

Neural Data Science

Spike detection and feature extraction

Prof. Dr. Philipp Berens

Hertie Institute for AI in Brain Health, Tübingen



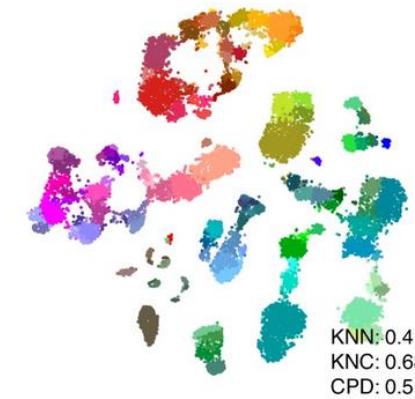
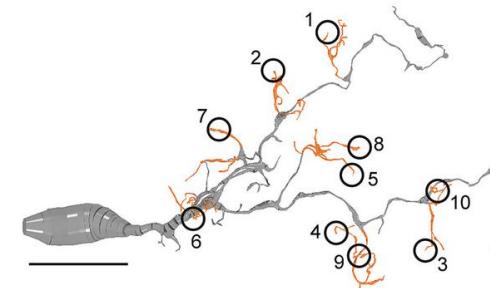
My lab





Topics & interests of the lab

- ML for models of circuits & computations in the retina
- ML for single cell transcriptomics in neuroscience
- AI-based medical diagnostics in ophthalmology





Screenshot of a web browser showing the GitHub profile of berenslab. The profile page displays four repositories: RFest, MorphoPy, sparseBottleneck, and EphysExtraction. The right sidebar shows top languages (Jupyter Notebook, Python, C++, MATLAB, Dockerfile) and a list of 21 people.

berenslab

Berens Lab @ University of Tübingen
Data Science lab at the Institute of Ophthalmic Research, University of Tübingen
Tübingen, Germany <http://www.berenslab.org> philipp.berens@uni-tuebingen.de

Repositories 41 Packages People 21 Teams 1 Projects Settings

Find a repository... Type: All Language: All Customize pins New

RFest
A Python 3 toolbox for neural receptive field estimation using splines and Gaussian priors.
matrix-factorization splines jax receptive-field evidence-optimization
● Jupyter Notebook GPL-3.0 1 ⚡ 5 ① 1 (1 issue needs help) 10 Updated 1 hour ago

MorphoPy
● Jupyter Notebook GPL-3.0 2 ⚡ 6 ② 0 Updated 1 hour ago

sparseBottleneck
A sparse bottleneck neural network to predict electrophysiological properties of neurons from their gene expression.
visualization machine-learning lasso sparse neural-networks electrophysiology omics
● Jupyter Notebook 0 ⚡ 0 ① 0 10 Updated 5 hours ago

EphysExtraction
Code to extract electrophysiological parameters of neurons.
● Jupyter Notebook 2 ⚡ 1 ① 0 10 Updated 6 days ago

Top languages
● Jupyter Notebook ● Python
● C++ ● MATLAB ● Dockerfile

People 21 >

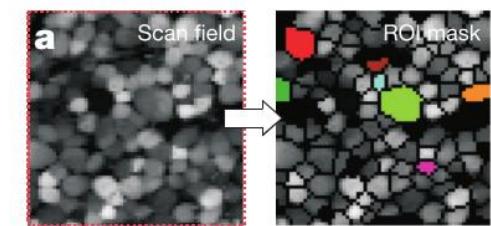
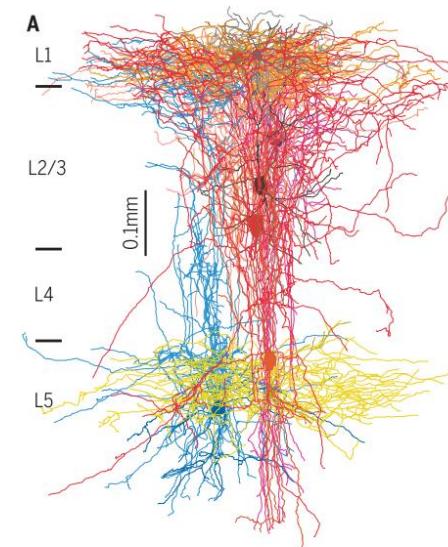
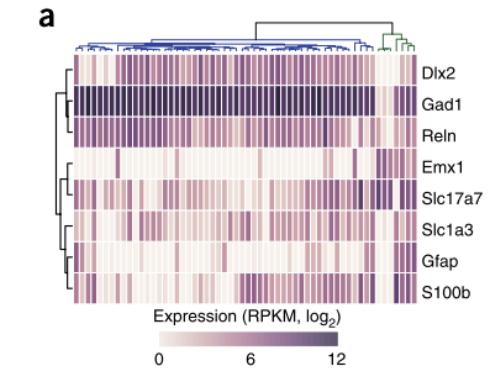
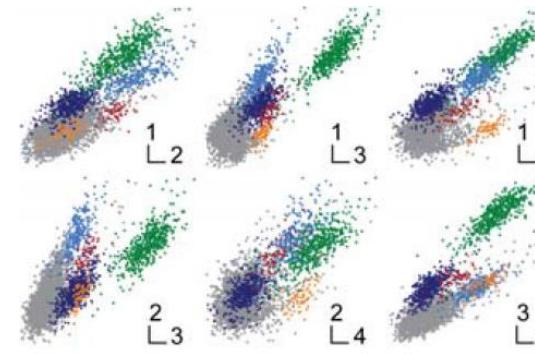
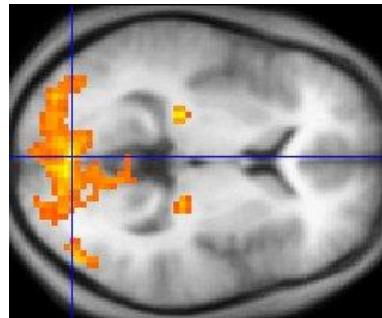
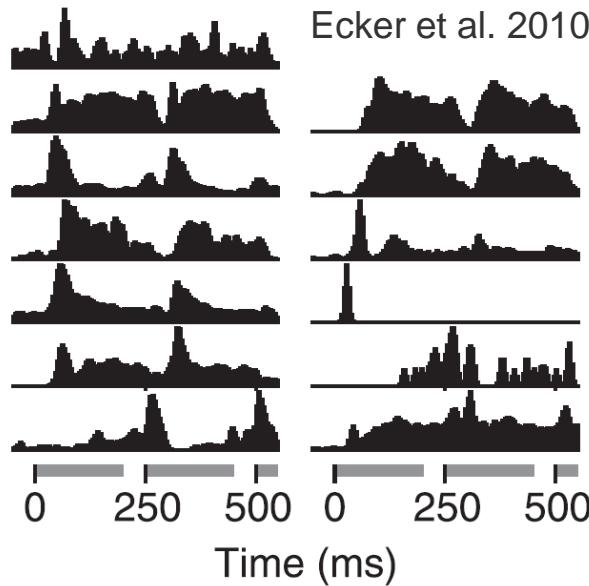
Invite someone

Why is there this course?

- You know about
 - Machine Learning
 - Signal Processing
 - Neural Coding
 - Neural Dynamics
 - Bioinformatics
- So why care?
 - Different types of data (time series, images, graphs...)
 - Practical approach to data science (independent of topic)

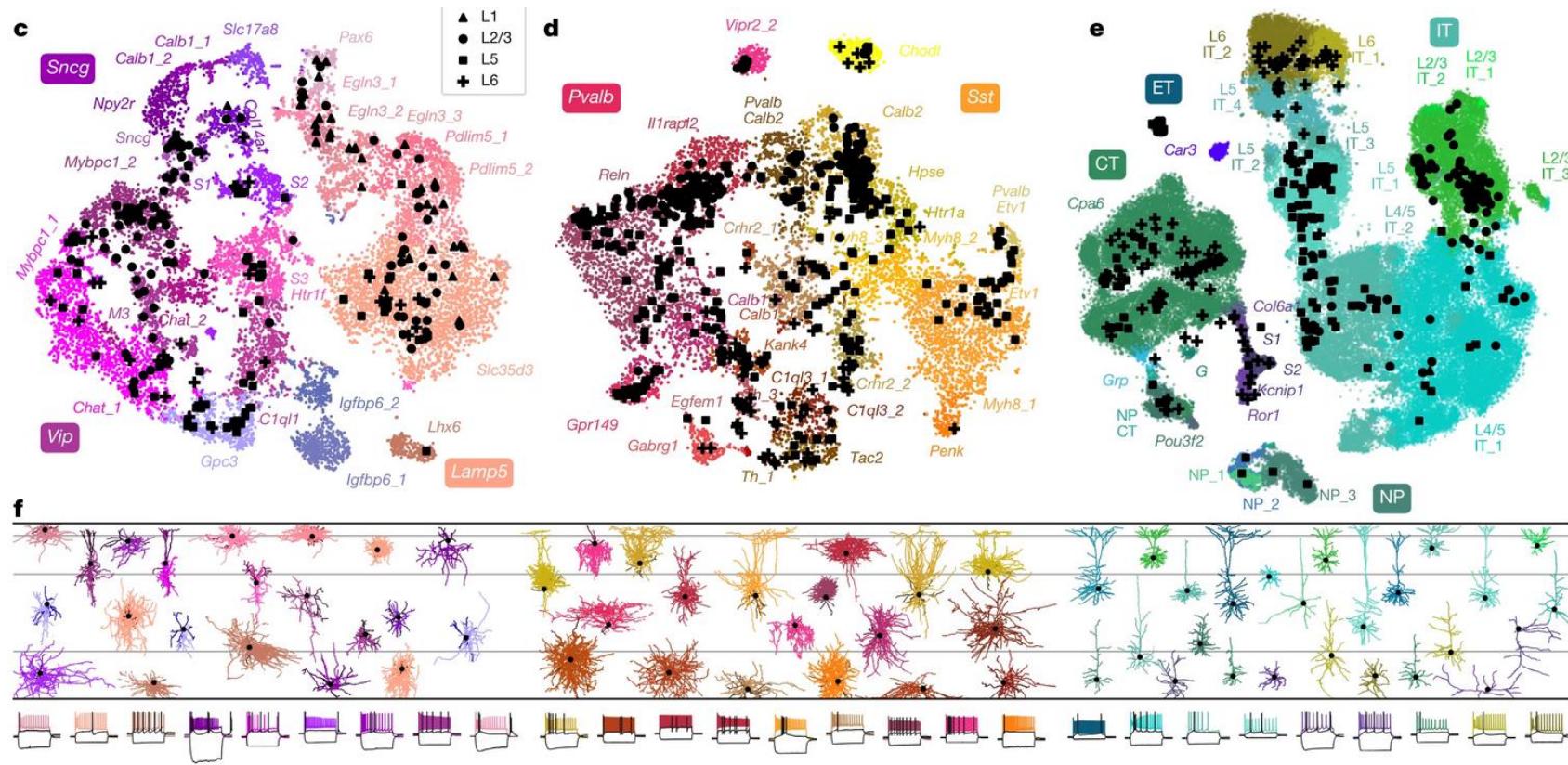


Neural data



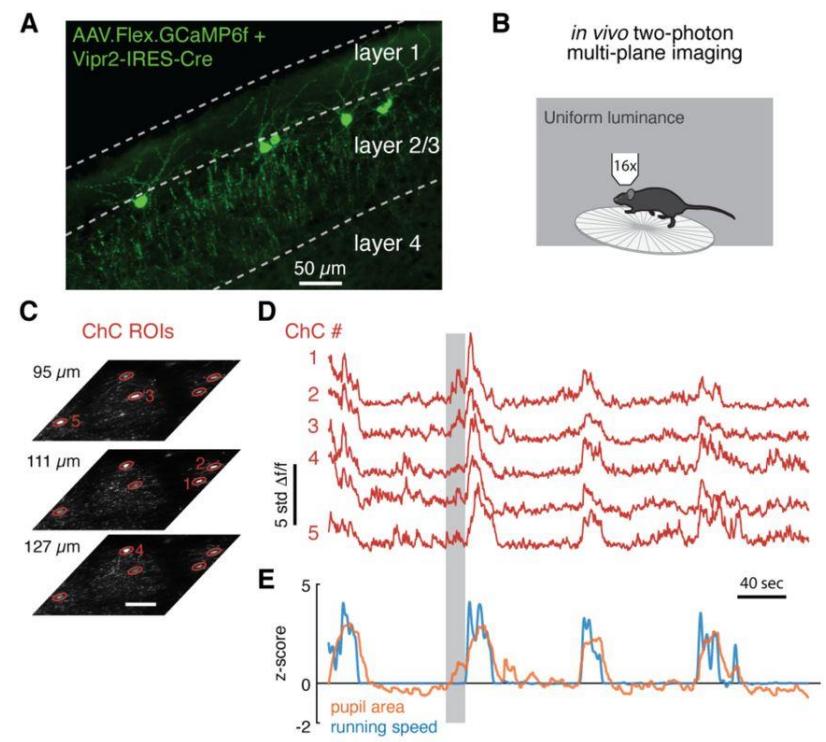
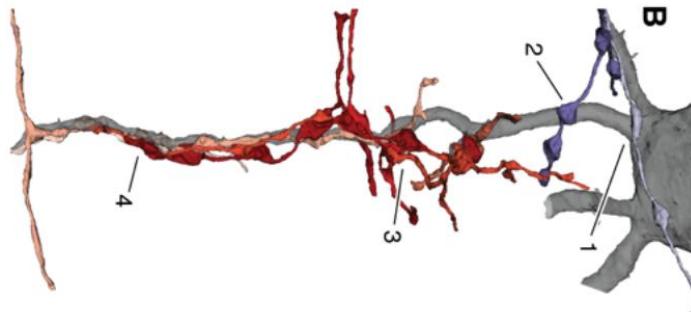
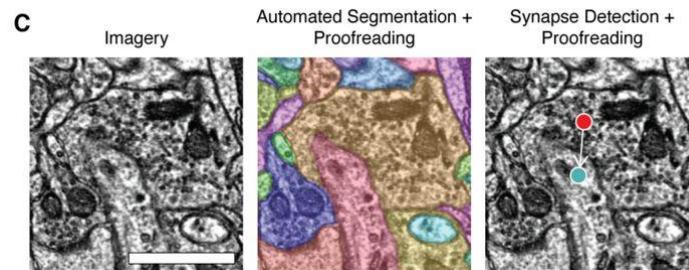
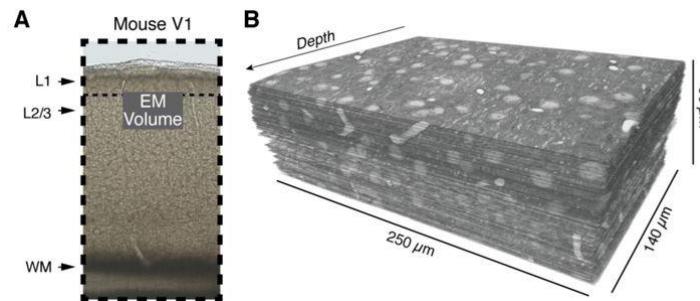


