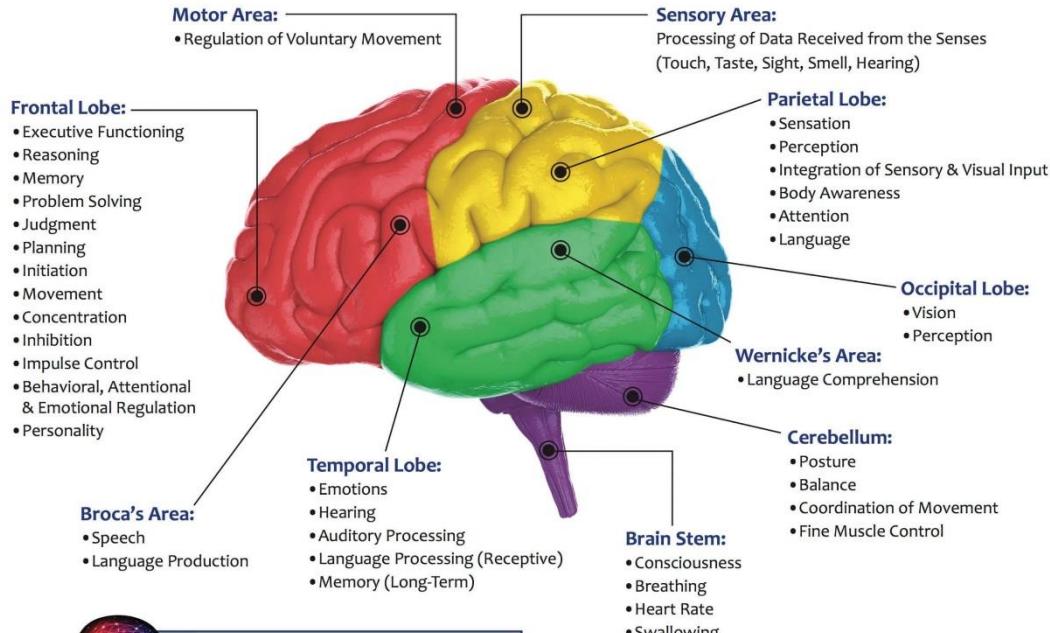
PNAS April 23, 2019 116 (17) 8554-8563; first published April 11, 2019; <https://doi.org/10.1073/pnas.1812995116>



# Connectivity

# The brain does it, but ... where?

## Brain Structure and Function



**Dr. Roseann Capanna-Hodge  
& Associates**

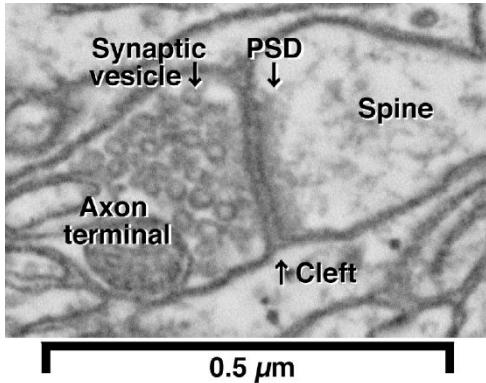
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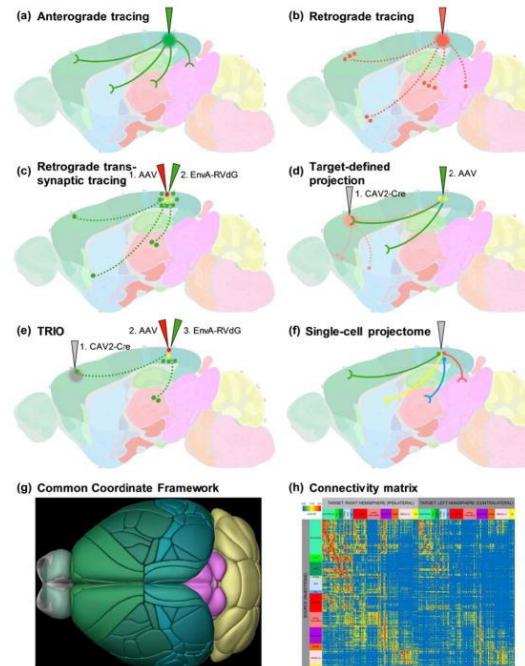
# Connectivity analysis

Micro [ $\mu\text{ms}$ ]



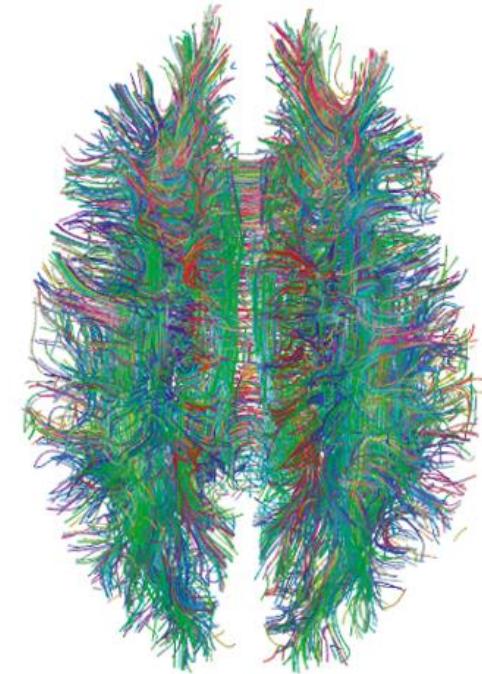
<https://blogs.zeiss.com/microscopy/en/brain-circuits/>

