



# Computational Neuroscience

## Lecture 5: Large-scale electrophysiology

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# Agenda

Large-scale electrophysiology

Data analysis

Modeling

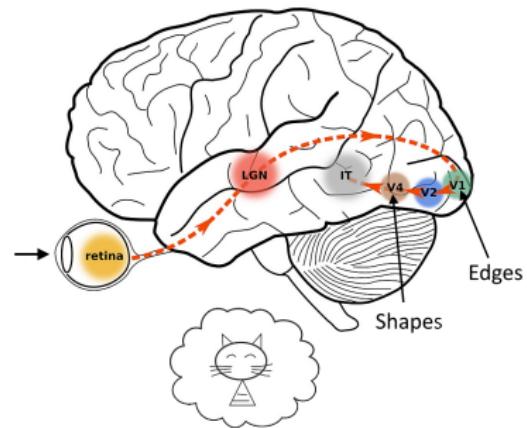
## Large-scale electrophysiology

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# System level

A lot of processes involve multiple areas of a brain.

- Information processing
- Motor control
- Disease abnormalities

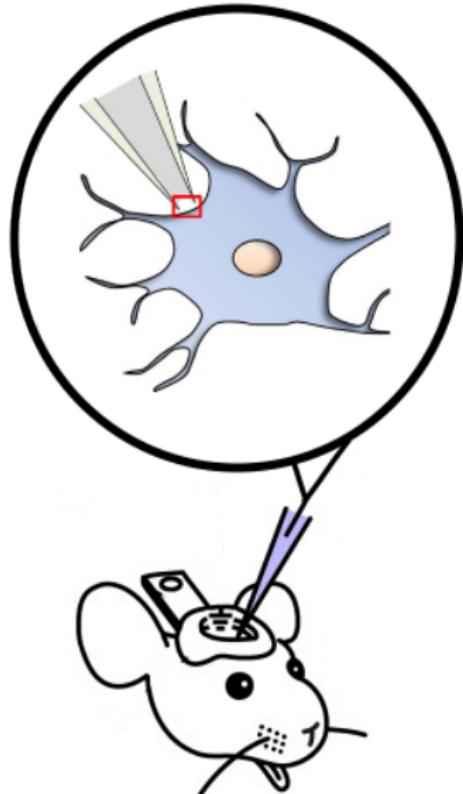


## Single neuron recordings

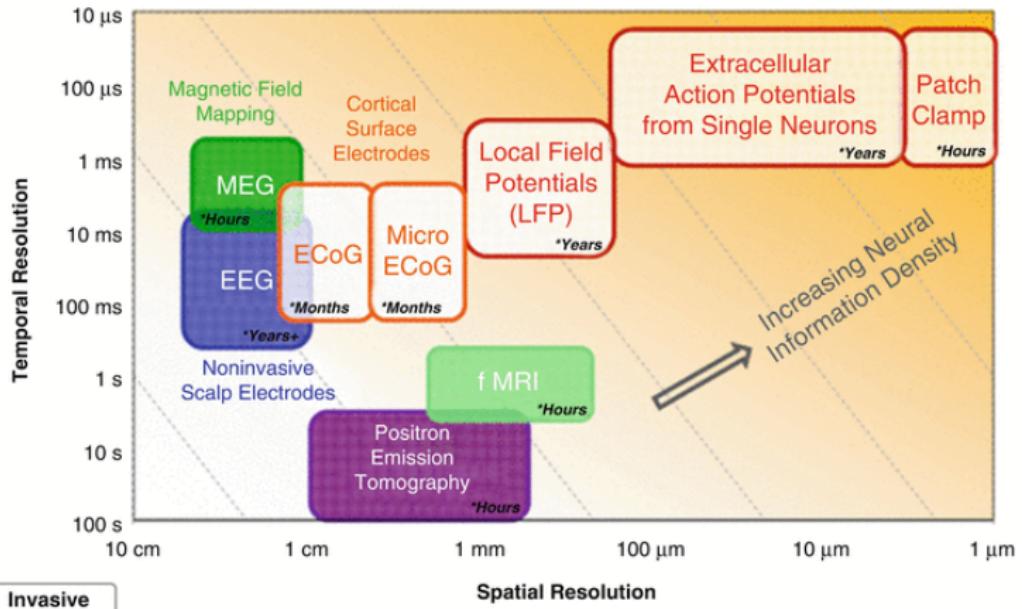
Using patch clamp we can record activity of a single cell.