Multimodal data



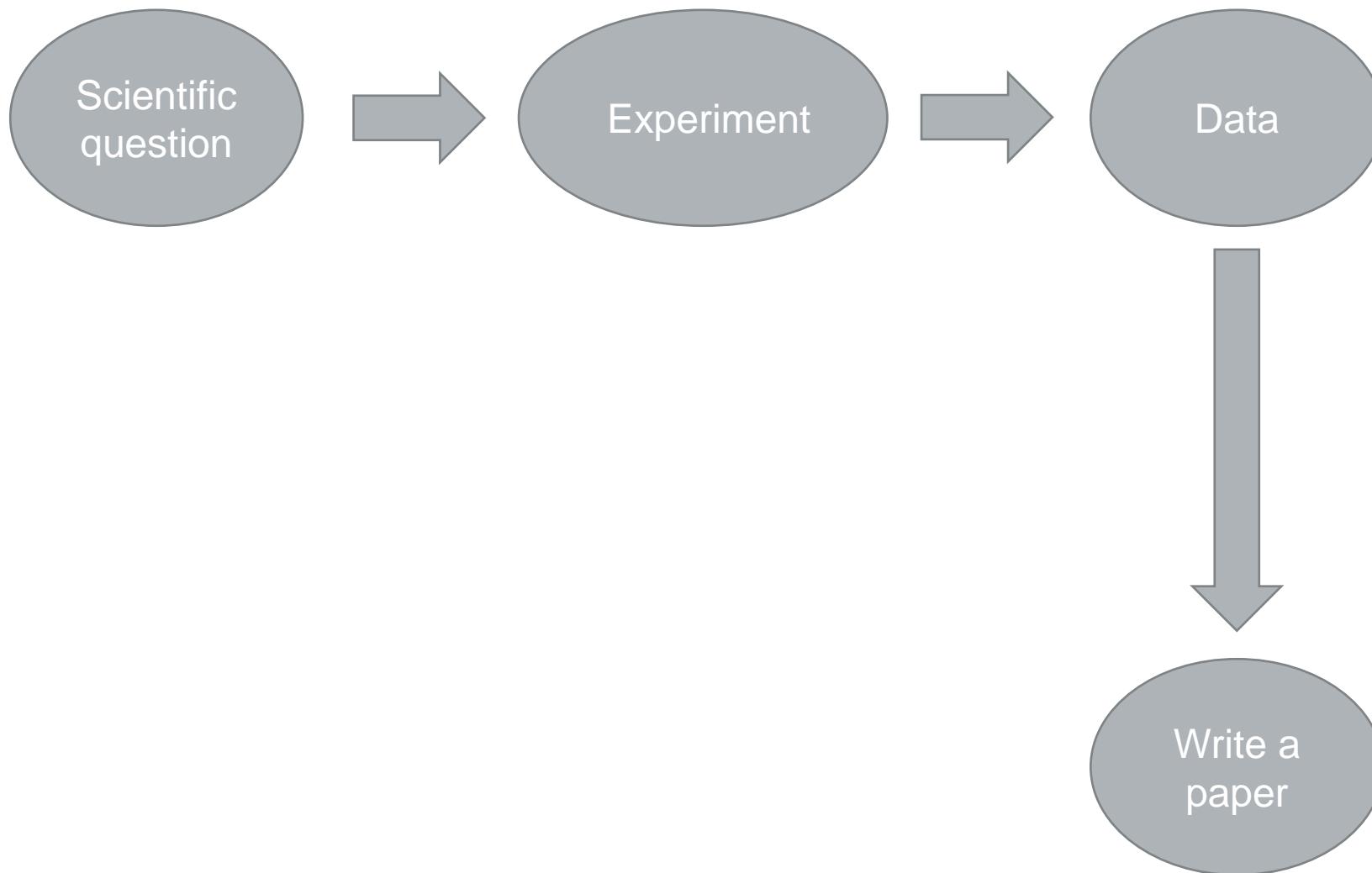


Multimodal data



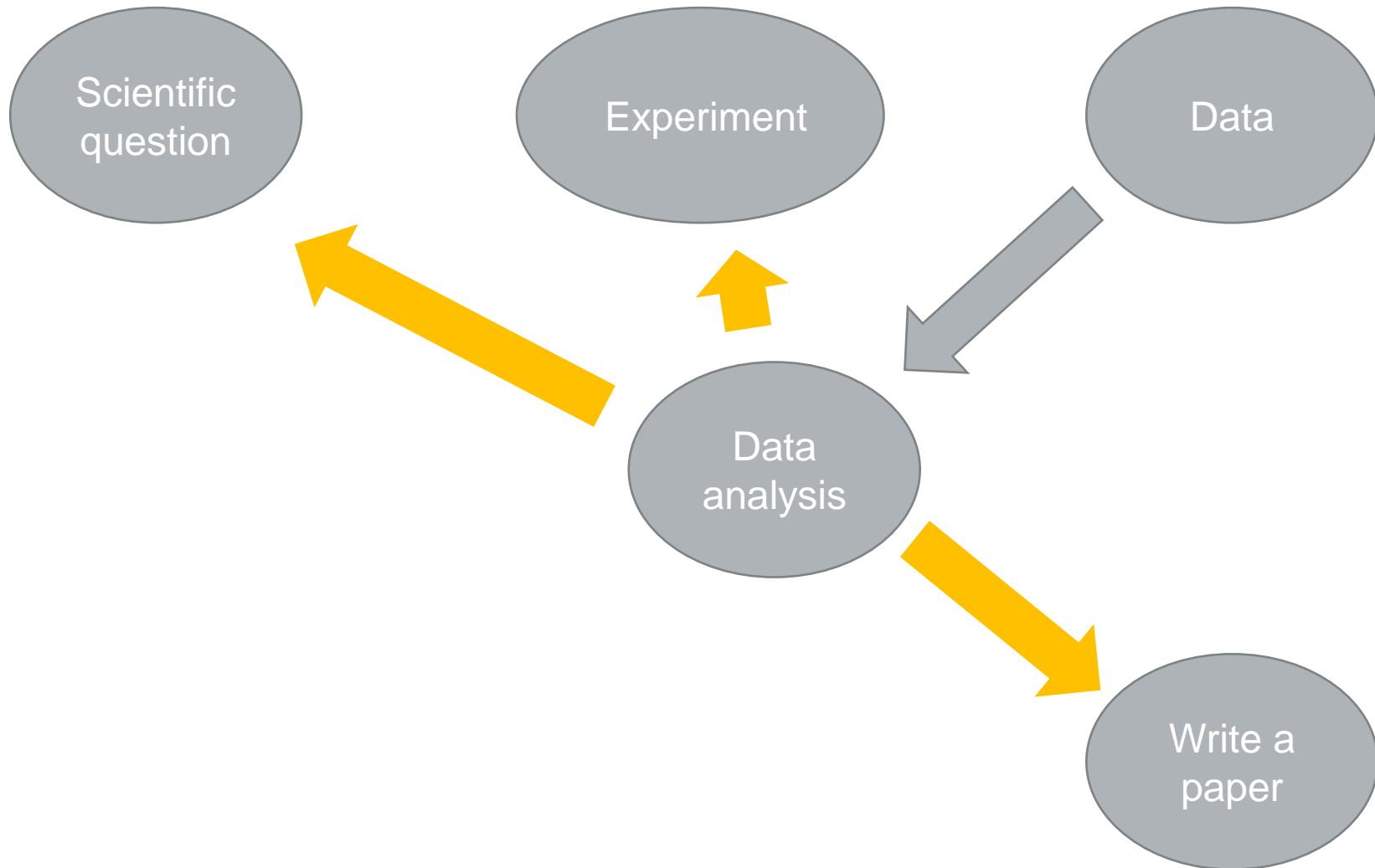


An ideal world



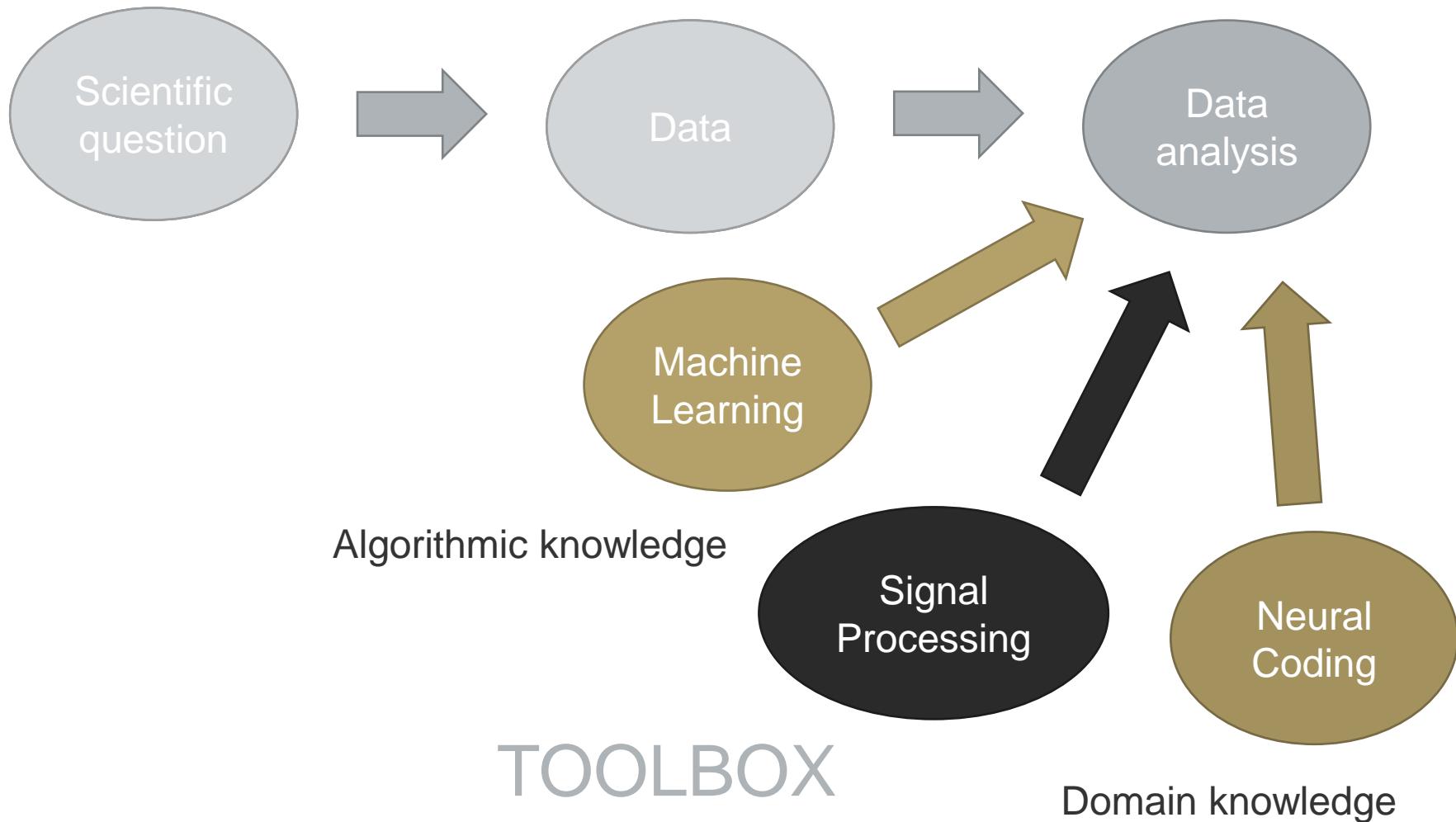


An alternative view





How Does Data Analysis Work?



Learning targets

- Learn about common problems in neural data science
- Analyse different data types
- Implement and apply basic algorithms to solve them
- Learn about advanced solutions
- Learn how to analyse complex real world datasets

- Practise a data science philosophy
 - Plot raw data
 - Look at examples
 - Test algorithms on artificial data
 - Be critical with your results
 - Let the problem determine the technique



What knowledge is helpful for the course?

- Python programming
- Machine learning knowledge
 - Clustering
 - Regression
 - Classification
- Some neuroscience context
 - Ask if you don't understand the purpose of something!

Ressources

- Anaconda Python distribution [\[link\]](#)
- Python tutorial on [collab](#)
- Youtube lecture [Introduction to Machine Learning](#)
- Lab [github](#)
- Lab [website](#)

How does this course work? (1/2)

- Lecture (Wednesday, 10-12 am)
 - Problem statement & possible solutions
 - Algorithmic details and application issues
 - Goal: working knowledge of important problems & techniques, literature overview
- Tutorial (Friday, 12am-2pm)
 - Tutors: Jonas Beck, Jan Lause & Ziwei Huang
 - 10 min presentation by PhD student
 - Discuss problem statement and open questions
 - Live coding & best practice feedback

How does this course work? (2/2)

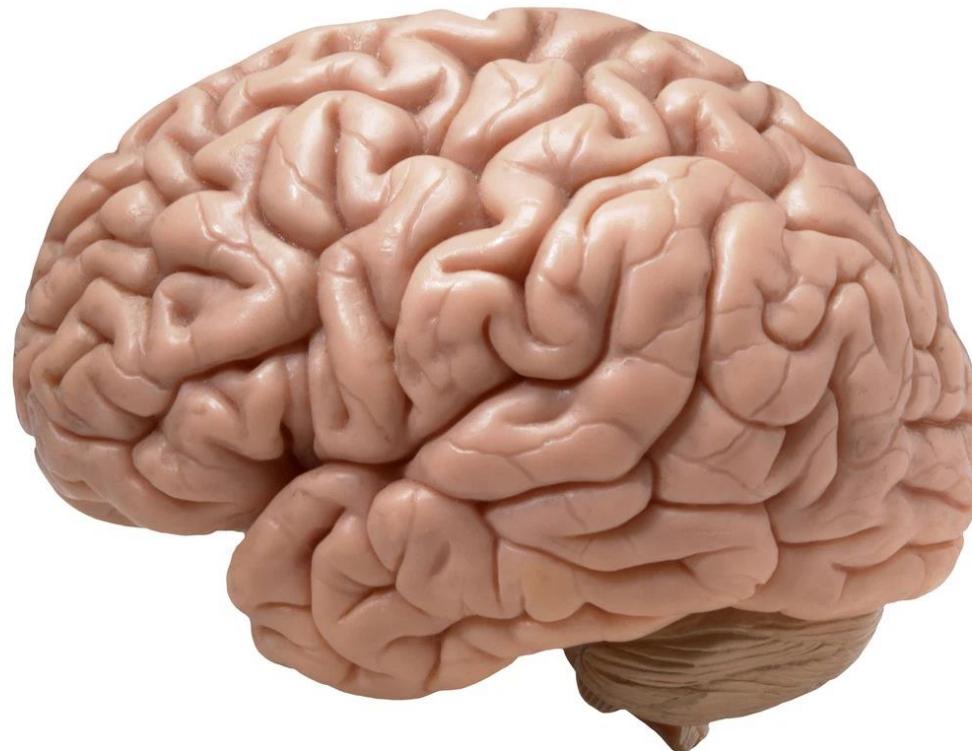
- Programming exercises (60% of grade)
 - Work on real-world problems and **do** analysis
 - Implement algorithms discussed in lecture as model solution
 - Start programming on Fridays in tutorial
 - Work in groups of 2-3 students
- Final project (40% of grade)
 - Work on final project after end of June
 - Describe problem statement, solutions, findings, well-prepared figures, brief discussion
 - In Jupyter Notebook
- No exam

Policies

- No late submissions.
- Use any available material, including Python libraries (unless we specifically ask you not to do this).
- Talk to others about the problems, but
 - credit any source in the code
 - write your own code.
- Work as a team.
- If you have feedback how to improve the course, talk to us.