Meso [100  $\mu\text{ms}$ ]



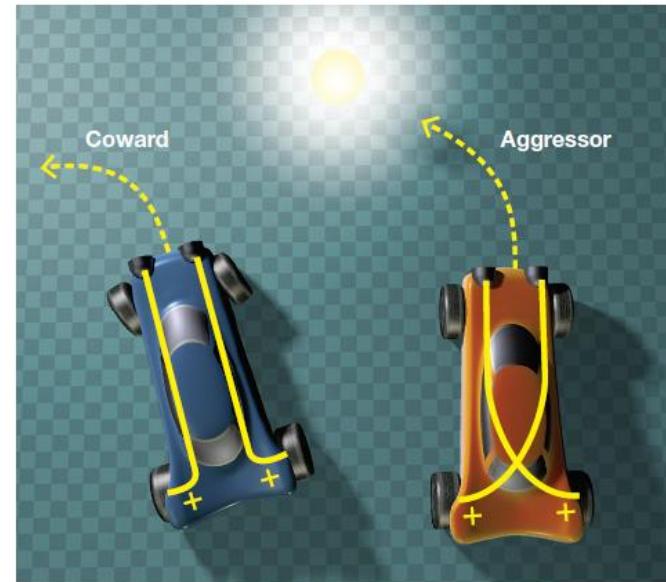
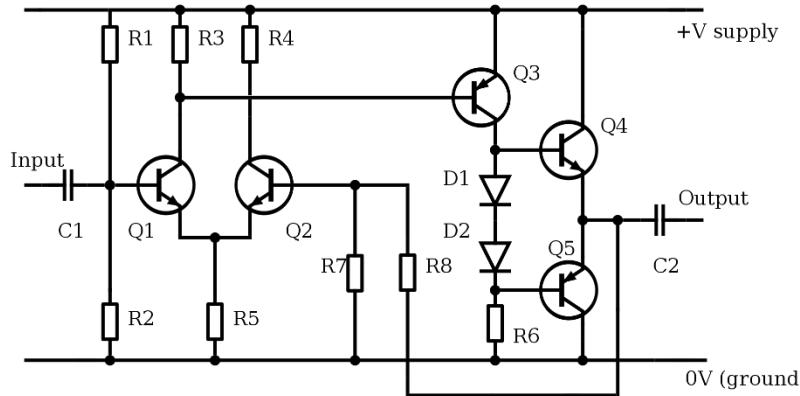
Zeng, Curr Opin Neurobiol 2018

Macro [mms]



Xavier Gigandet  
et al., 2008

# Why is it important?



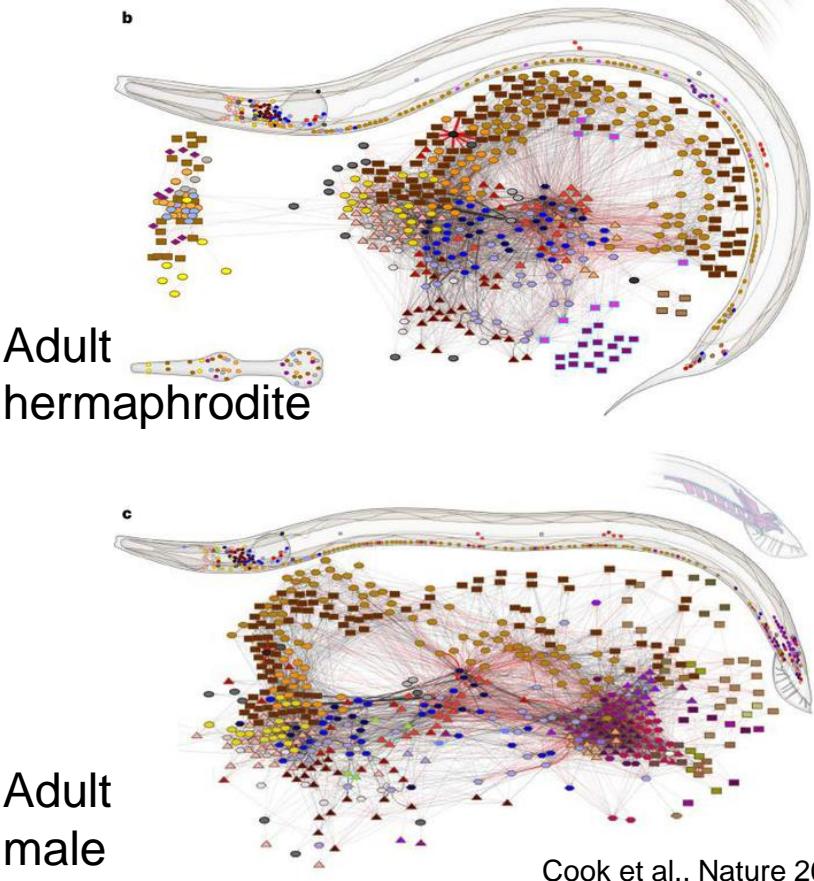
Knowing the circuitry helps in identifying the purpose

[https://en.wikipedia.org/wiki/Amplifier#/media/File:Amplifier\\_Circuit\\_Small.svg](https://en.wikipedia.org/wiki/Amplifier#/media/File:Amplifier_Circuit_Small.svg)