Cons:

- Difficult to perform in-vivo
- Can't do it with humans
- It is just a single cell



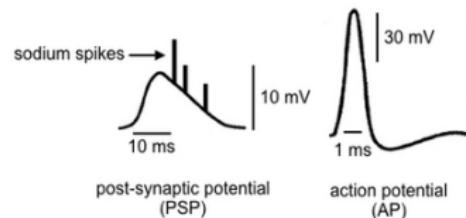
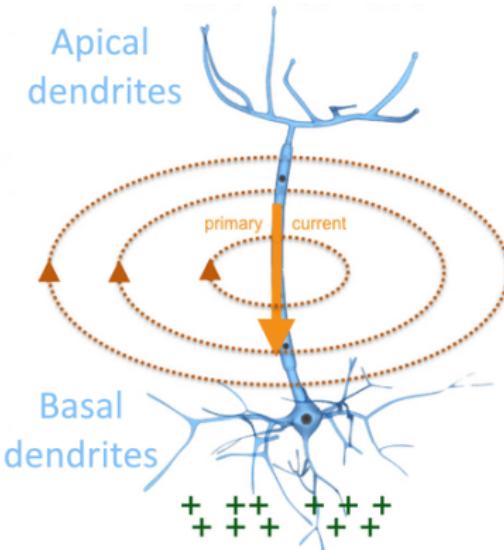
# Imaging techniques



\*Longevity of Monitoring Technique

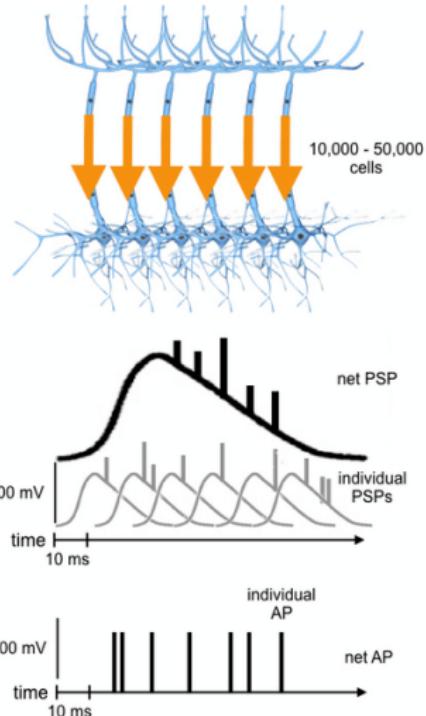
# Single neuron

Electric current produces a magnetic field which can be measured as a potential difference between and a reference.



# Neuronal population

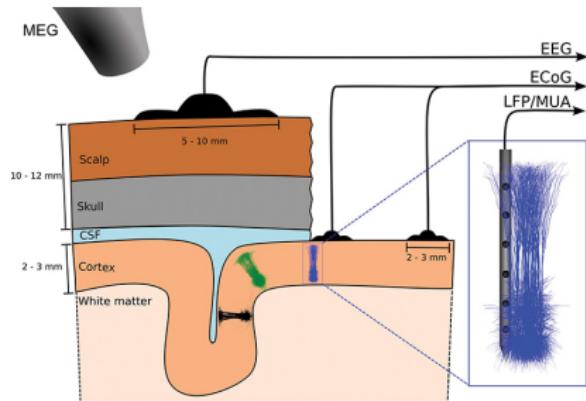
In case of neuronal population, fields from multiple neurons interact: they sum or may even cancel each other.



# Recording process

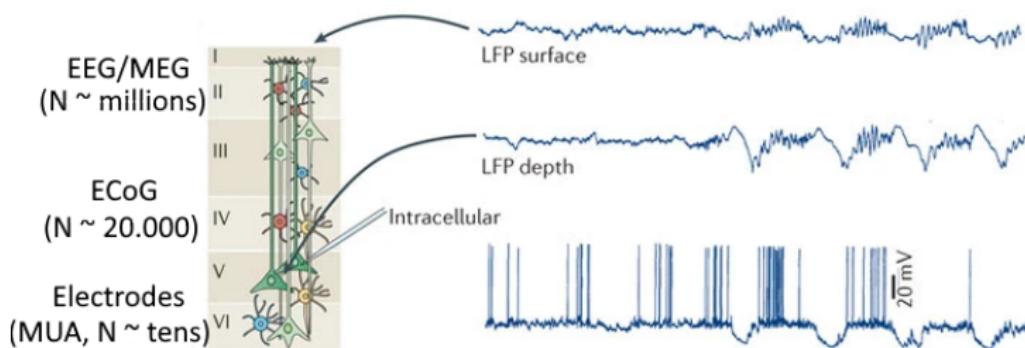
Anatomy plays a huge role in modality of a neural data.