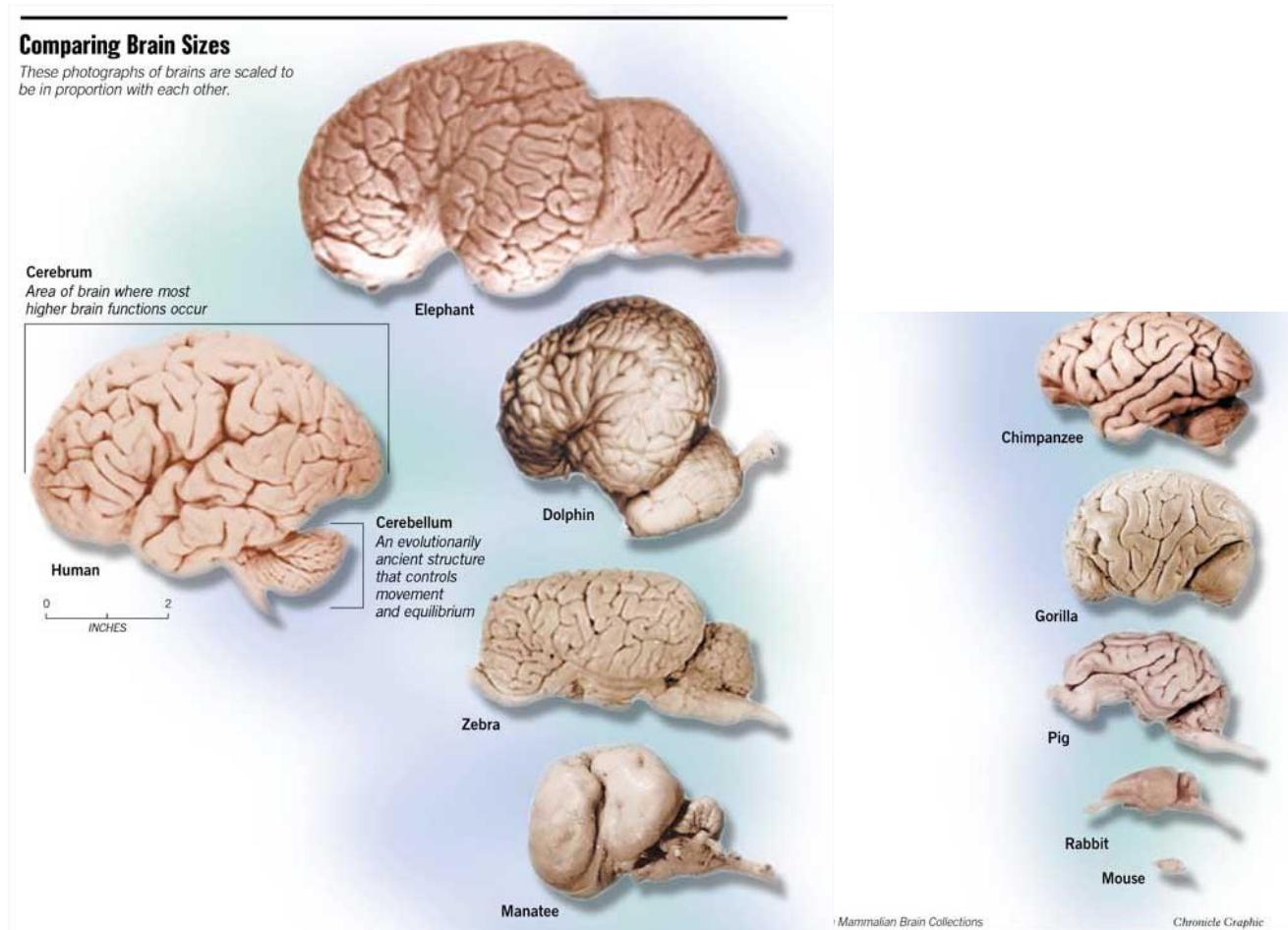


The human brain



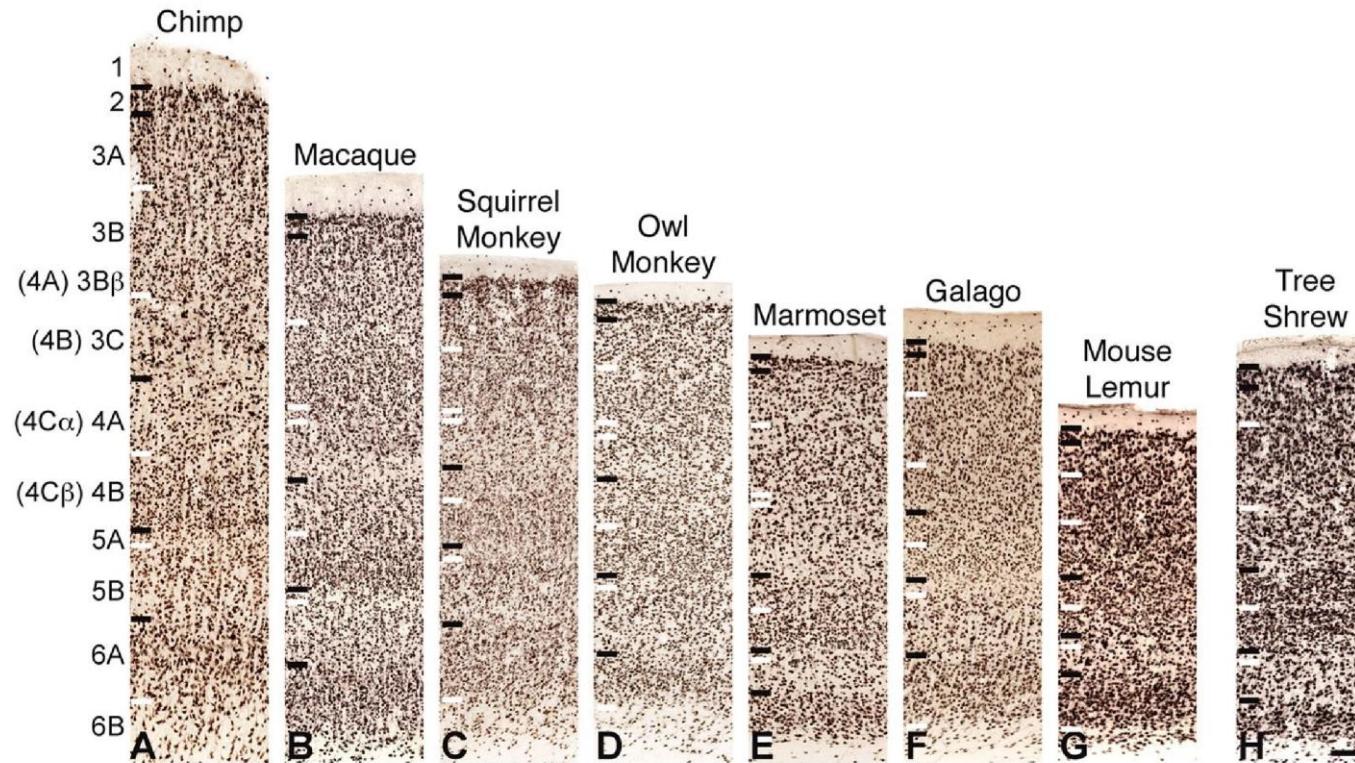


Other brains





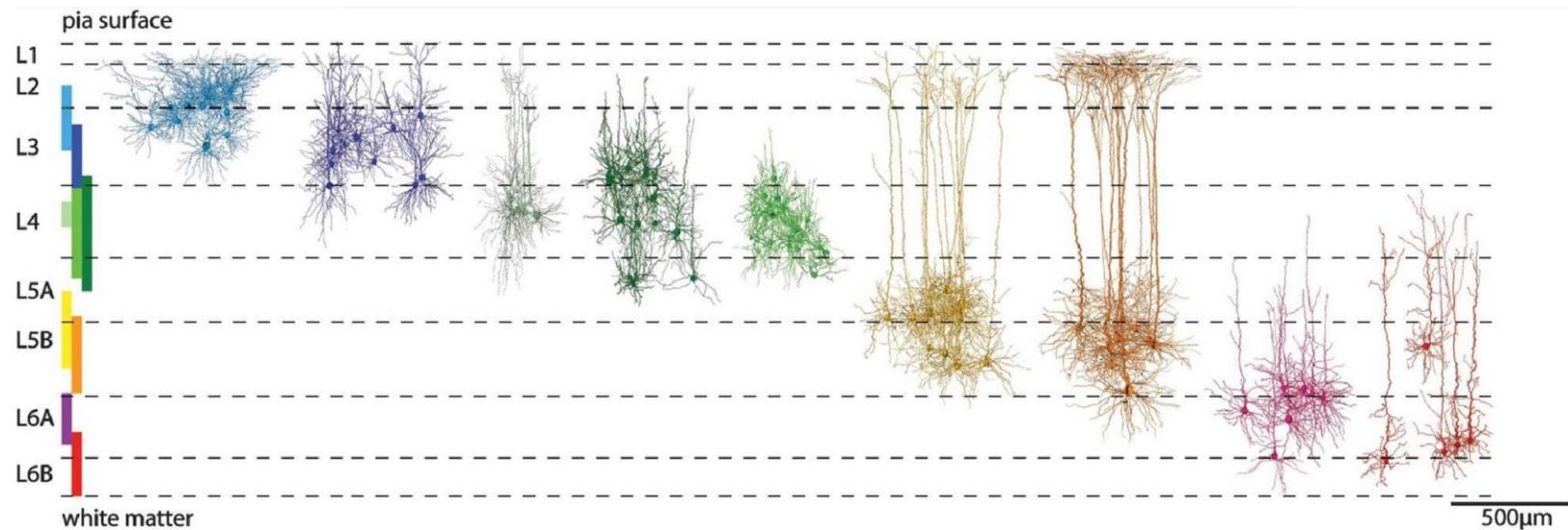
Layered cortex



Balaram & Kaas 2014 Front Neuroanat



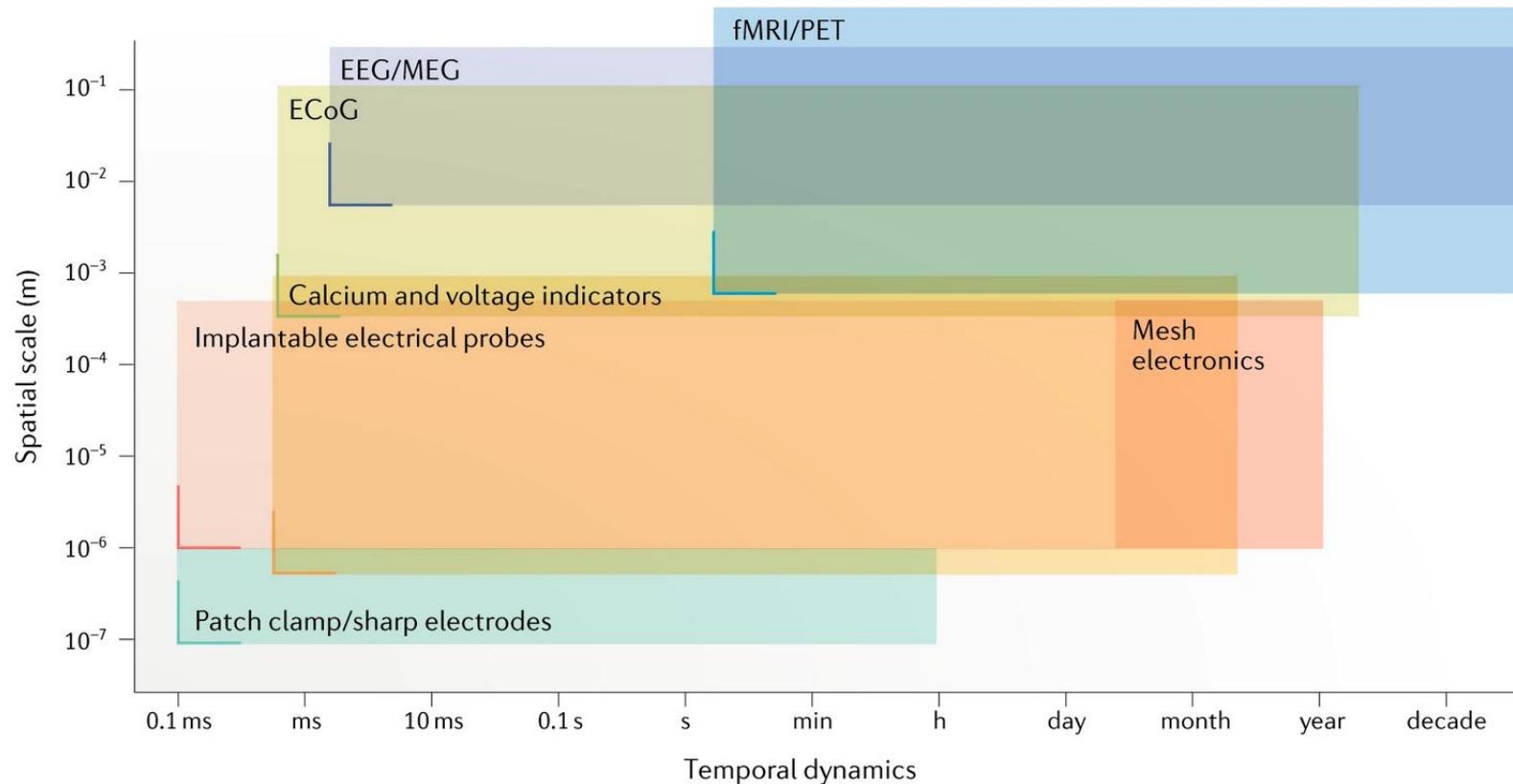
Different cells





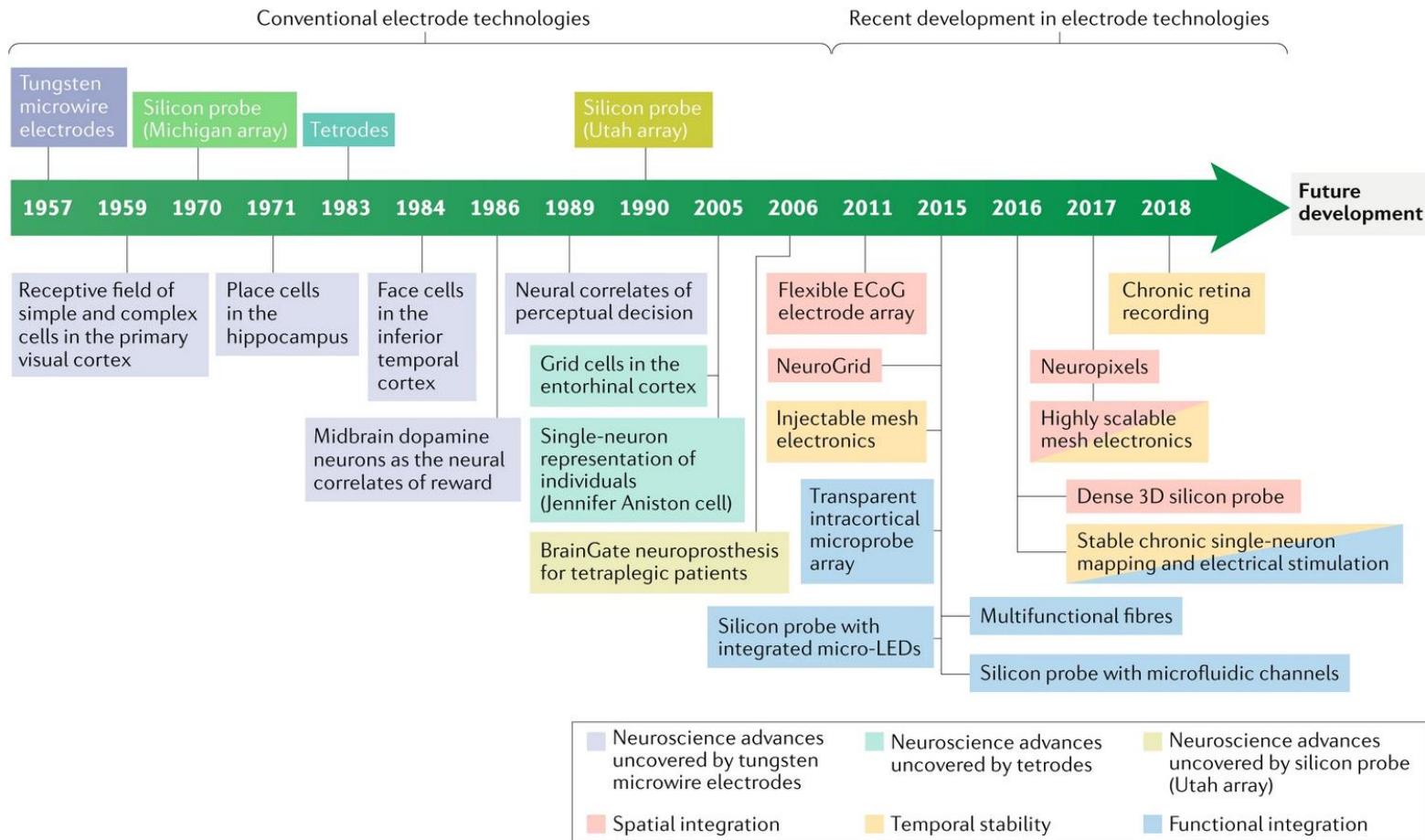
Methods for recording brain activity

Spatiotemporal limitations of existing neurotechnologies



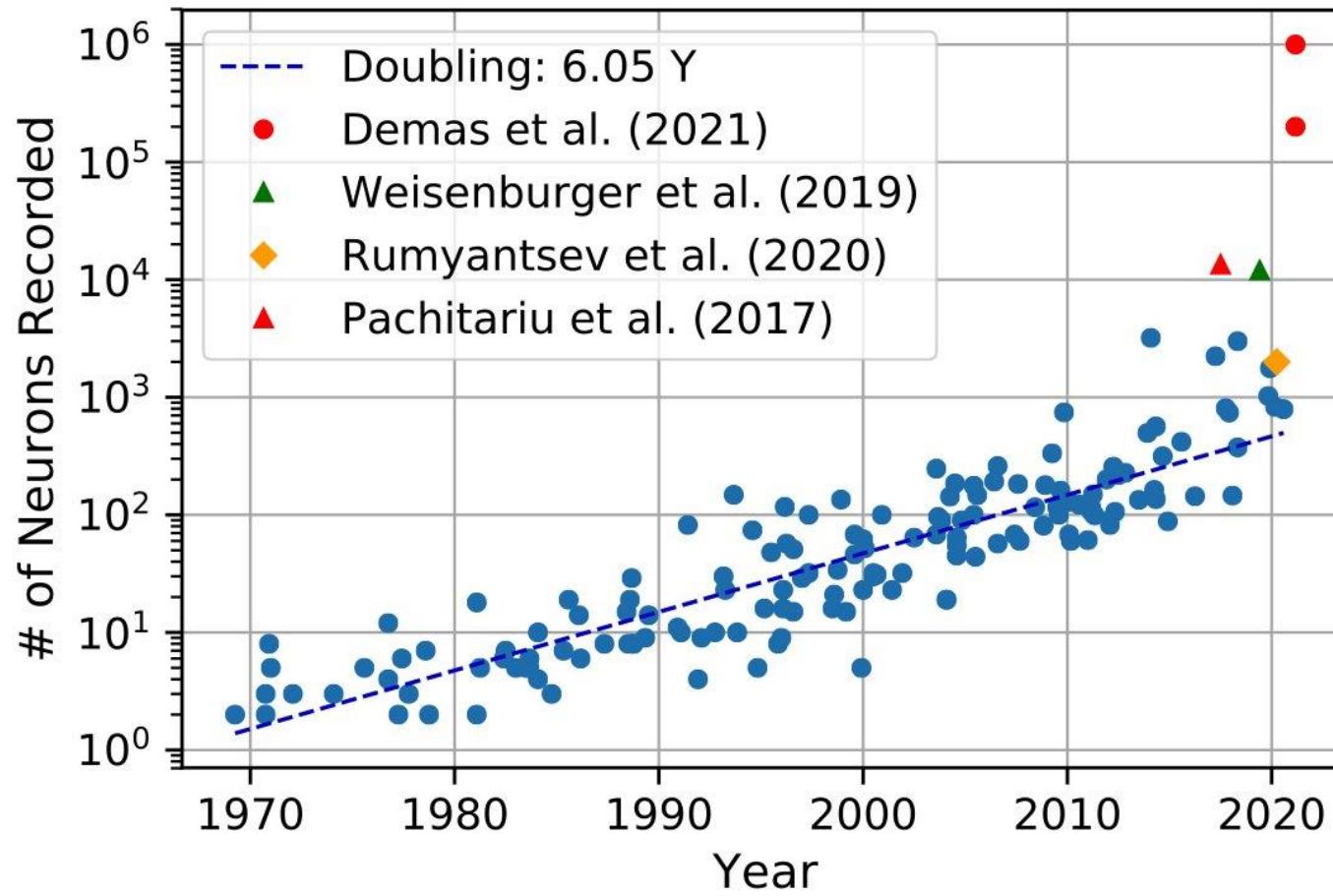


Methods for recording brain activity



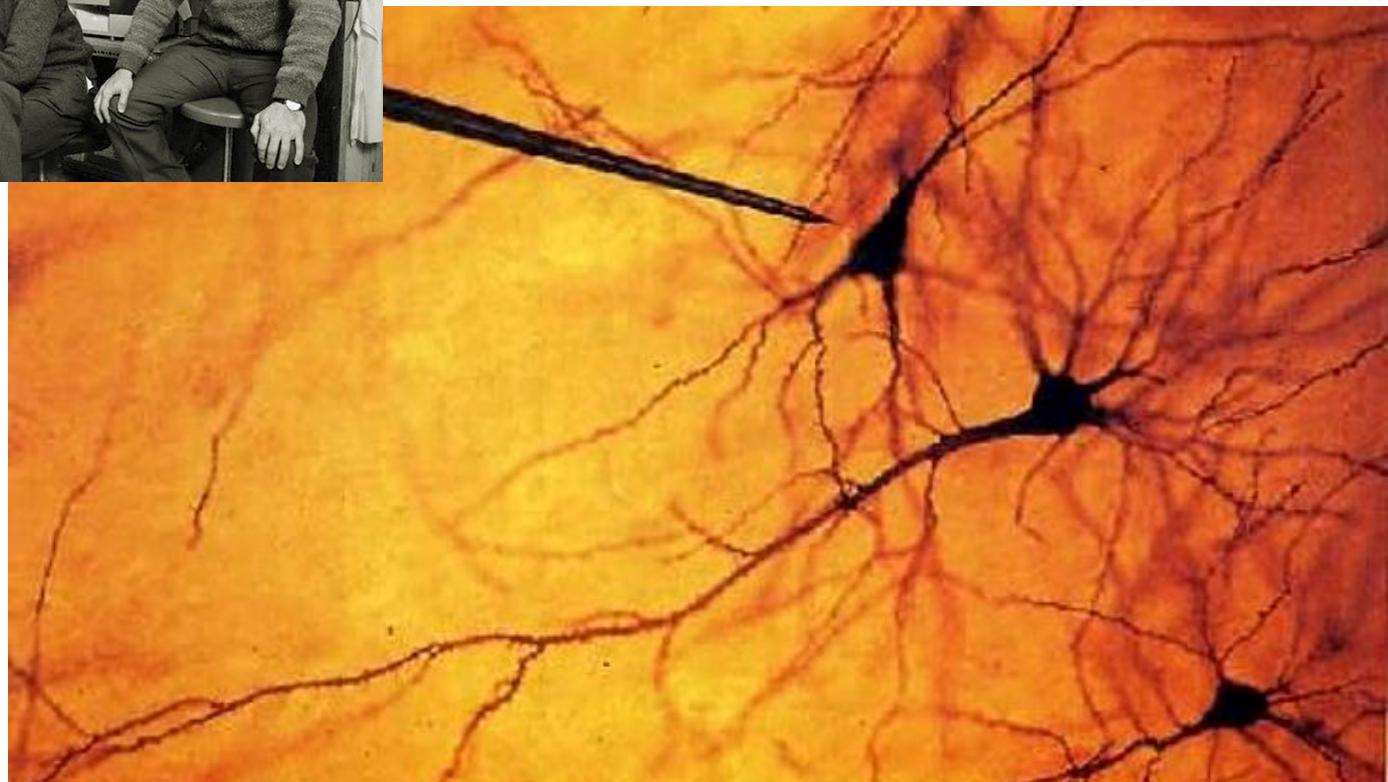


New techniques allow more neurons



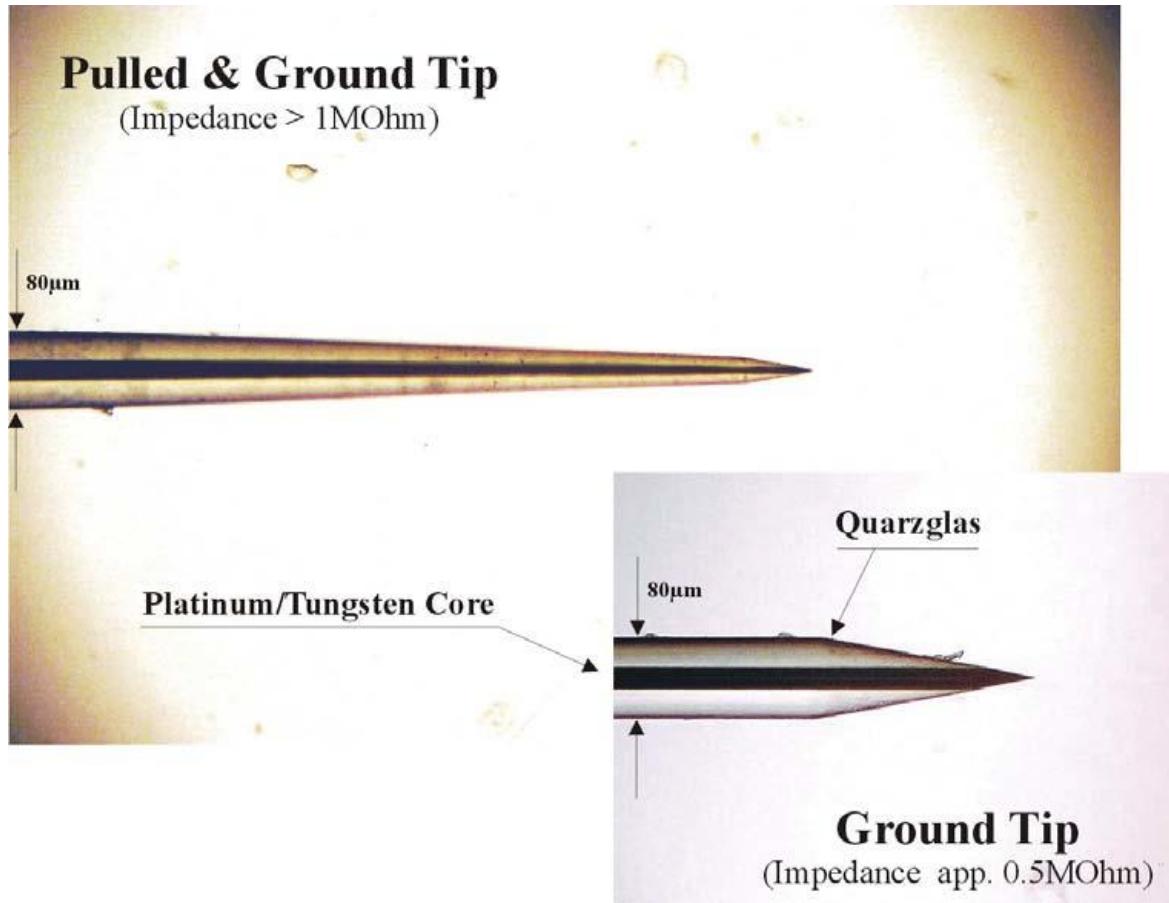


David Hubel & Thorsten Wiesel



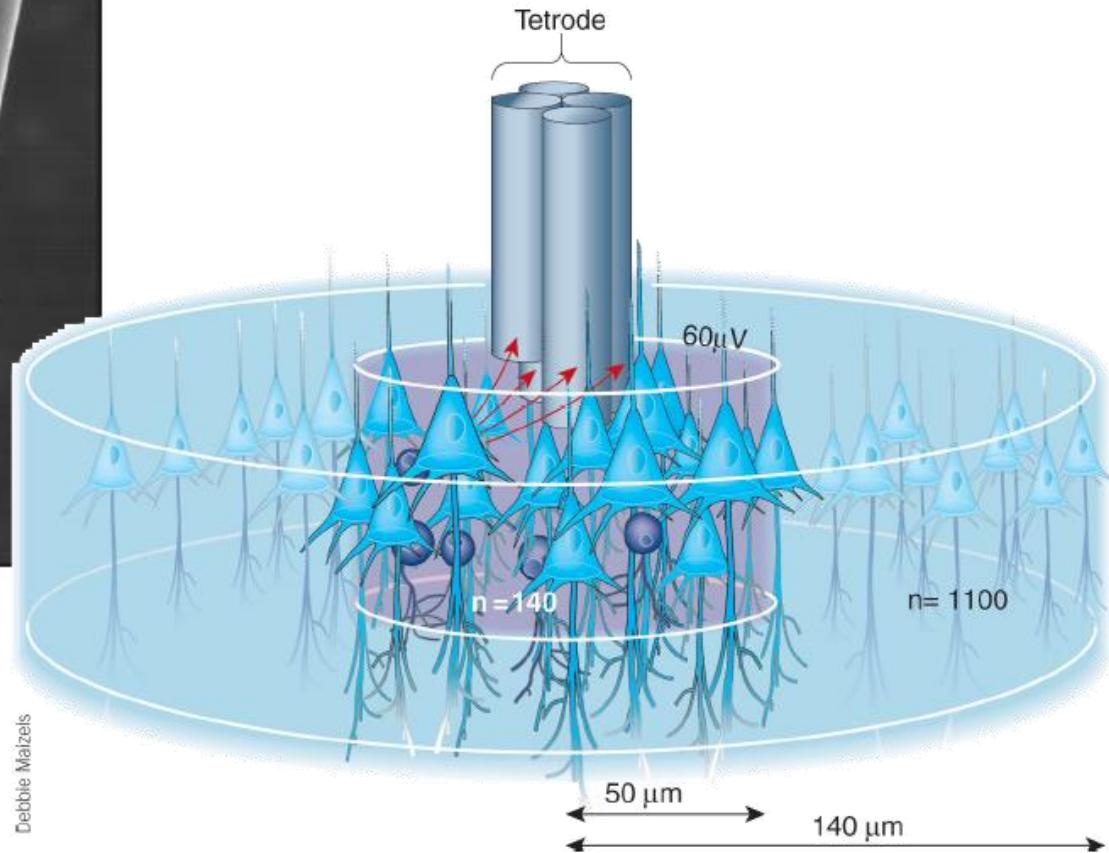
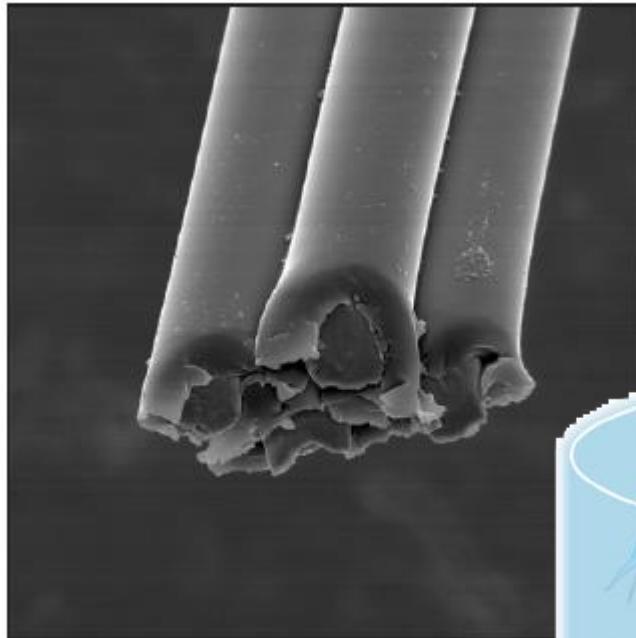