# *C. elegans* connectome

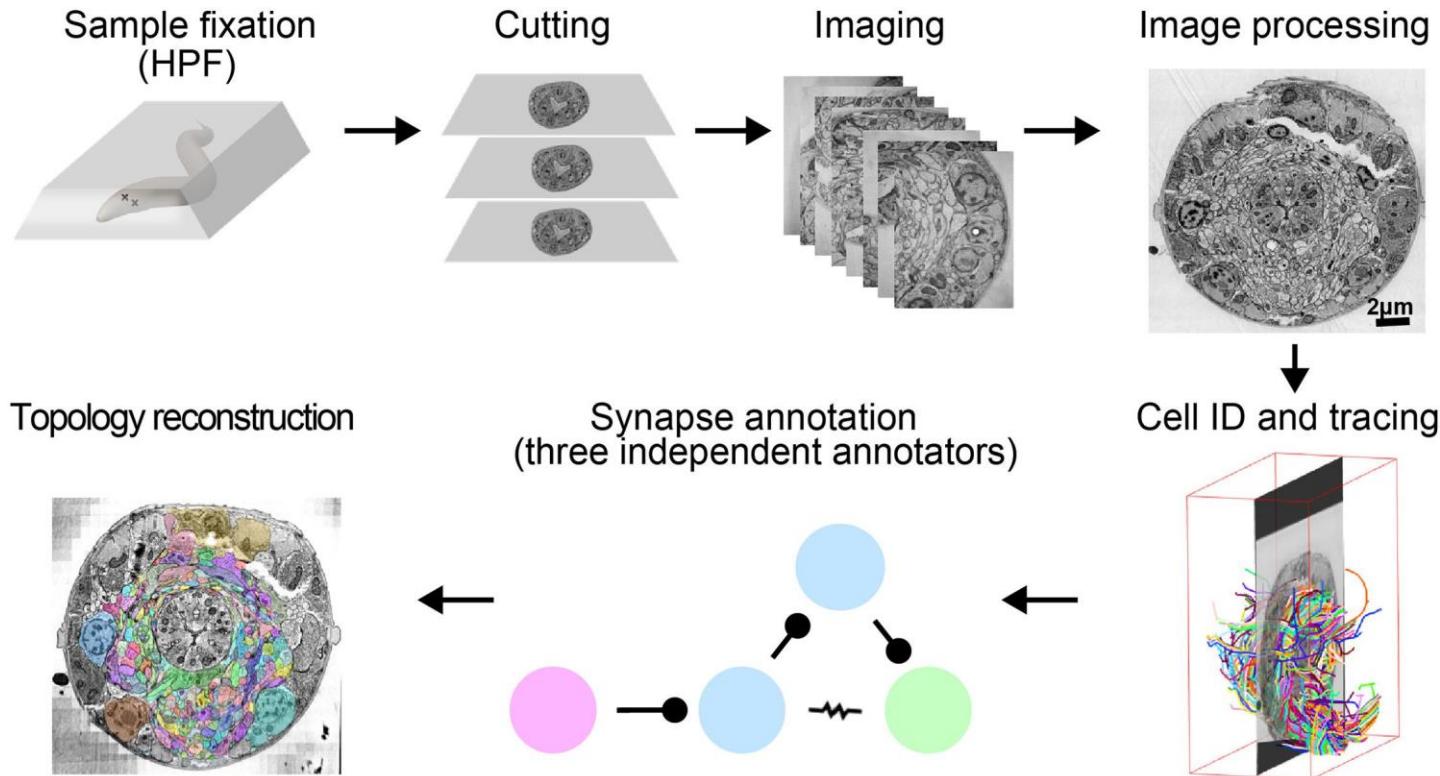


© Bob Goldstein

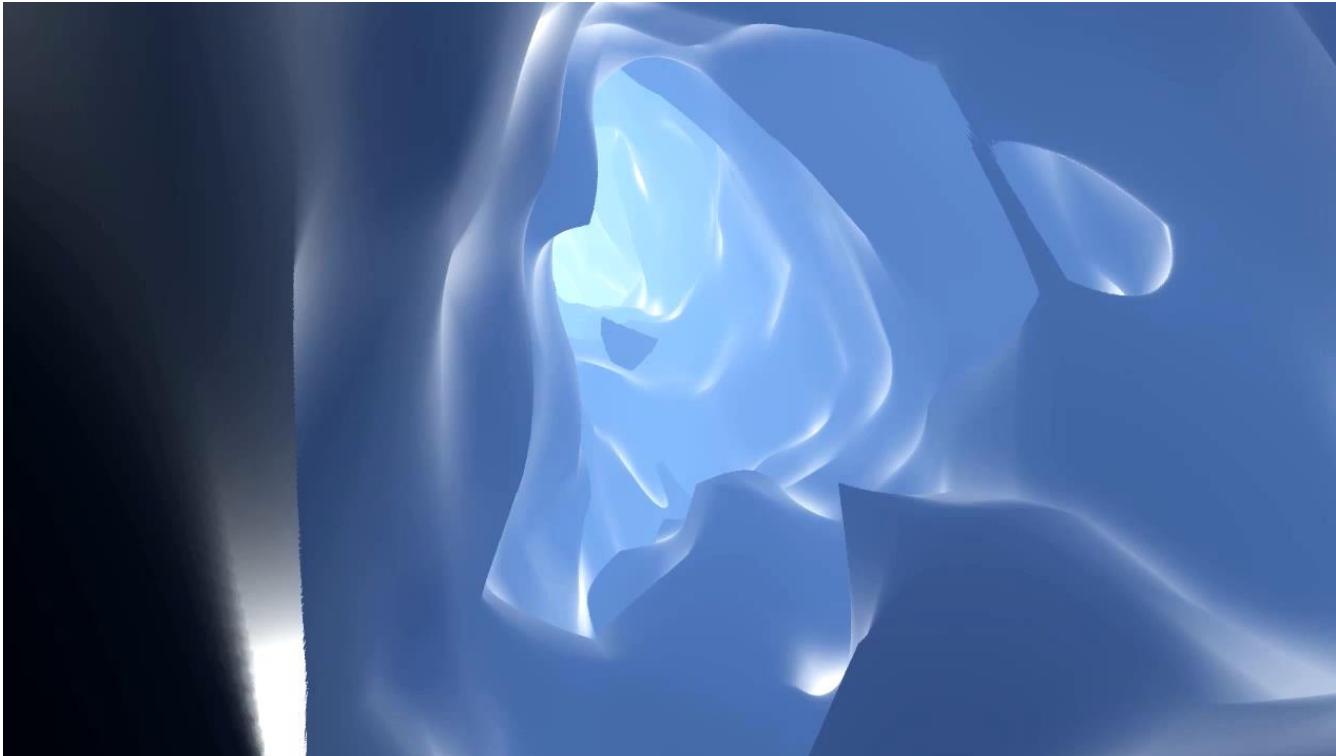


Cook et al., Nature 2019

# Electron microscopy



## Gamification of tasks



# Using AI for connectomics analysis

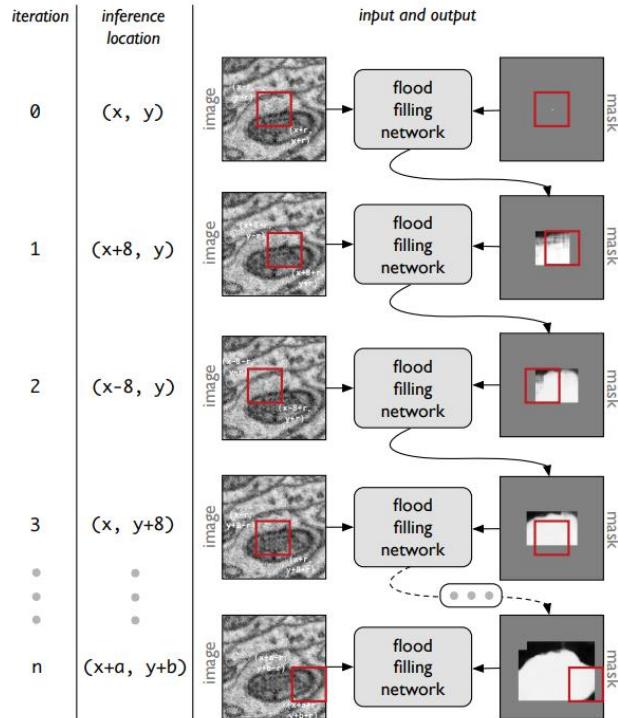