Tungsten microelectrodes



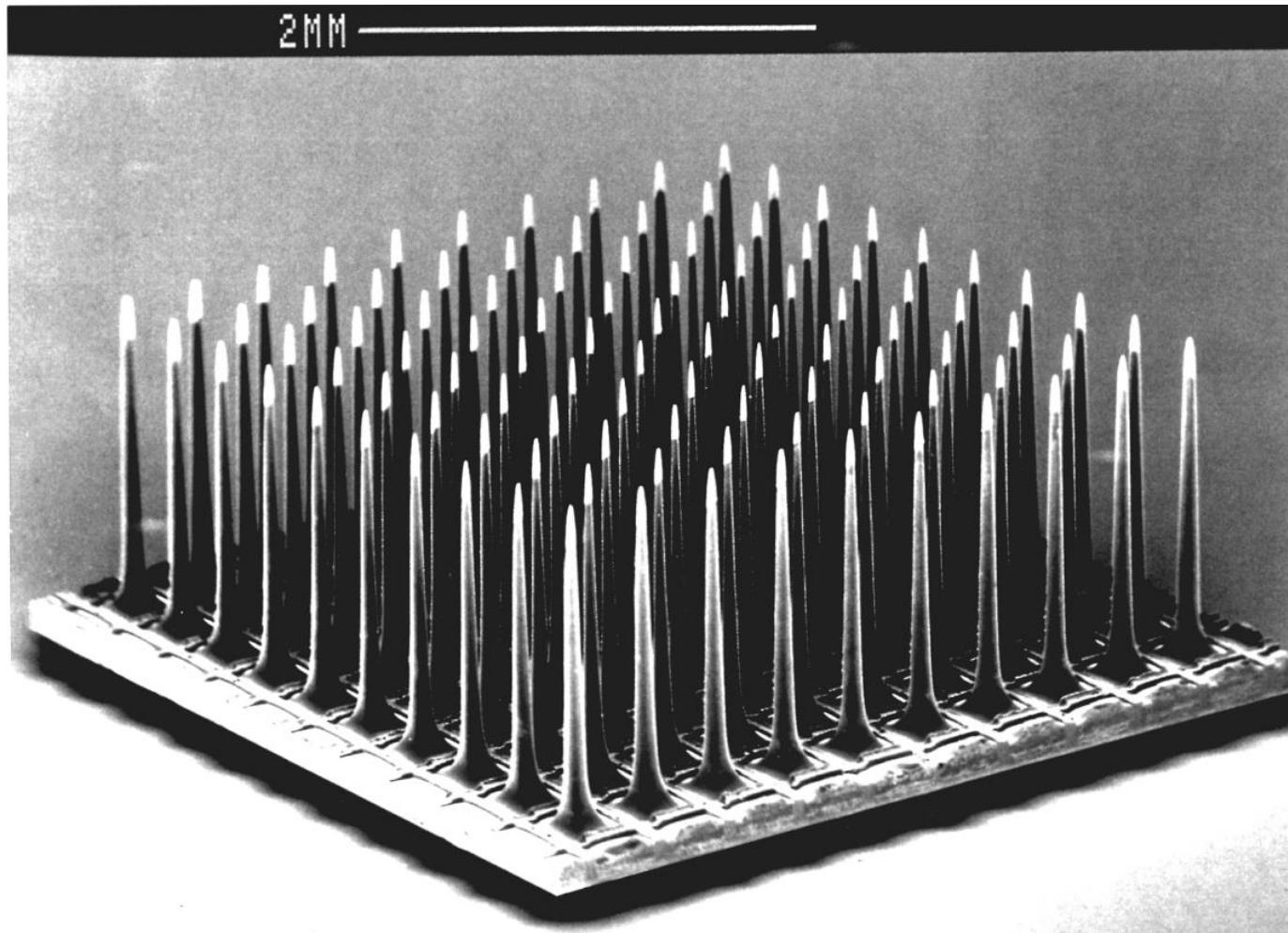


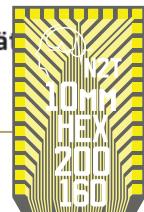
Tetrodes



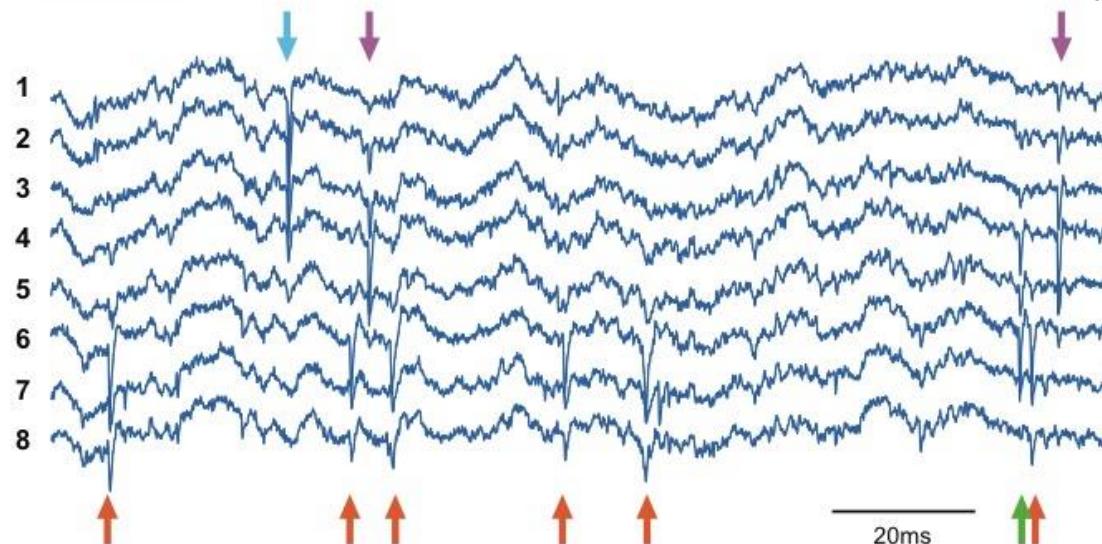
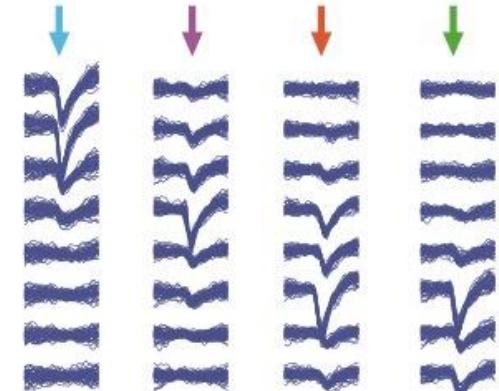
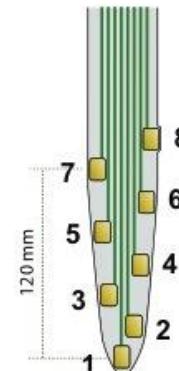
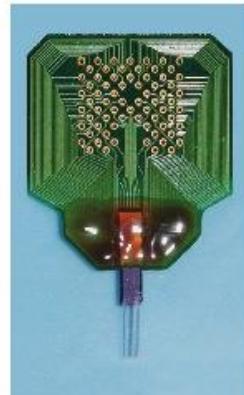
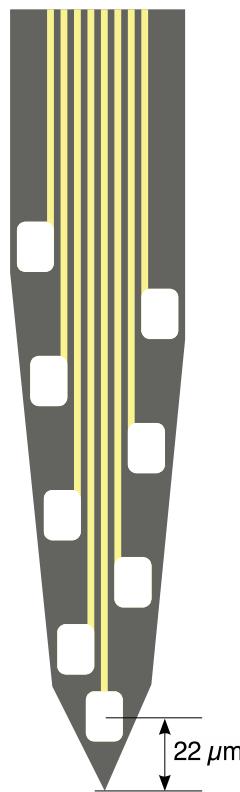


Utah array





Silicon probes



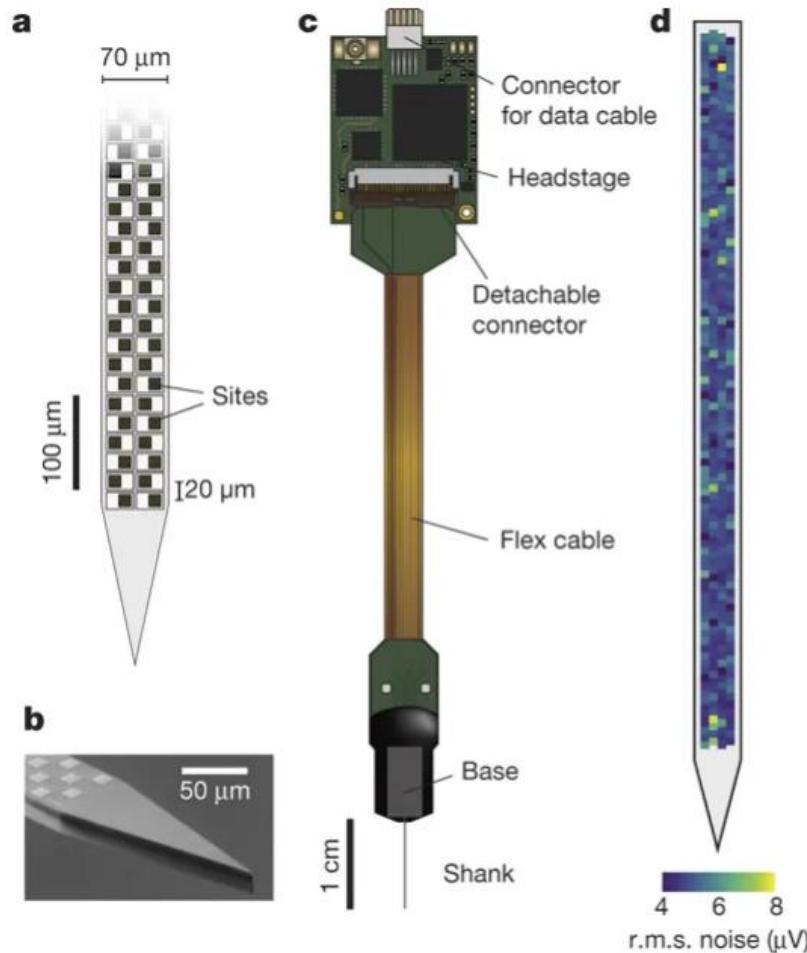
NeuroNexus

10 mm

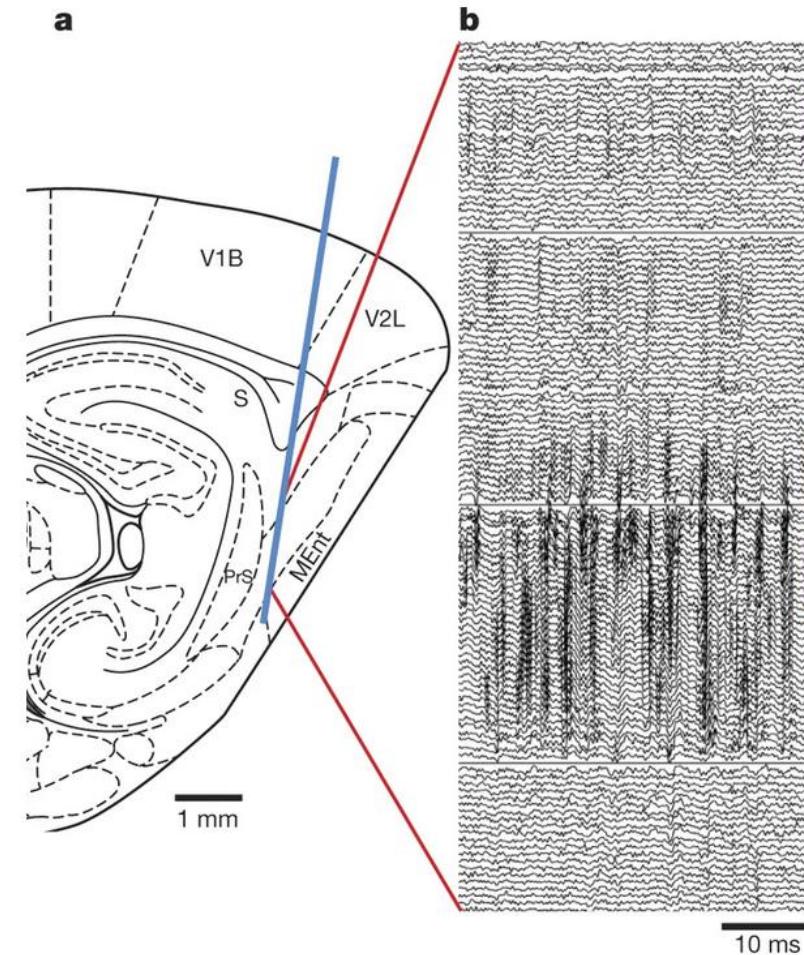
0.6 mm



Neuropixels



960 sites





Neuropixels

Science

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HOME > SCIENCE > VOL. 372, NO. 6539 > NEUROPIXELS 2.0: A MINIATURIZED HIGH-DENSITY PROBE FOR STABLE, LONG-TERM BRAIN RECORDINGS

RESEARCH ARTICLE

Neuropixels 2.0: A miniaturized high-density probe for stable, long-term brain recordings

NICHOLAS A. STEINMETZ , CAGATAY AYDIN , ANNA LEBEDEVA , MICHAEL OKUN , MARIUS PACHITARIU , MARIUS BAUZA , MAXIME BEAU ,

JAI BHAGAT , CLAUDIA BÖHM , [...], AND TIMOTHY D. HARRIS 

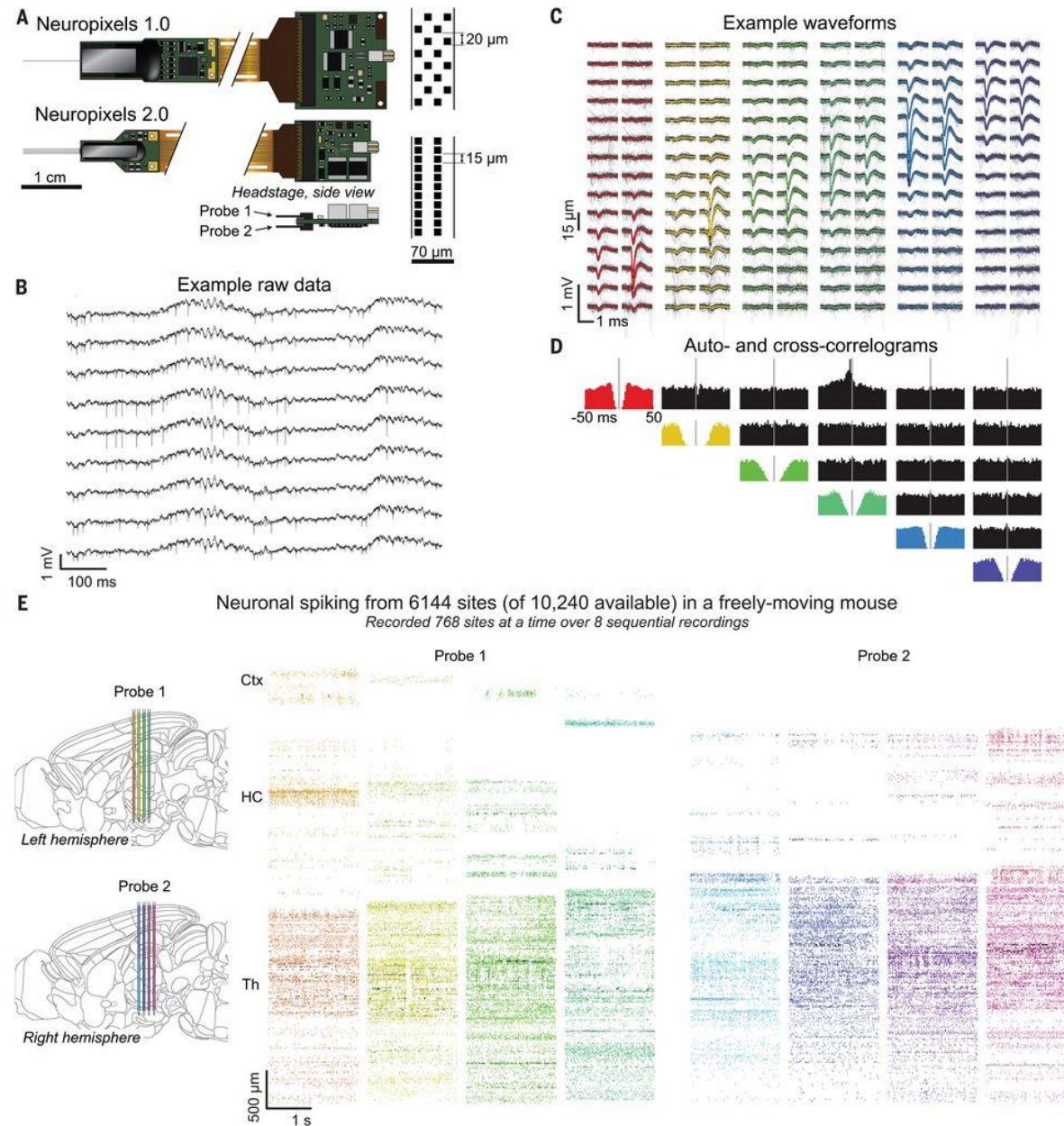
+29 authors

[Authors Info & Affiliations](#)

SCIENCE • 16 Apr 2021 • Vol 372, Issue 6539 • DOI: 10.1126/science.abf4588

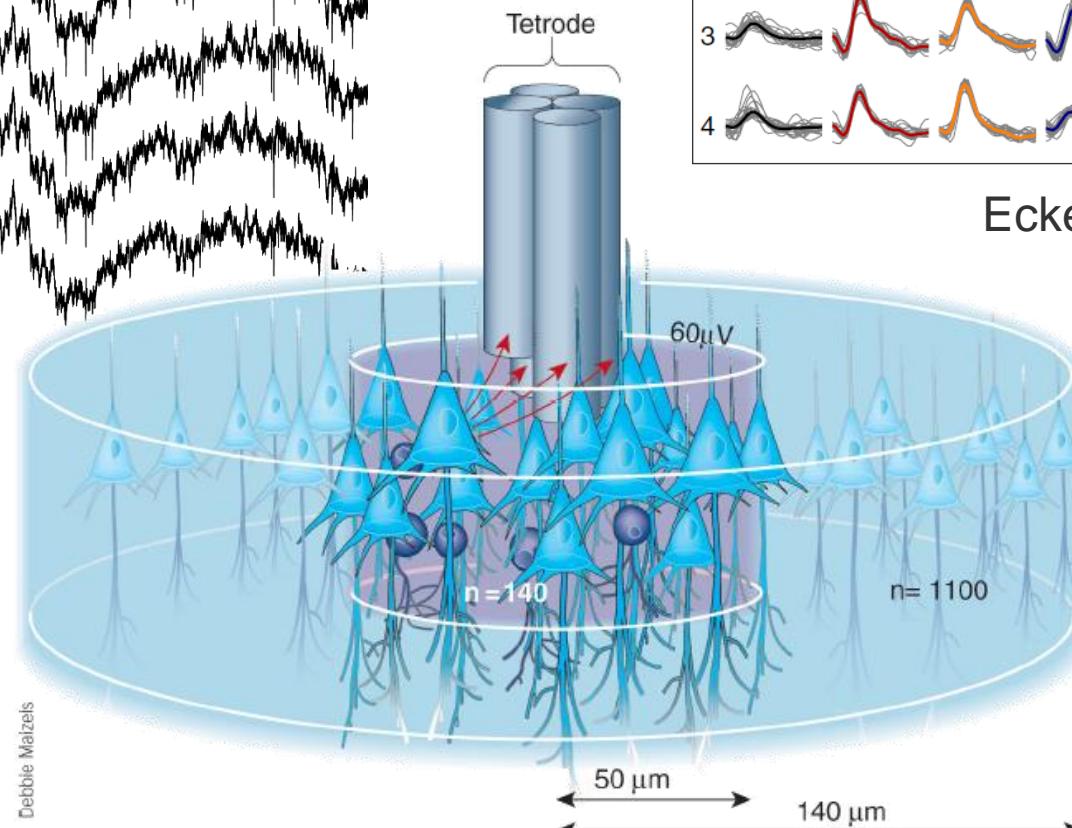
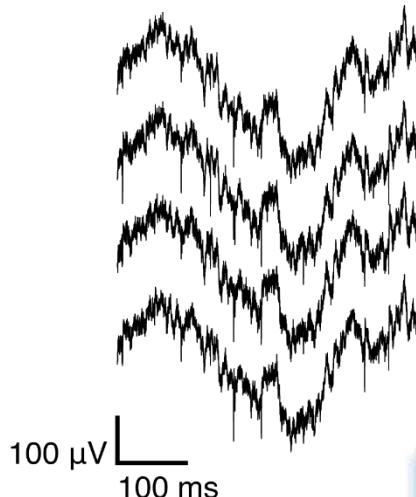
 13.221  170