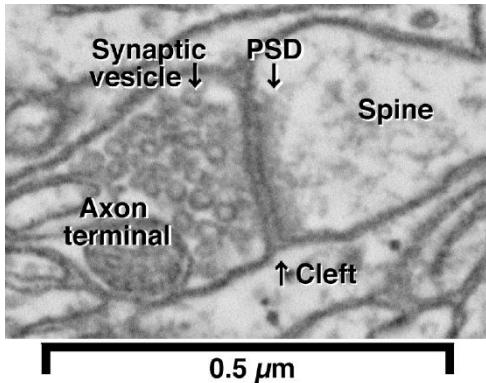


Figure 2: Schematic of multiple-field-of-view inference of a flood-filling network.

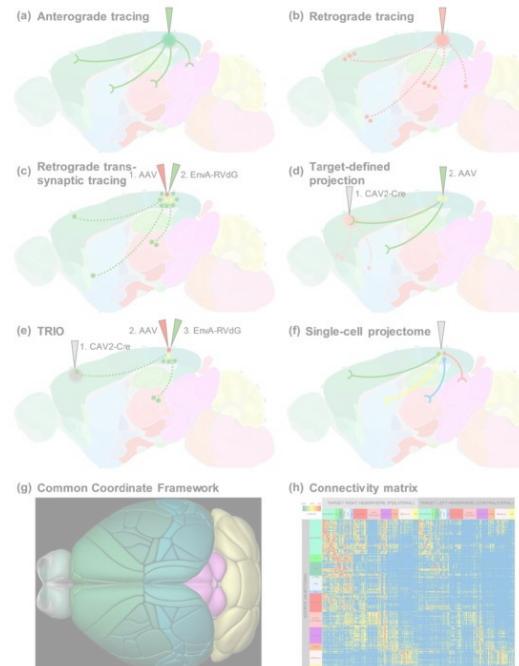
# Connectivity analysis

Micro [ $\mu\text{ms}$ ]