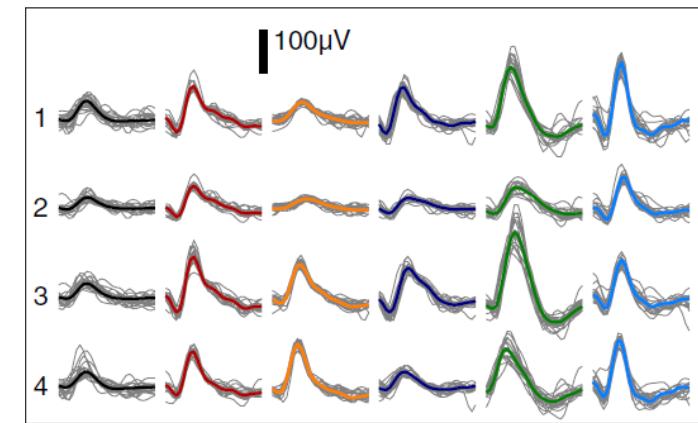




The Problem



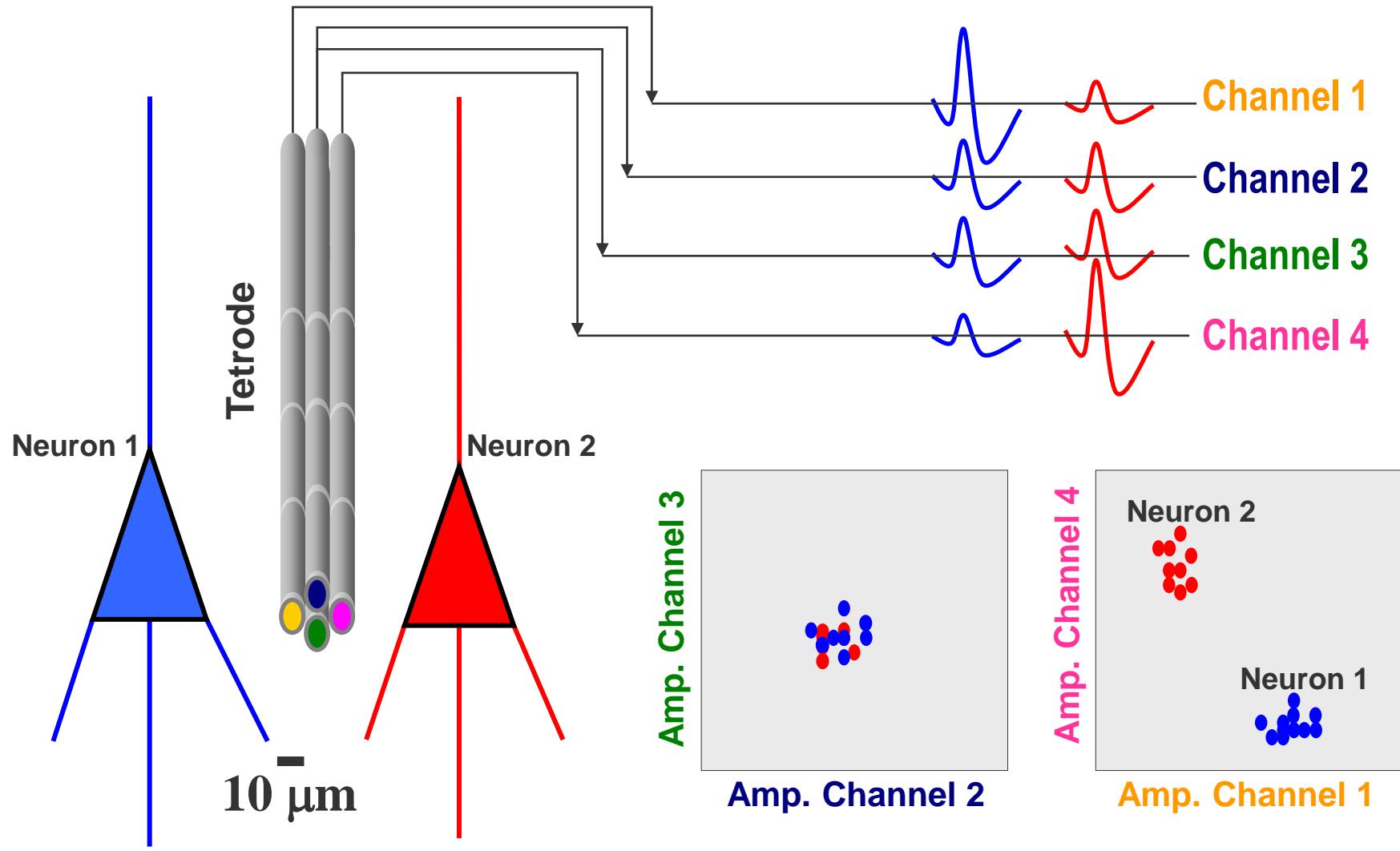
Buszaki, 2004



Ecker et al., 2010



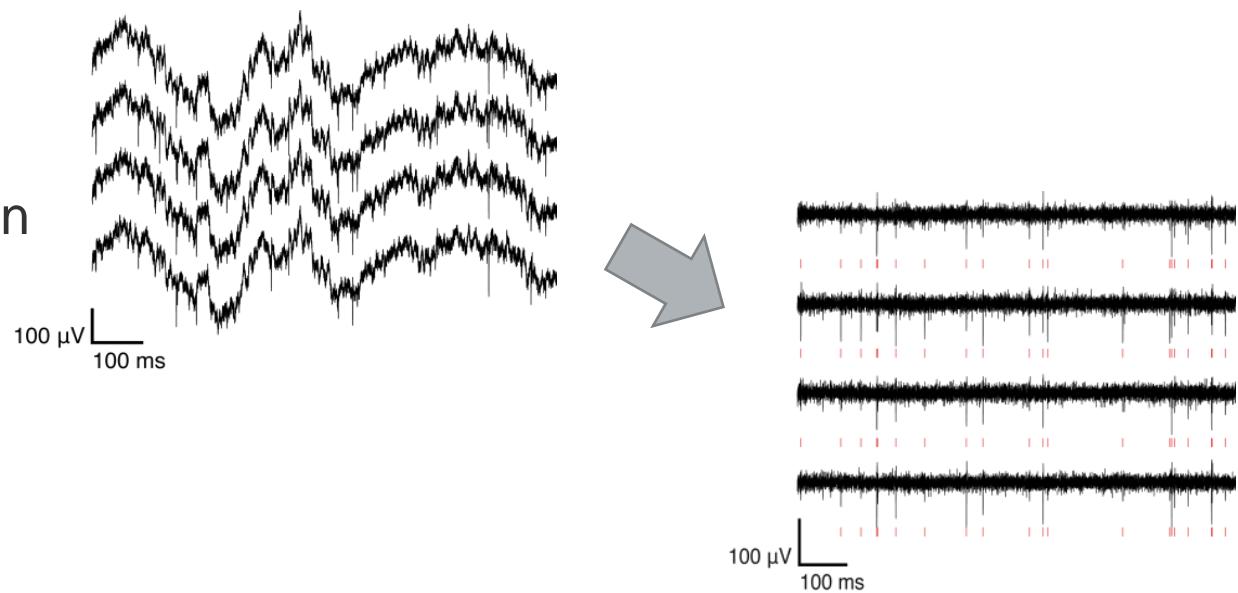
Triangulation





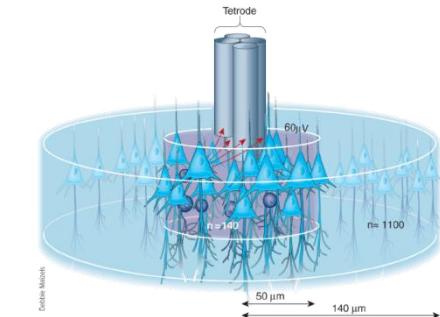
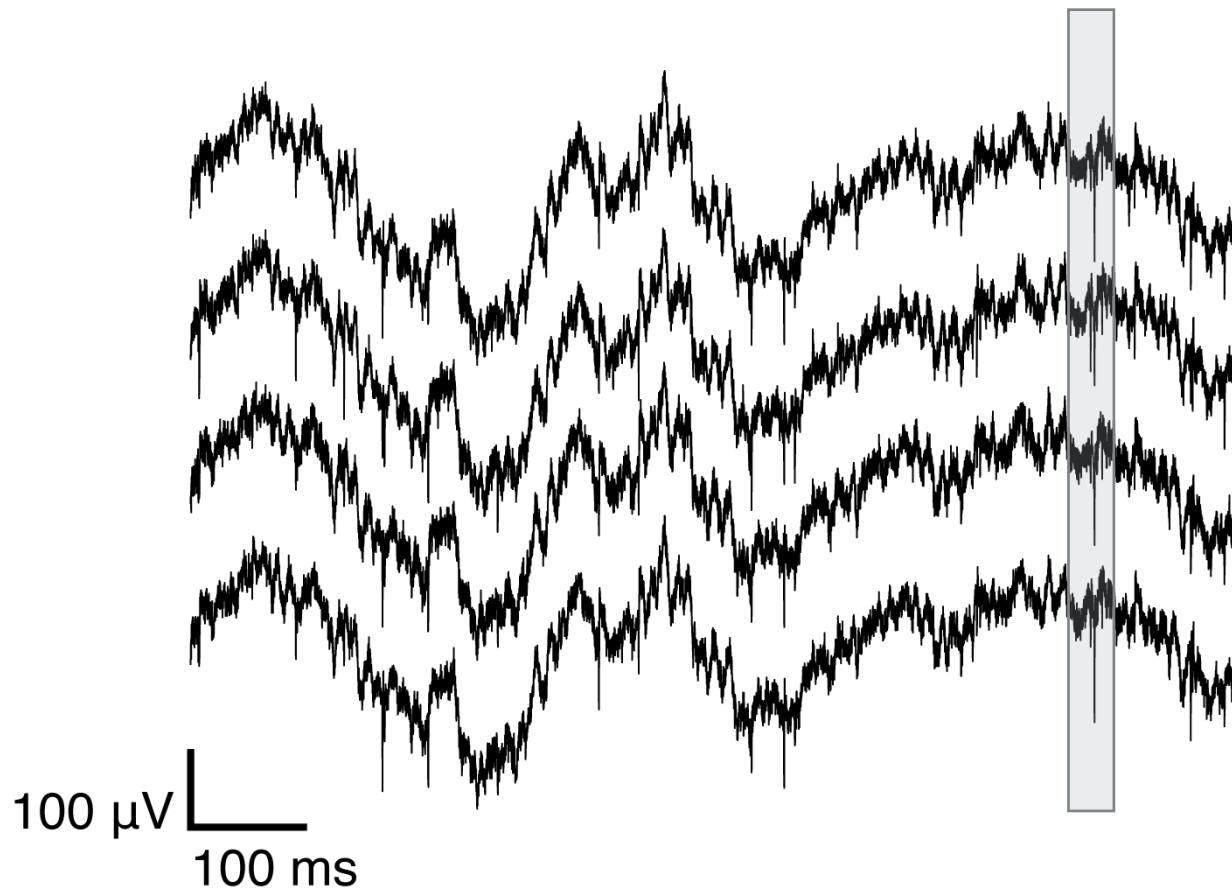
Spike sorting

- Raw data
- Spike detection
- Feature extraction
- Clustering
- Verification





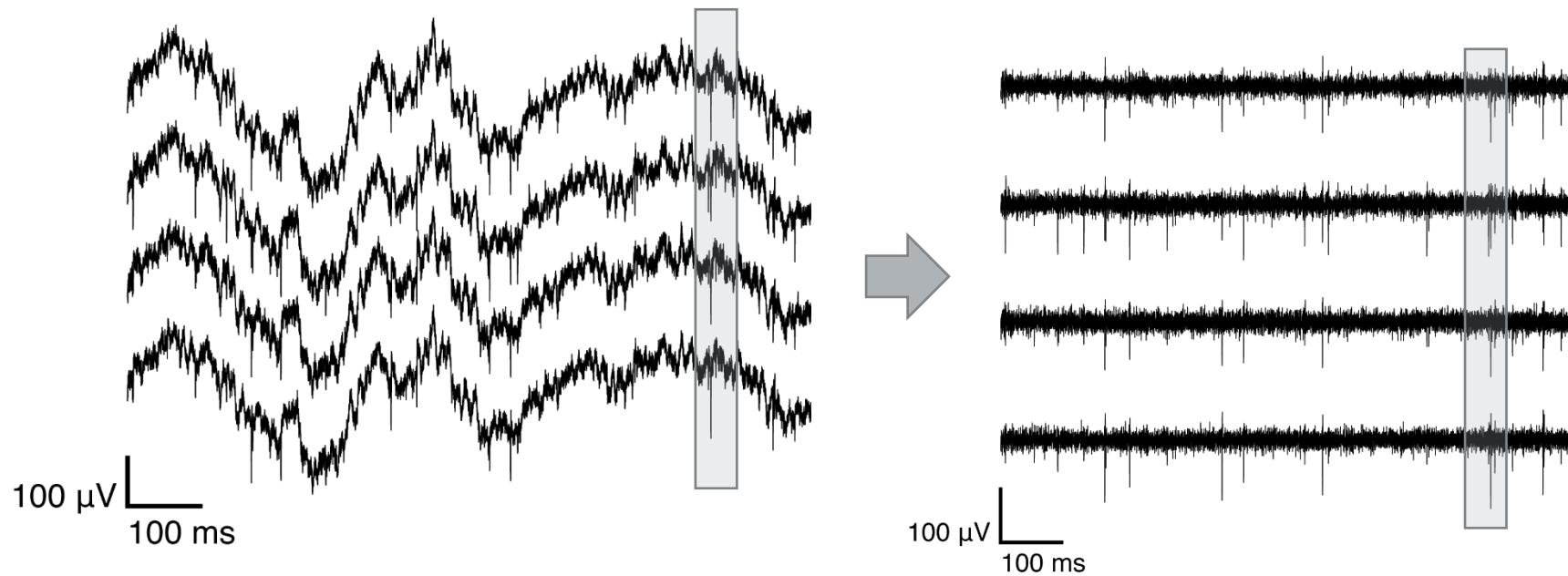
Raw signal



Tetrodes: 4 channels in parallel!



Remove LFP and high frequency noise

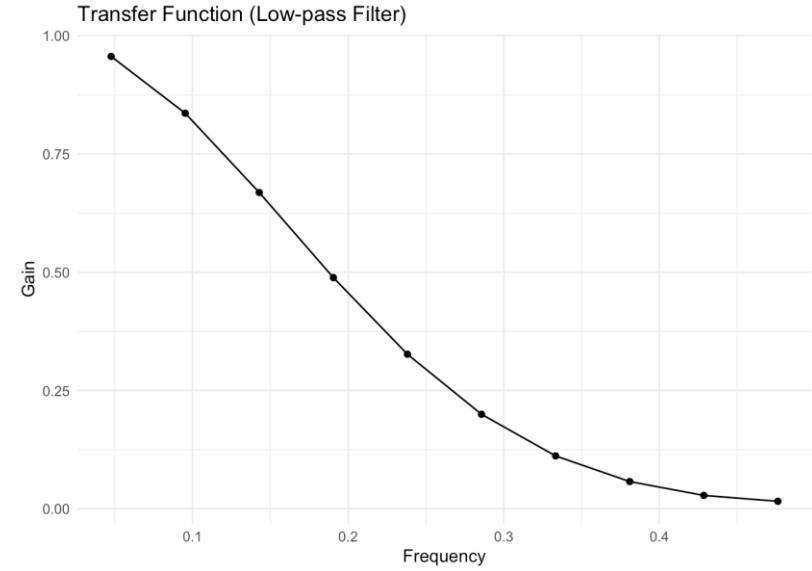
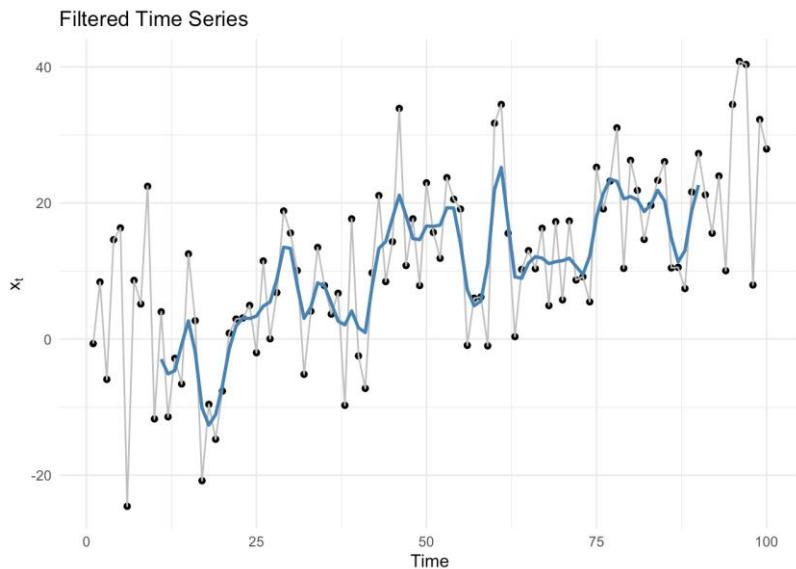




A quick detour on time series filtering

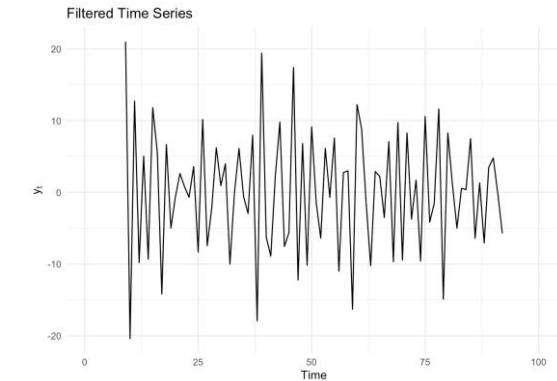
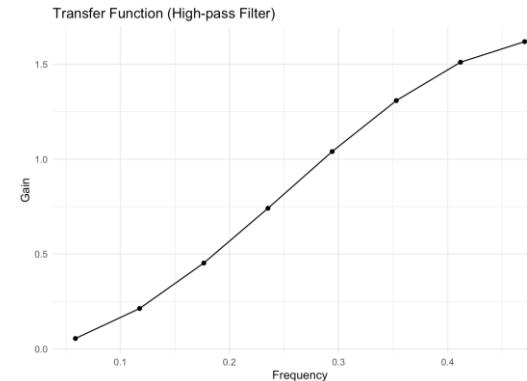
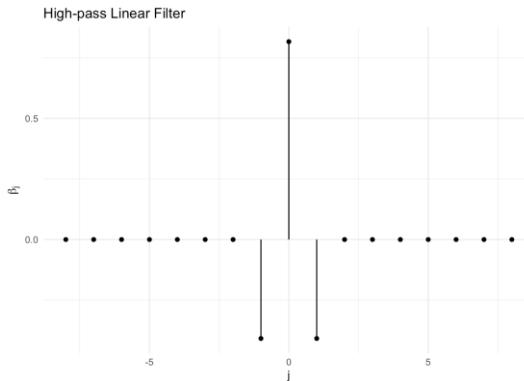
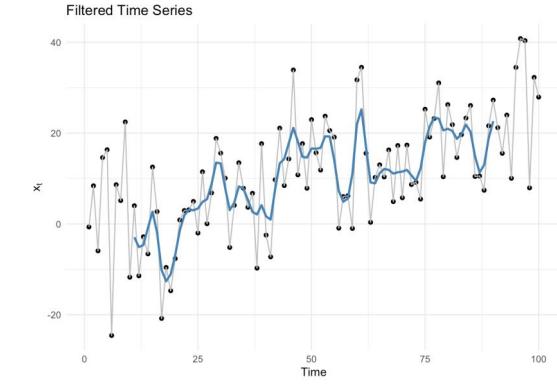
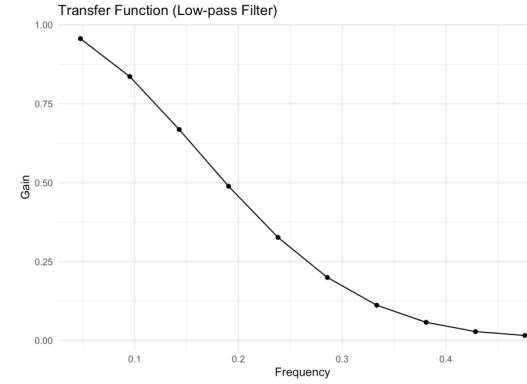
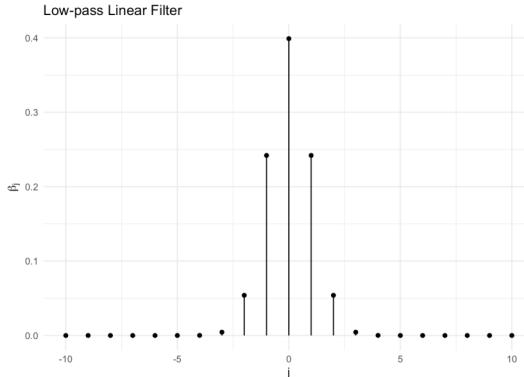
<https://bookdown.org/rdpeng/timeseriesbook/filtering-time-series.html>

$$y_t = \sum_{j=-\infty}^{\infty} \beta_j x_{t-j}$$



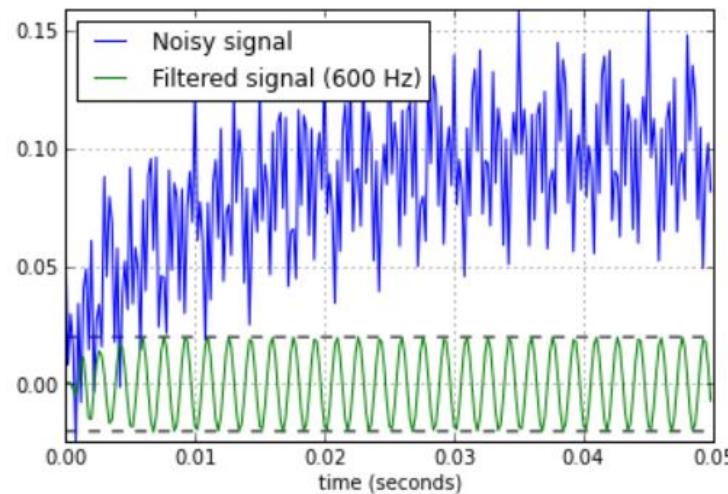
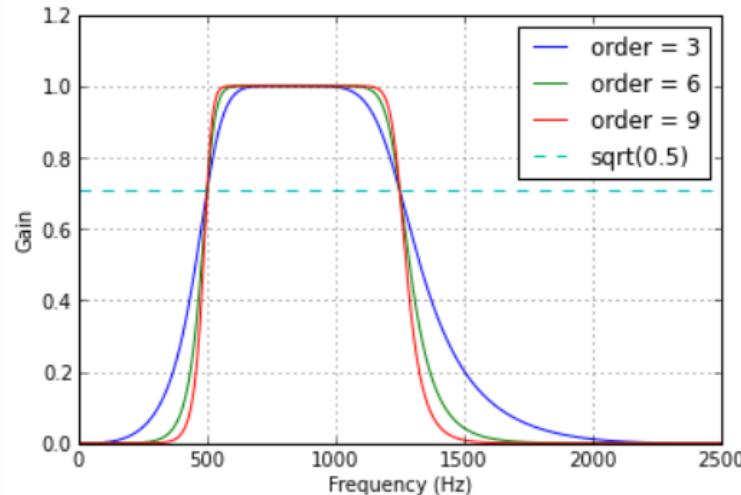
A quick detour on time series filtering

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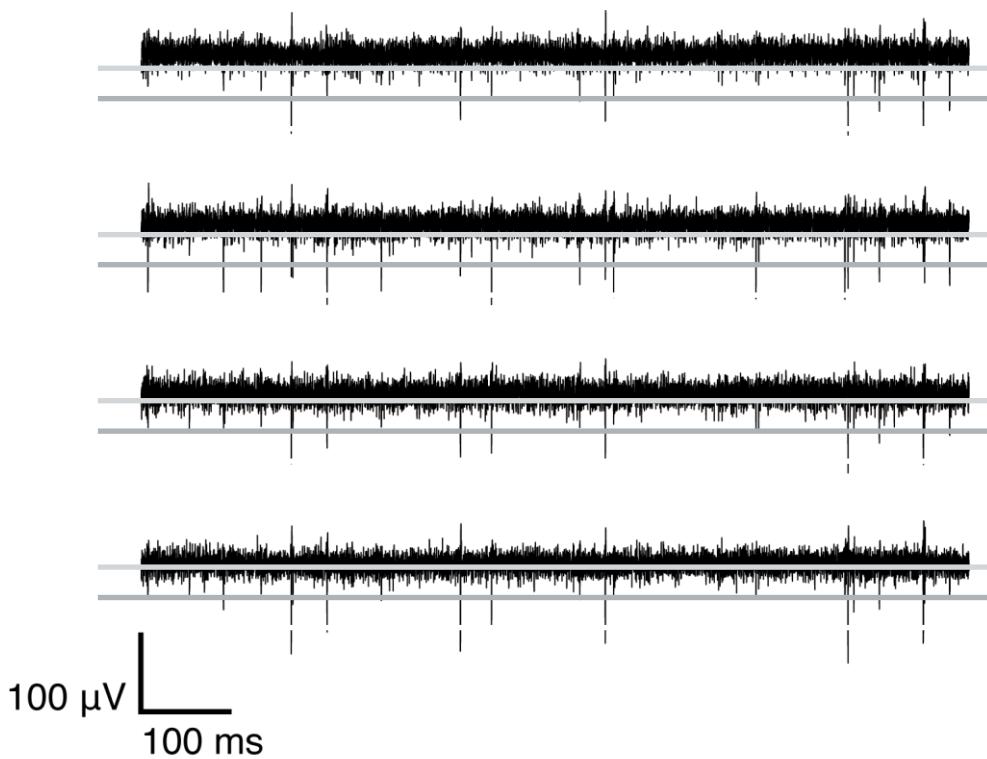