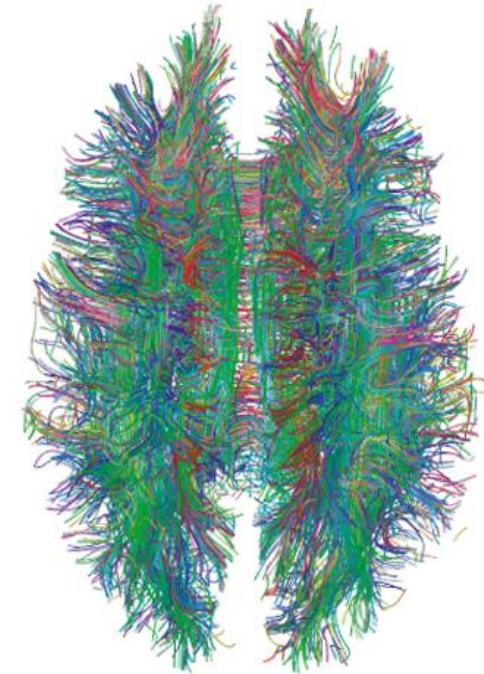
<https://blogs.zeiss.com/microscopy/en/brain-circuits/>

Meso [100  $\mu\text{ms}$ ]



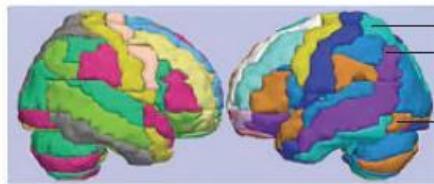
Zeng, Curr Opin Neurobiol 2018

Macro [mms]

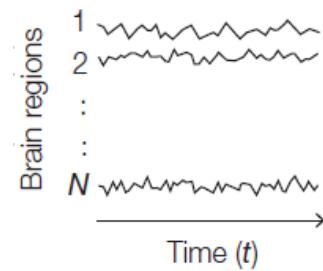


Xavier Gigandet  
et al., 2008

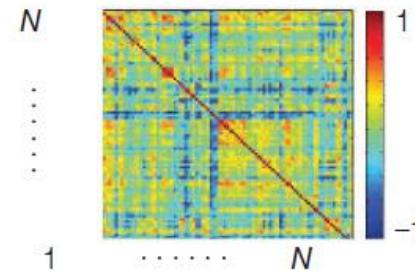
# Construction a human brain network



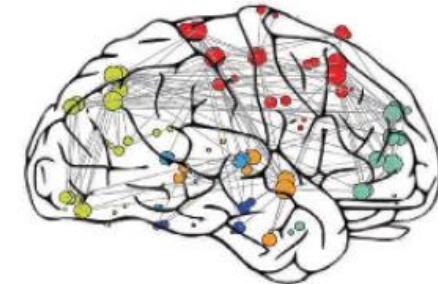
① Anatomical nodes



② fMRI time series



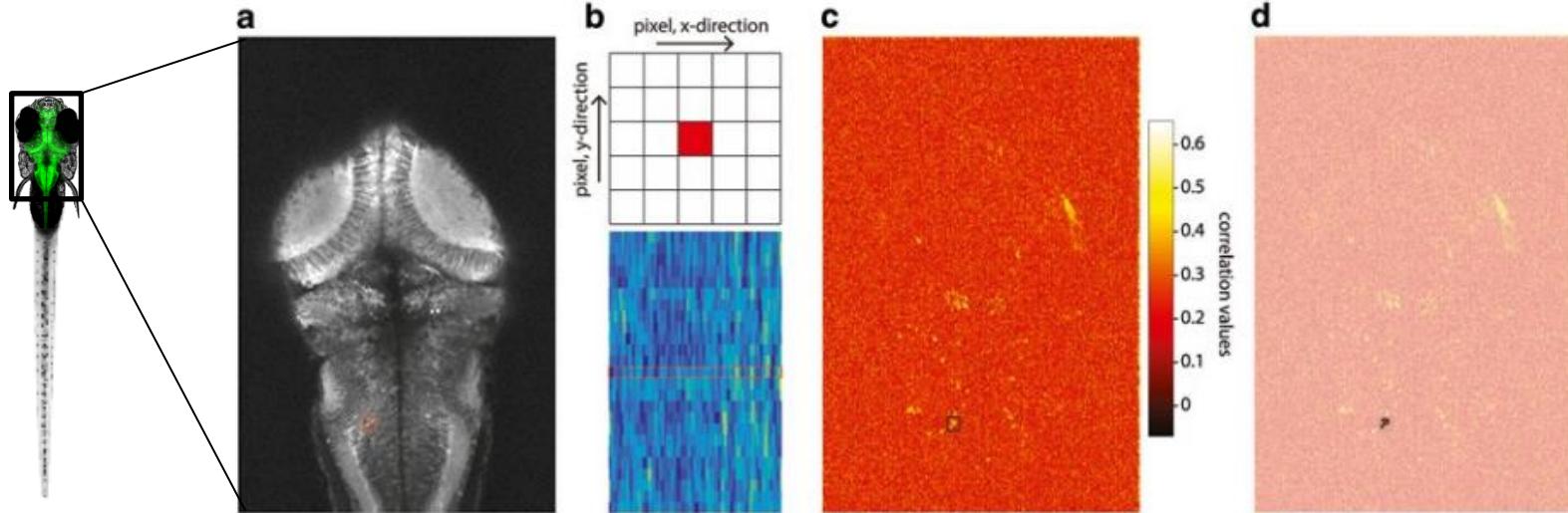
③ Association matrix



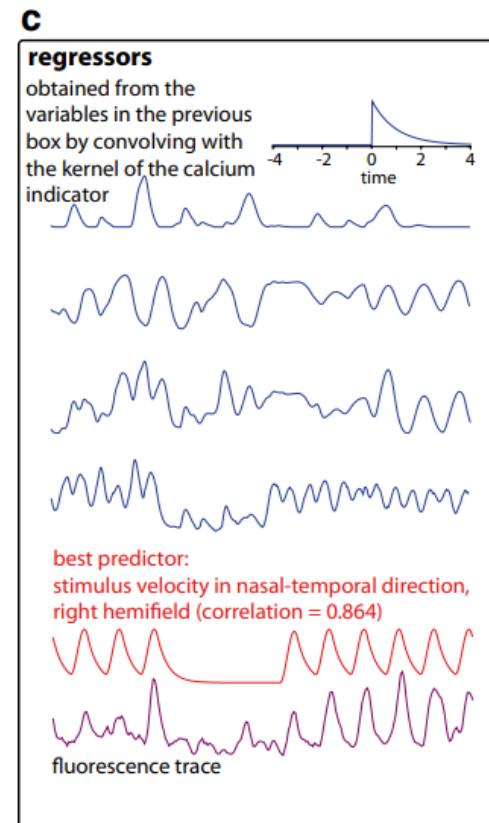
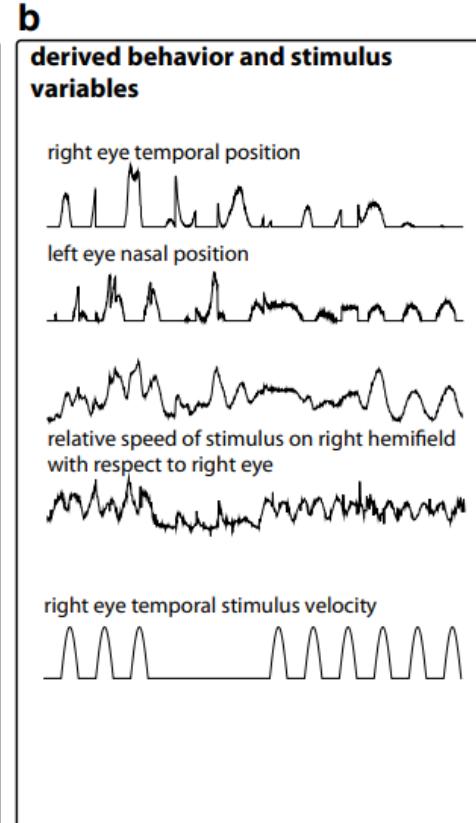
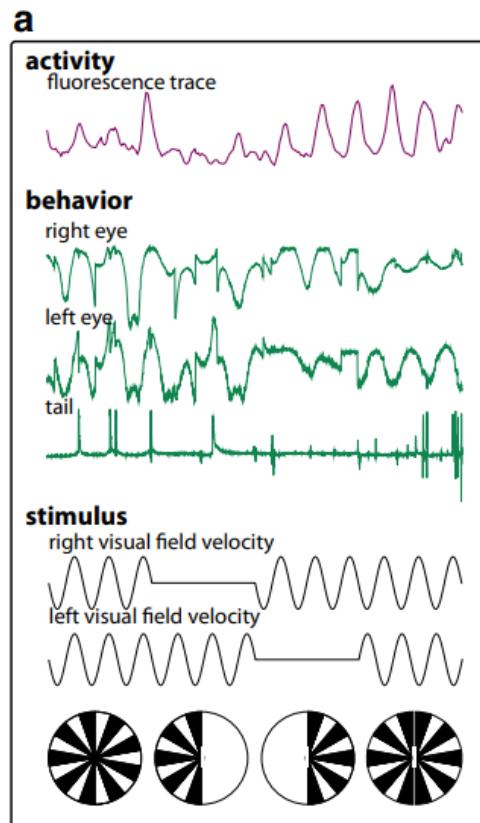
④ Connectivity map

# Voxel-based correlation map

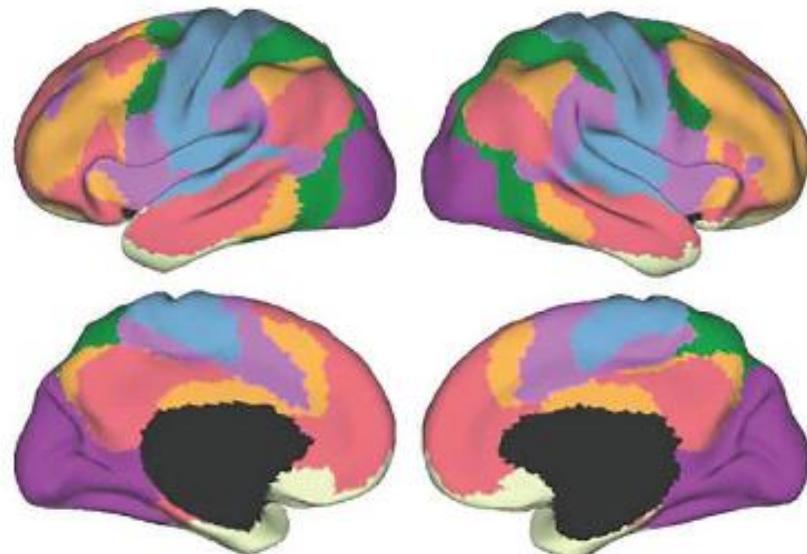
## Unbiased voxel-based self-correlation



# Voxel-based correlation maps



Discovery sample

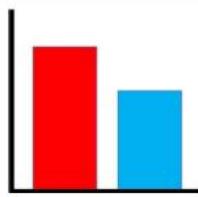
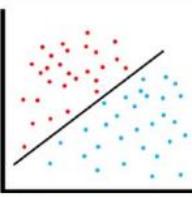
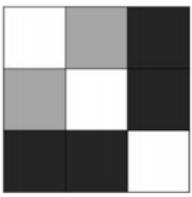