Butterworth bandpass filter





Spike detection



Threshold at $N\sigma$

Low threshold

High threshold

Robust estimation of σ :

$$\hat{\sigma} = median \left(\frac{|x - \bar{x}|}{0.6745} \right)$$

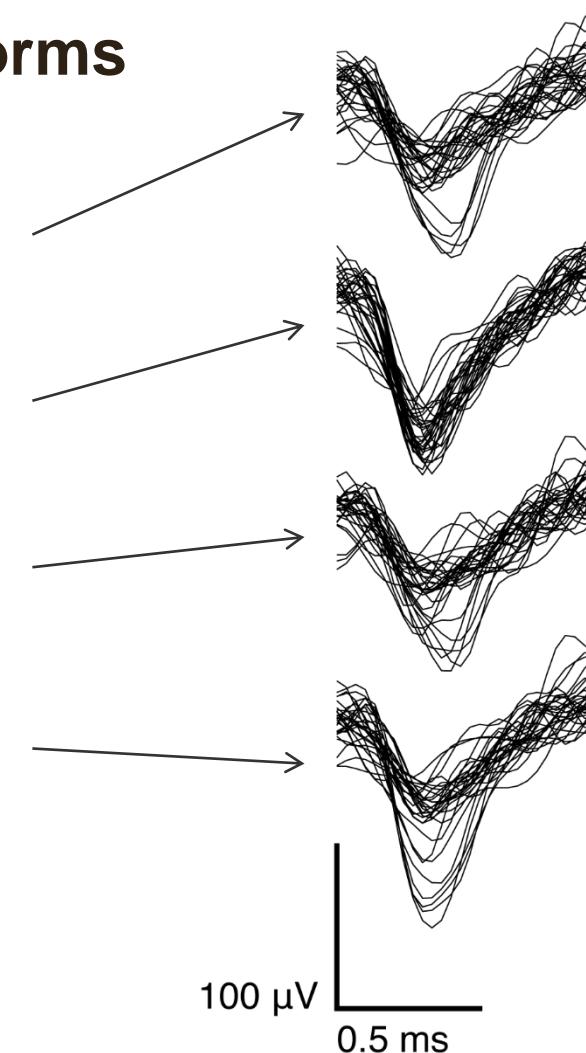
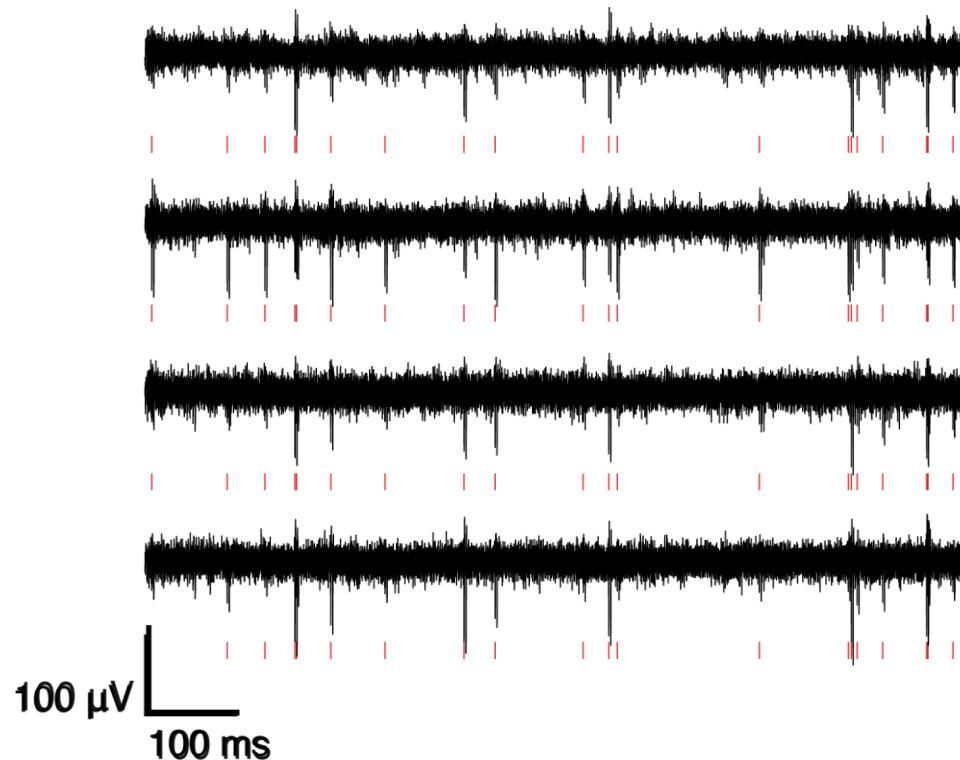


Why is this an estimate of the standard deviation?

- $MAD = \text{median}(|x - \bar{x}|)$
- $\frac{1}{2} = P(|X - \mu| < MAD) = P\left(\frac{|X - \mu|}{\sigma} < \frac{MAD}{\sigma}\right) = P\left(|Z| < \frac{MAD}{\sigma}\right)$
- $\Phi\left(\frac{MAD}{\sigma}\right) - \Phi\left(-\frac{MAD}{\sigma}\right) = \frac{1}{2}$
- $\Phi\left(\frac{MAD}{\sigma}\right) - 1 + \Phi\left(\frac{MAD}{\sigma}\right) = \frac{1}{2}$
- $\Phi\left(\frac{MAD}{\sigma}\right) = \frac{3}{4}$
- $\sigma = \frac{1}{\Phi^{-1}\left(\frac{3}{4}\right)} MAD = \frac{1}{1.4826} MAD = 0.675 MAD$

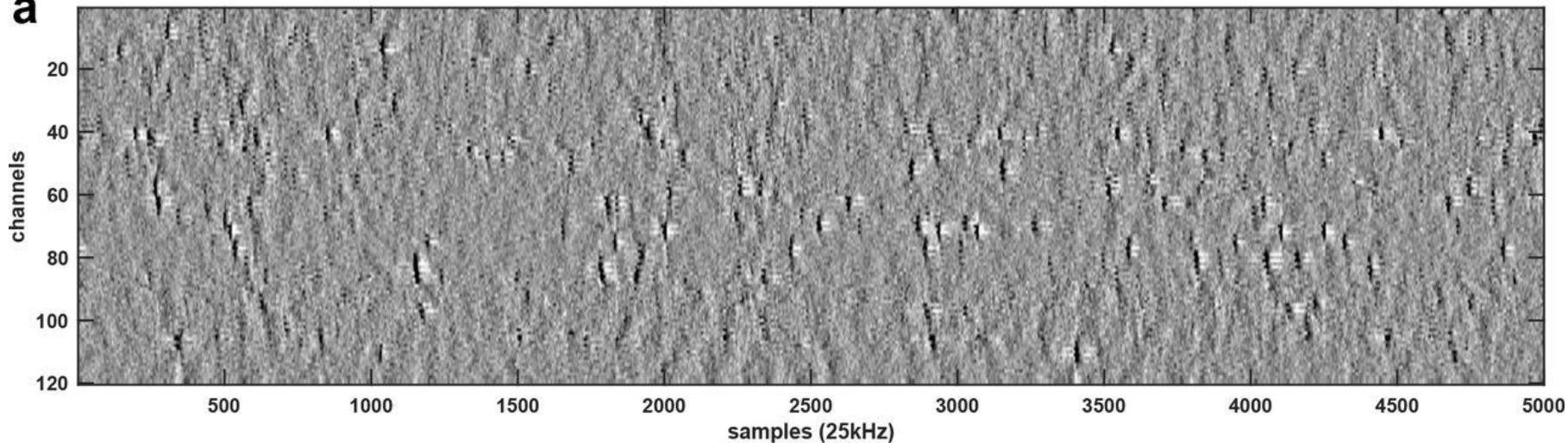


Detect spikes and extract waveforms

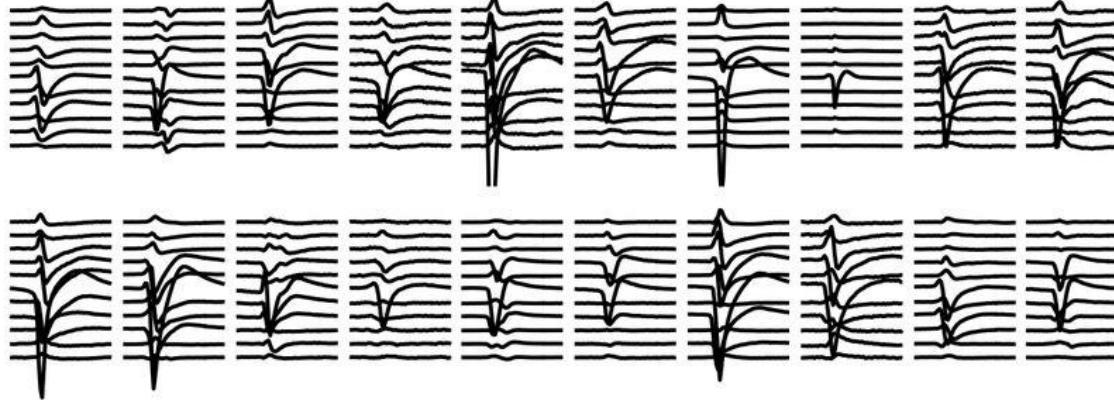




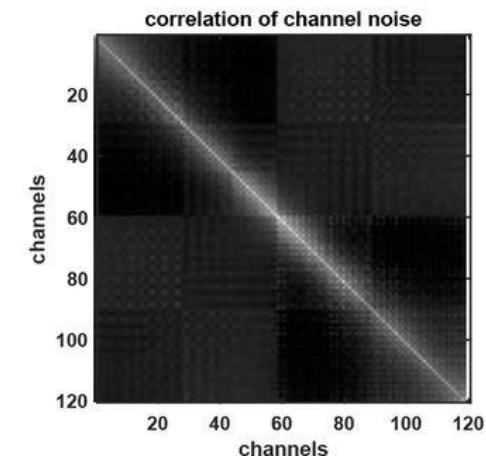
a



b



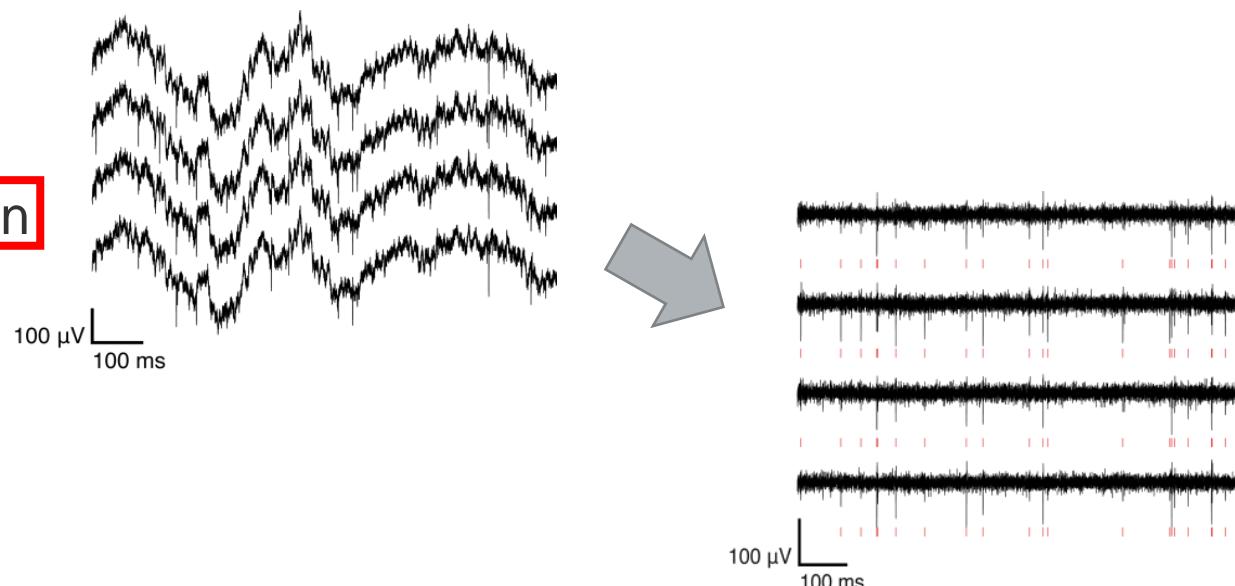
c





Spike sorting

- Raw data
- Spike detection
- Feature extraction
- Clustering
- Verification



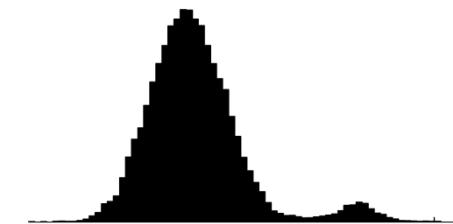
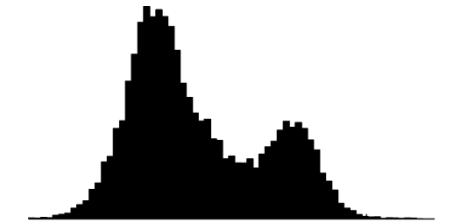
Problem: curse of dimensionality

- 4 channels \times 32 samples = 128 dimensions
- Problems:
 - Memory issues
 - Computing time
 - Model complexity / number of parameters
- Dimensionality reduction

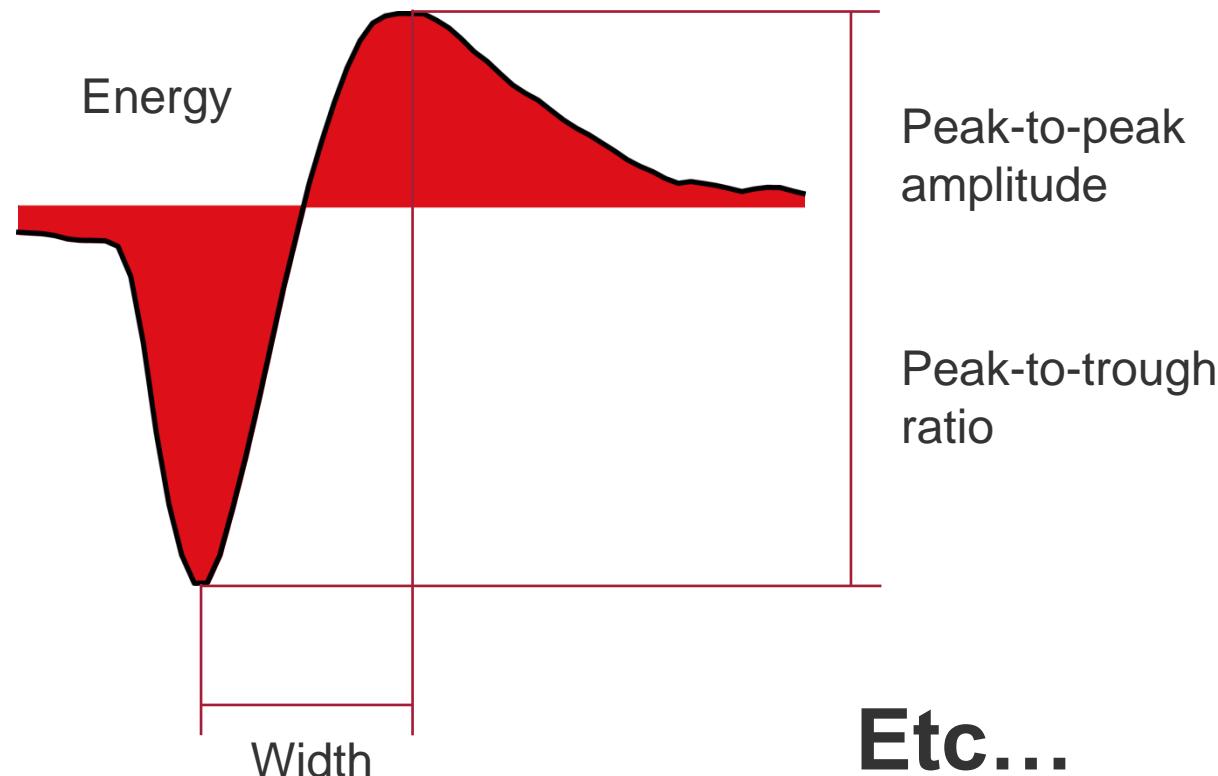


Which features to choose?