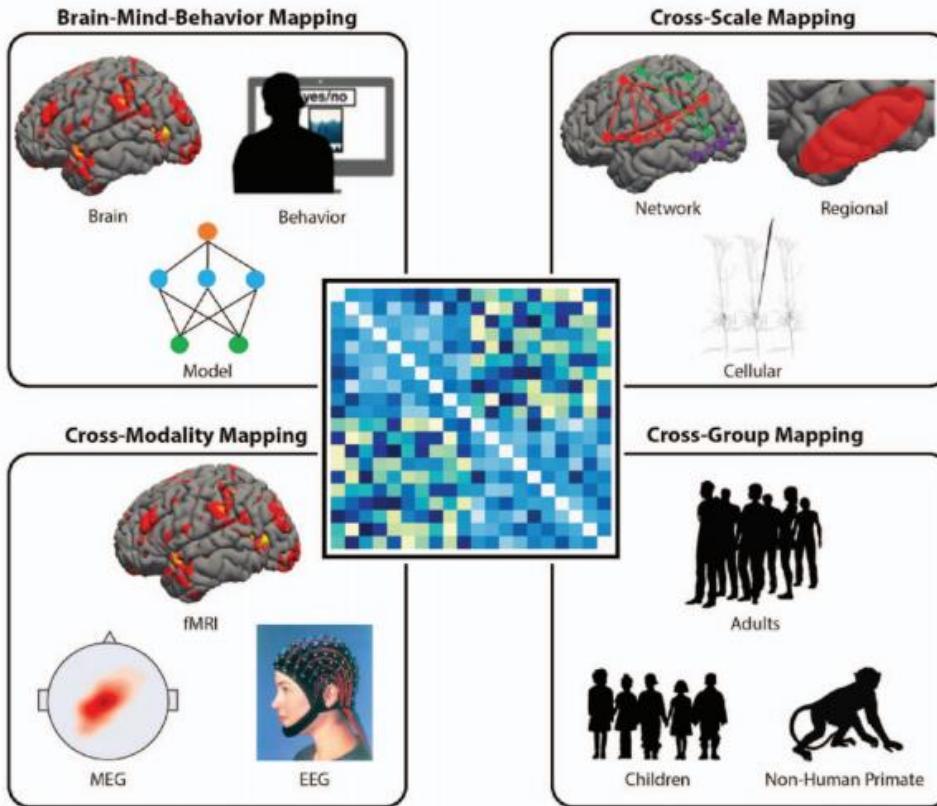
**a** Parcellation into 7 networks

- Visual
- Somatomotor
- Dorsal attention
- Ventral attention
- Limbic
- Frontoparietal
- Default