- Goal: small set of features that discriminate between different neurons
- Robust against noise?
- What is good may depend on the spike sorting algorithm (shape of distribution)



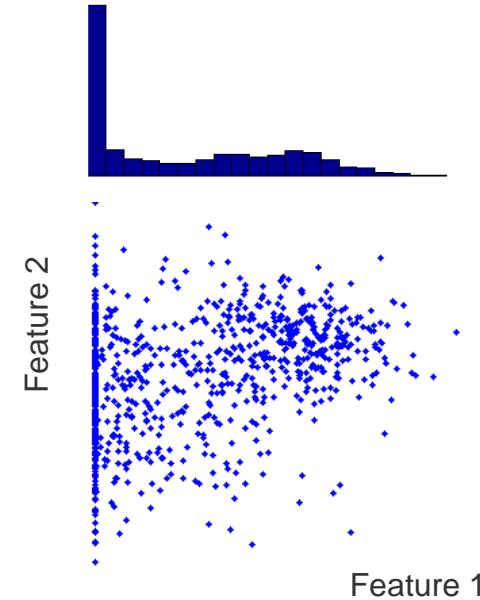
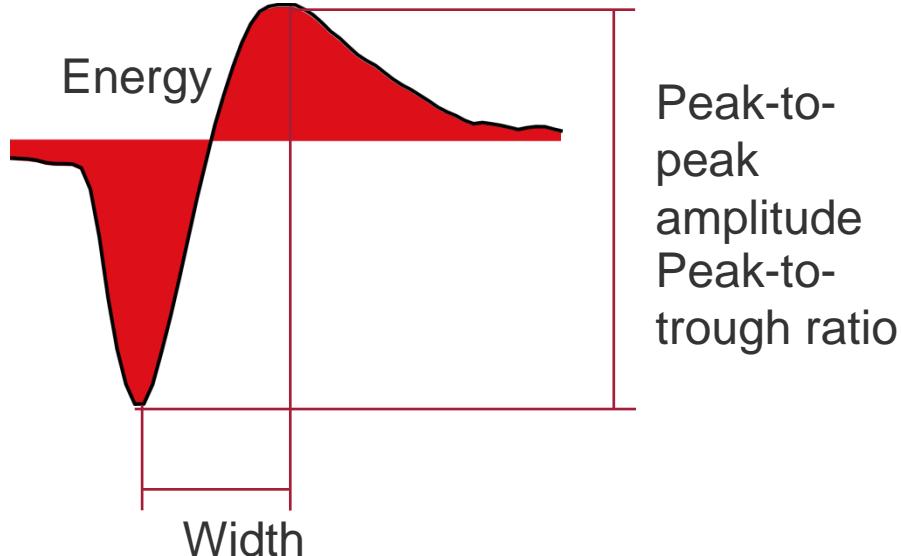
“Descriptive features”





Problems

- Sometimes undefined (no trough)
- Non gaussian distributions
- Correlated



See also
Quiroga et al., 2004



PCA

1. Find direction capturing maximum variance

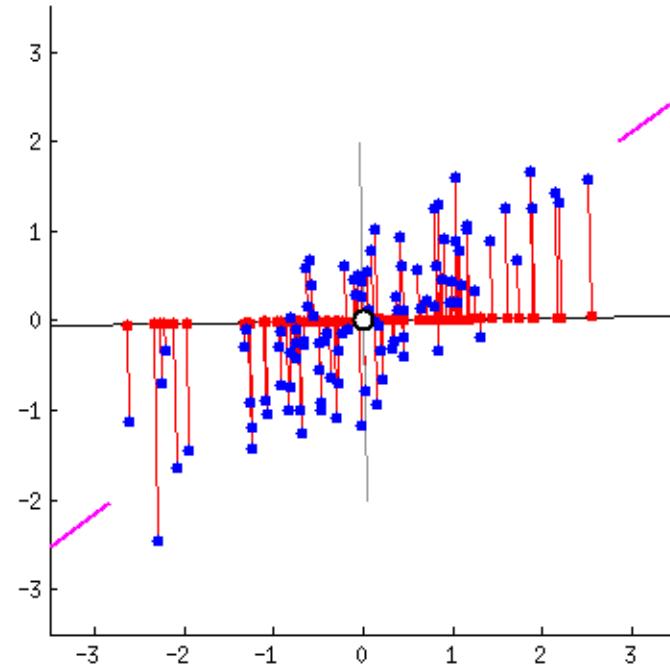
$$w = \arg \max_w \sum_i (w^T x_i)^2, \text{ s.t. } \|w\| = 1$$

2. Minimal reconstruction error

$$w = \arg \min_w \|X - w w^T X\|^2$$

→ solve eigenvalue problem

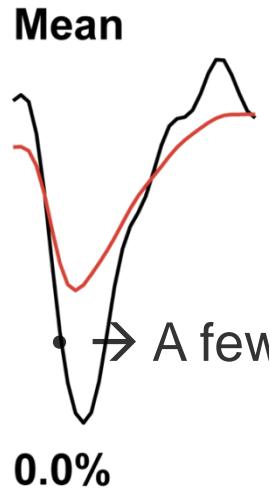
$$w = \text{eig}(\text{cov}(X))$$





Principal component analysis (PCA)

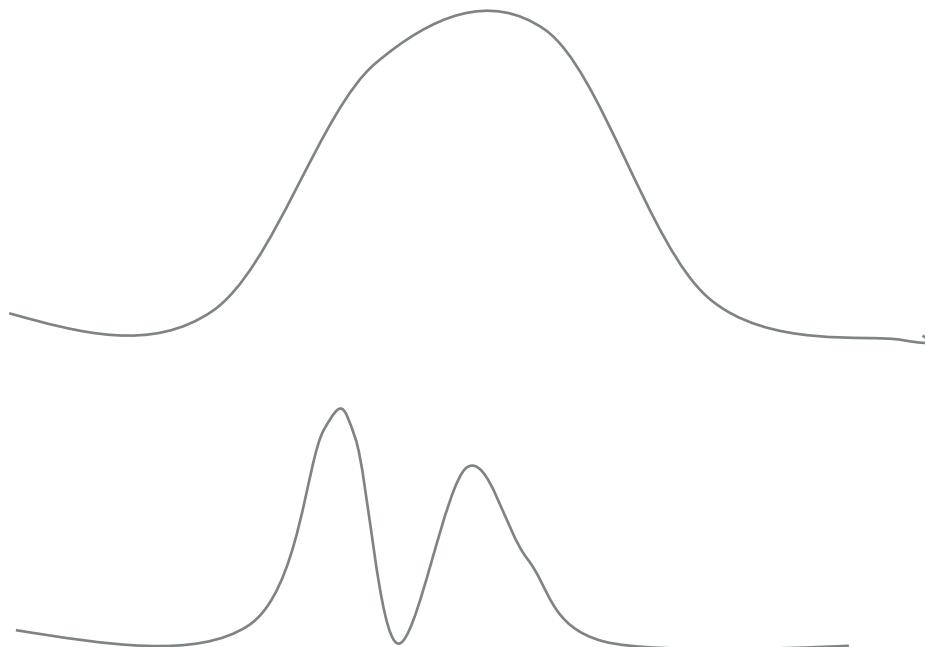
- Finds an orthogonal basis for the data
- First PC is the direction of largest variance





Problem with PCA

Largest variance – multiple peaks

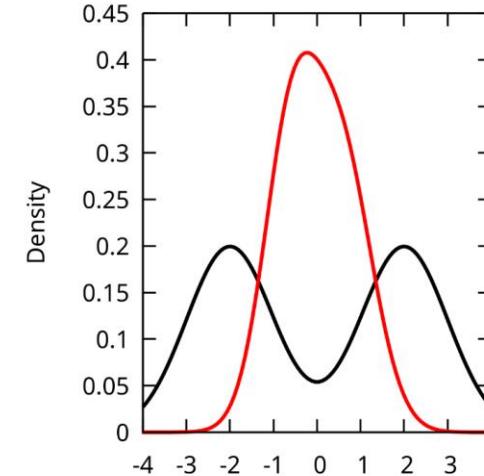
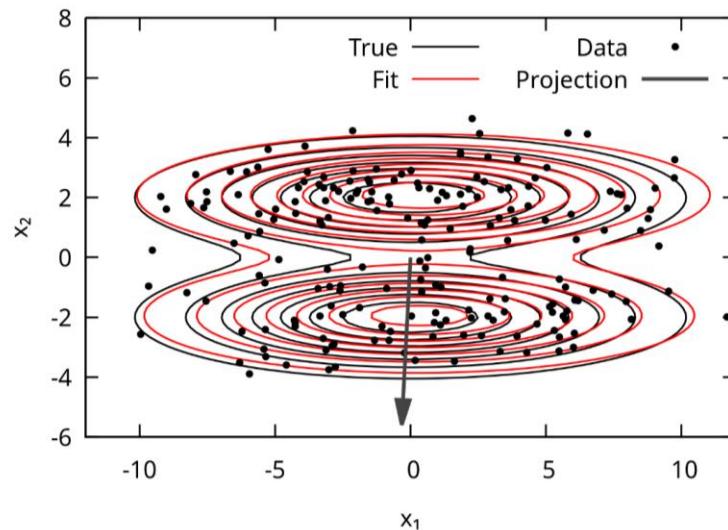
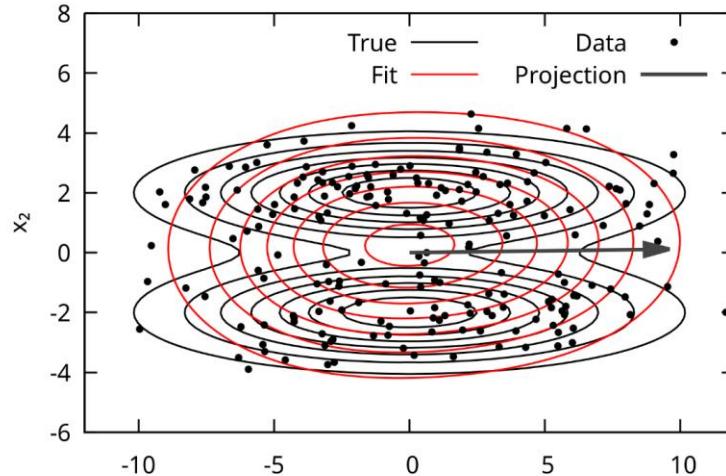


Larger variance

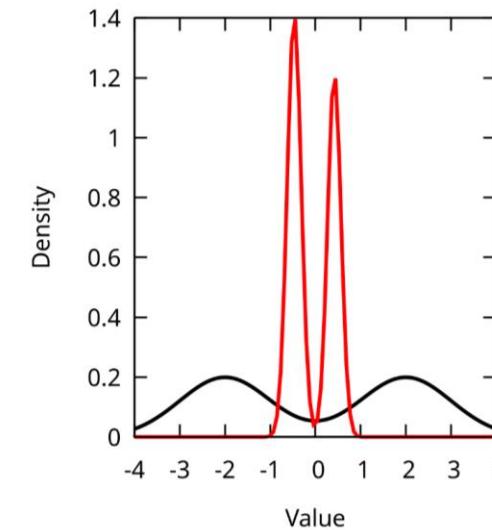
Better for clustering



Hierarchical mixture of Gaussians



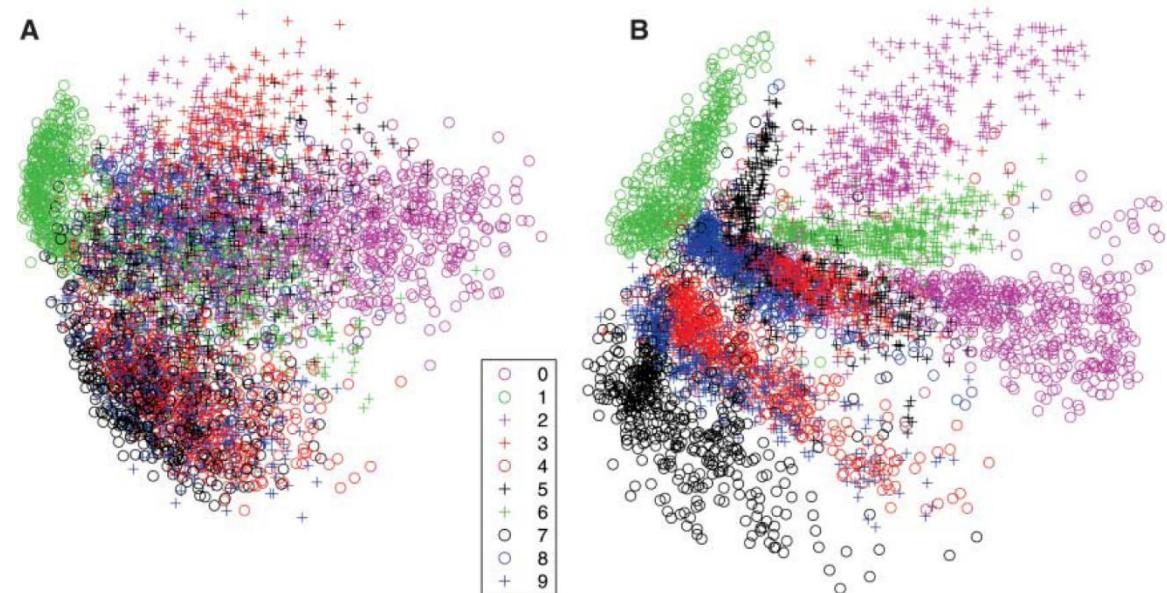
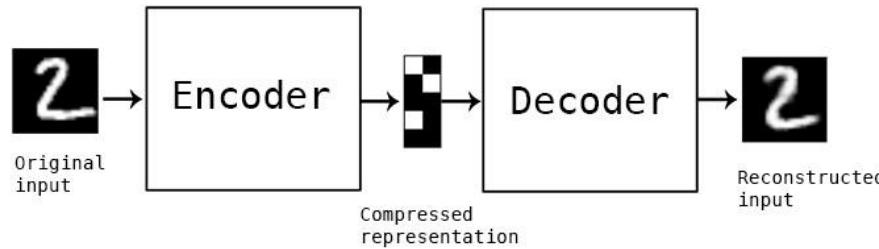
Two-stage
PCA + MoG



Joint PCA +
MoG

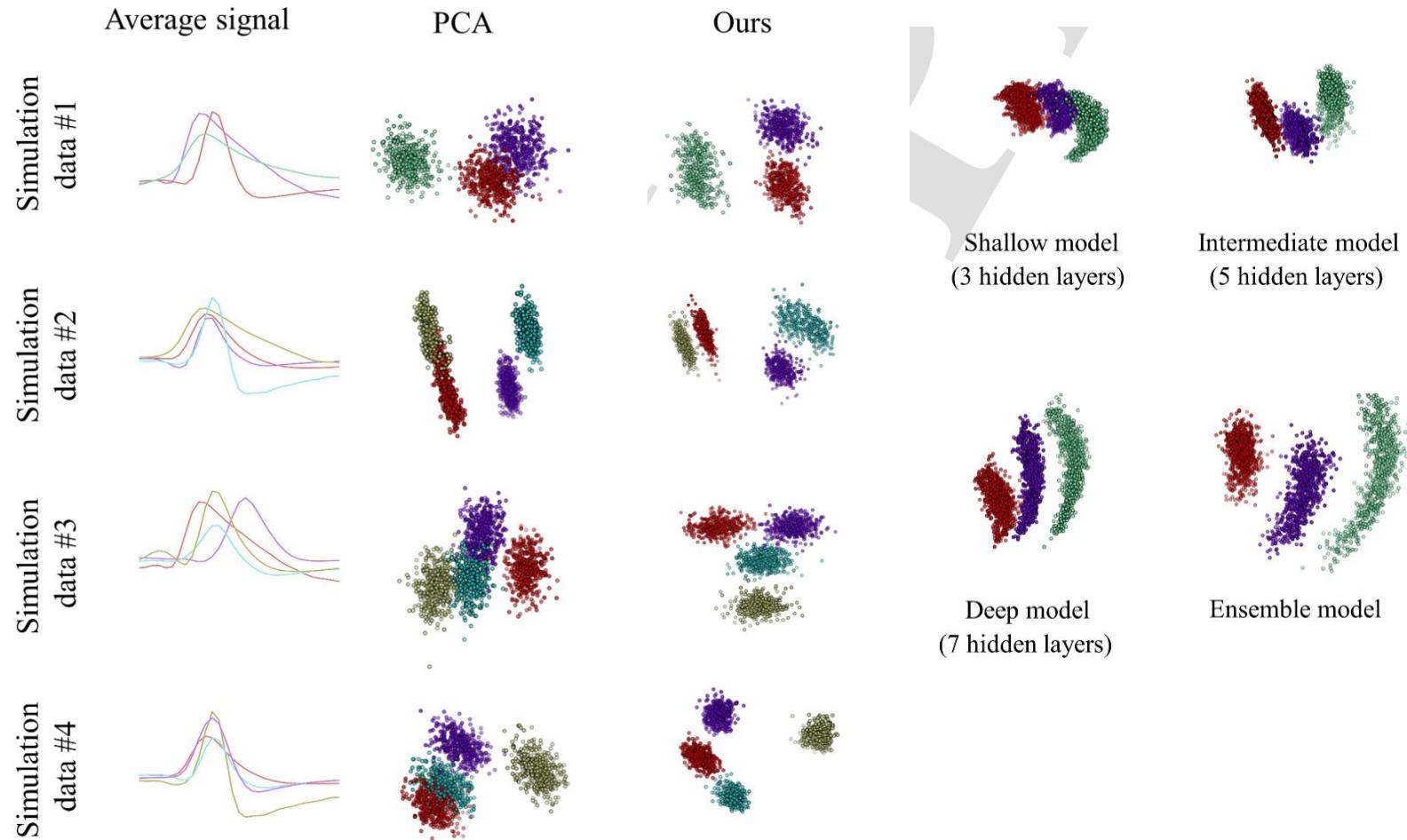


Autoencoder networks





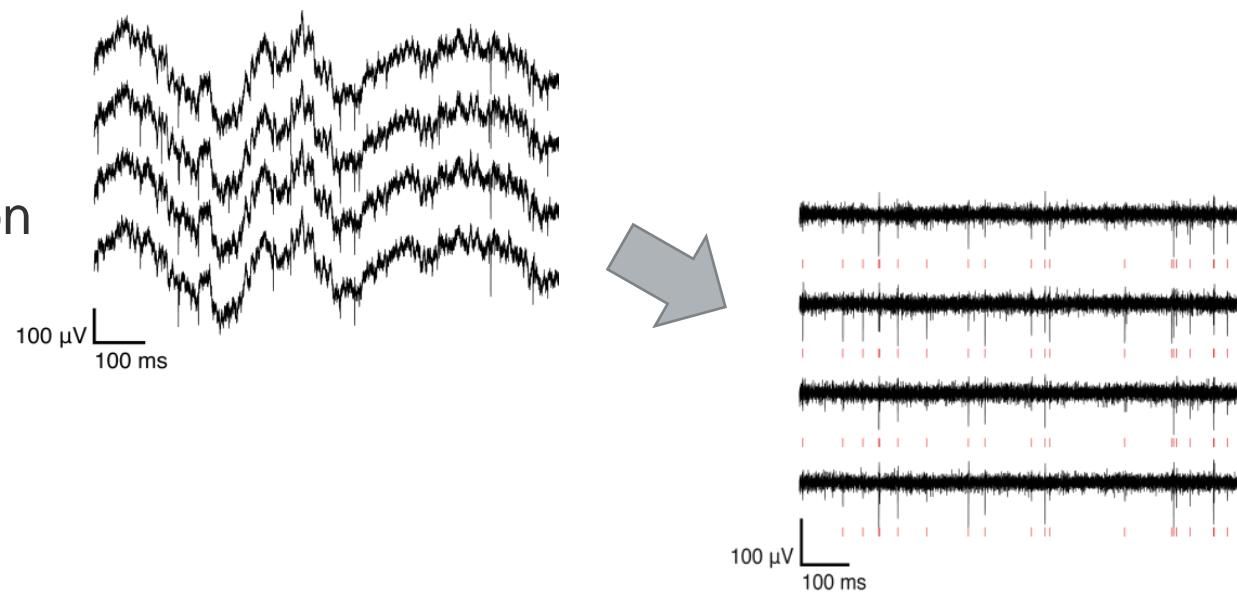
Example





Spike sorting

- Raw data
- Spike detection
- Feature extraction
- Clustering
- Verification





Whitening