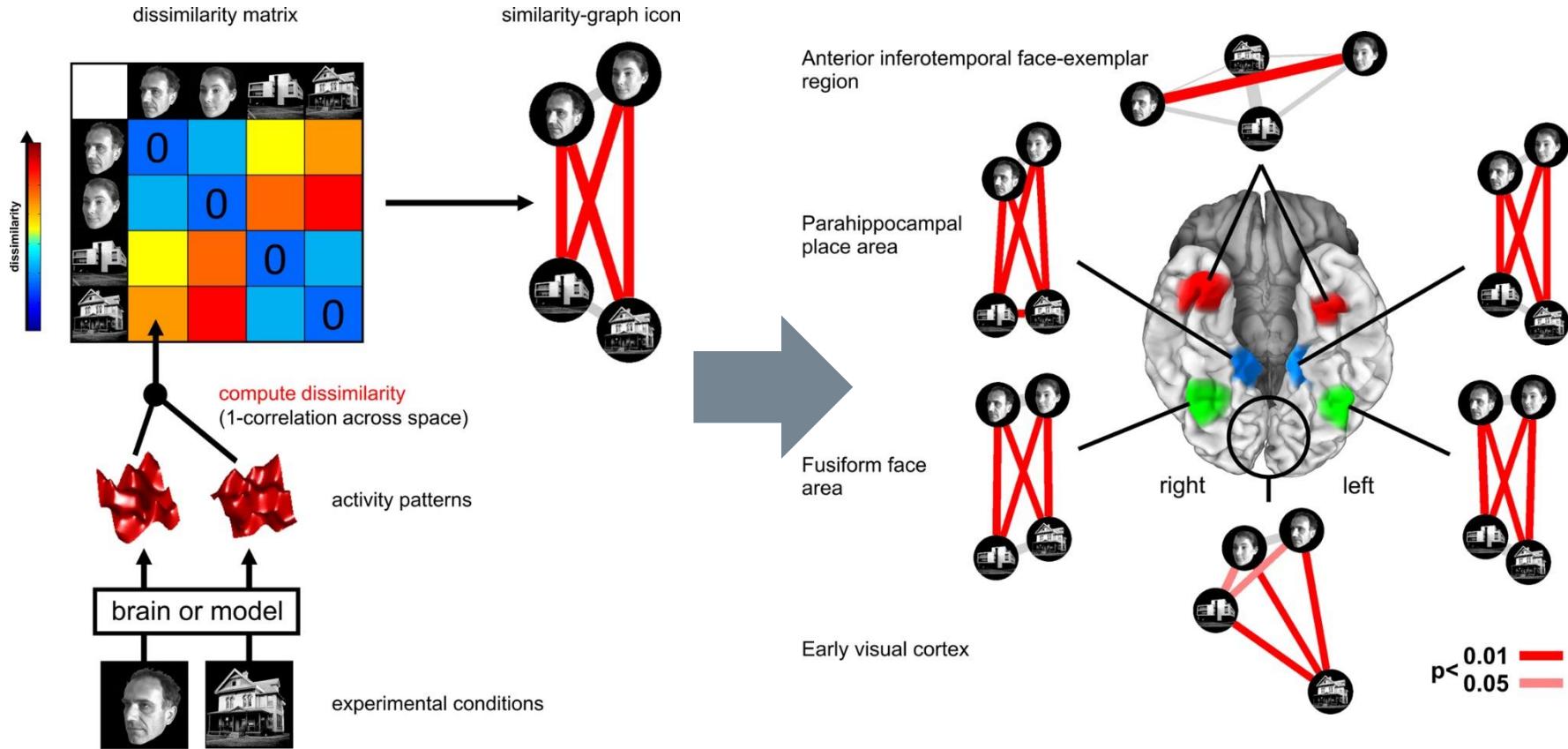
# Analytic approaches

Table 1. Comparison between different fMRI analytic approaches

			
<b>Granularity of representational inference</b>	Task/state level of information	Category and item level of information	Item level of information
<b>Handling multivoxel data</b>	Averaged across voxels	Jointly analyze across voxels	No requirement
<b>Inferred format of representation</b>	Discrete categories	Classification for discrete categories, regression for continuous dimensions	Discrete categories and continuous dimensions
<b>Implementation</b>	Contrast subtraction	Train-test learning phase	Representational dissimilarity matrix
<b>Algorithm</b>	Linear	Both linear and non-linear classifier	Mostly linear
<b>Data modelling in GLM</b>	Single-category modelling and aggregated across runs	Single-category modelling and then cross-validate across runs	Single-trial modelling, within- or between-runs
<b>Optimal study design</b>	Factorial design	Only few numbers of stimulus categories (<5), each with many repetitions for train-test learning	No limits on number of categories, stimuli with many features
<b>Testing computational models</b>	Easy (but univariate encoding models have to fit a model first using separate data)	Difficult (due to its decoding nature)	Easy (due to its encoding nature)
<b>Linking multimodal data</b>	Difficult	Difficult	Easy

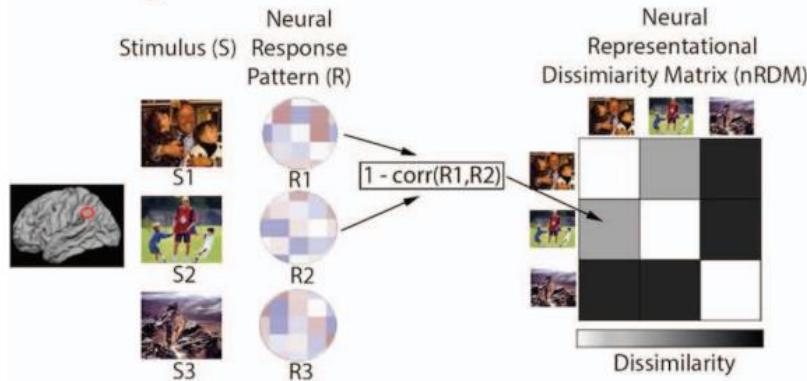


# Representational Dissimilarity Matrices (RDMs)

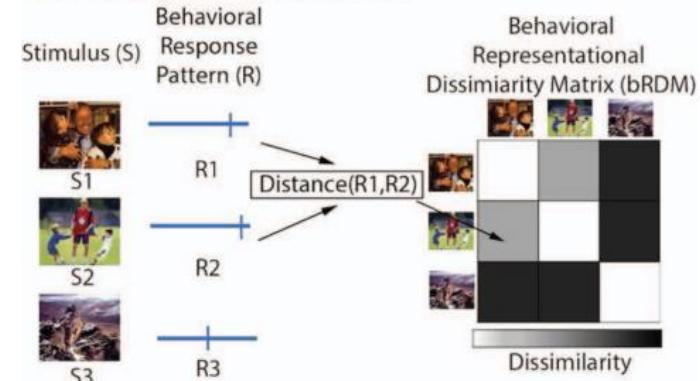


# Creating RDMs

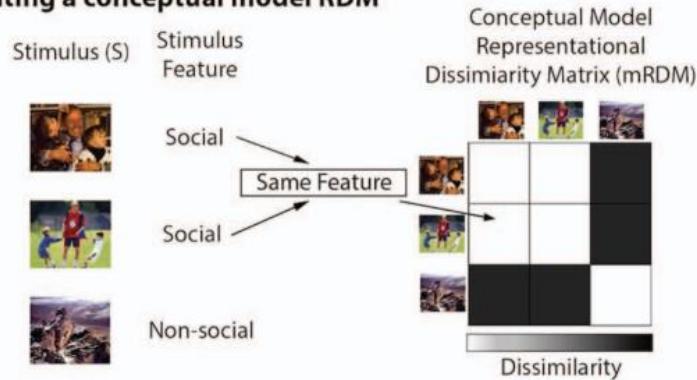
## A. Creating a neural RDM



## B. Creating a behavioral RDM



## C. Creating a conceptual model RDM



# RSA to uncover brain coding in humans and monkeys