- Neuron types
- Possible cancellation
- Amount of cells



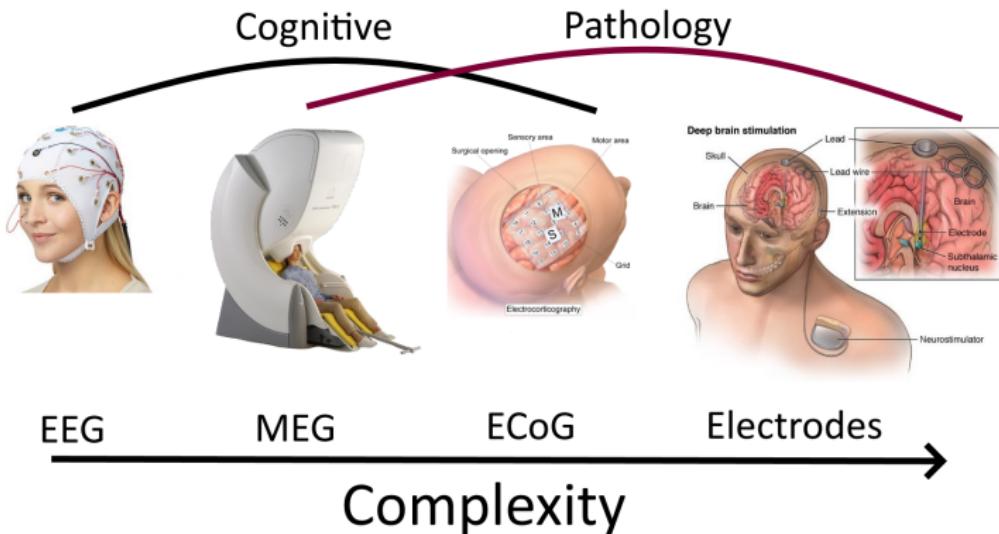
## Scale difference

Despite those methods have the same fundamentals, the data contains different modality (amount of neurons, neuronal types and data quality).



# Experimental difference

Hardware and preparations complexity leads to diverse experiment designs varying from one imaging method to another.



## Experimental difference

	Invasive	Mobile	Usage
EEG	No	Yes	Motor tasks, gaming, BCI
MEG	No	No	Information processing, memory
ECoG	Yes	Yes	Epilepsy, motor control, invasive BCI
MUA	Yes	No	Parkinson, subcortical activity

## Example: EEG

Hypothesis: can specifically designed games treat depression?

Limitations:

- Movement
- Whole-brain recordings
- Non-invasive

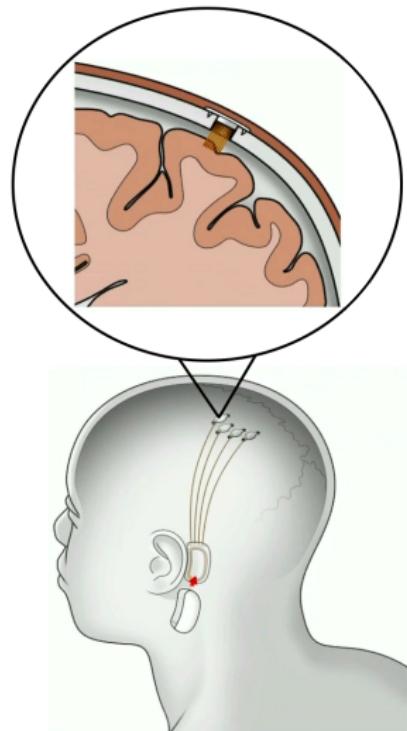


## Example: Invasive BCI

Invasive BCI's are used when you need to get high-quality & real-time data.

Limitations:

- Movable
- High time and spatial resolutions
- Low latency



## Example: MUA

Hypothesis: Parkinson disease is caused by broken activity of subcortical structures.

Limitations:

- Patients with Parkinson
- Single-cell analysis
- Deep brain recordings



## Data analysis

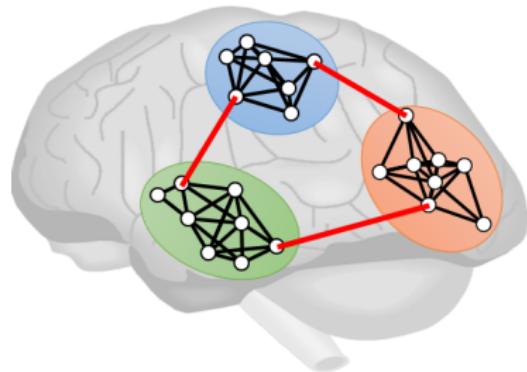
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# Small-world networks

Neurons are connected in a small-world manner and follow the next principles:

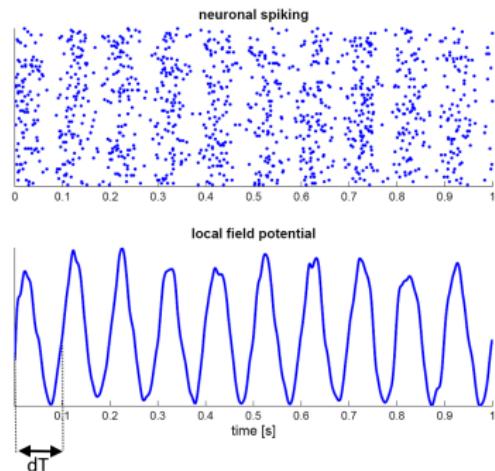
1. Dense connections within
2. Synchronized spiking

Example: cortical columns



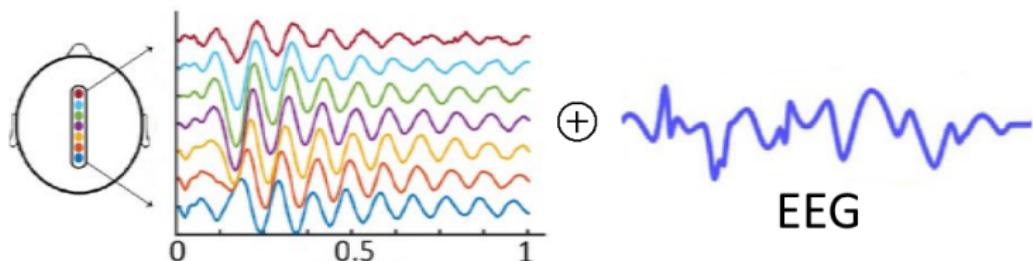
# Rhythms

Coupled spiking generates periodic signal with high magnitude when activity prevails and low otherwise.



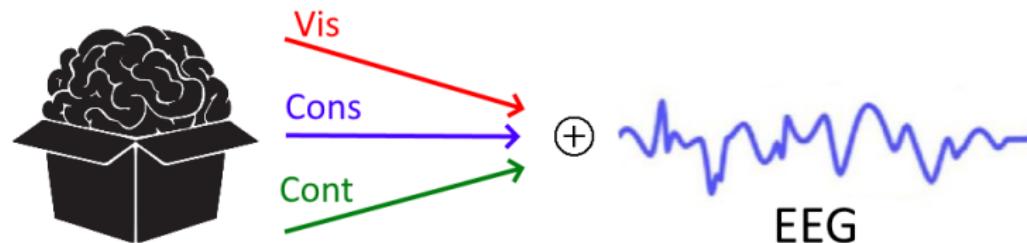
# Rhythms

Oscillatory activity from multiple sources aggregates into a single population signal.



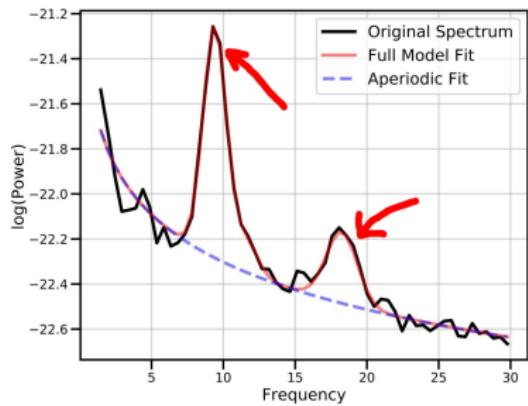
## Brain as black box

**Assumption:** because of physiology & nature of stimuli  
neurons work in different regimes. But we don't know its properties!



# PSD

We have an inverse task now:  
given a signal we want to get  
its spectrum or prevalence of  
frequency components.



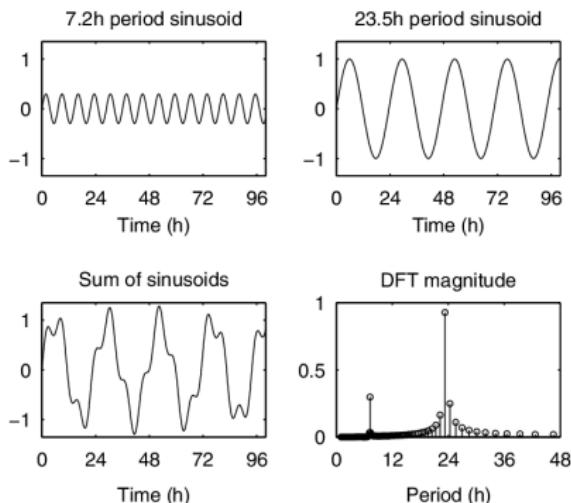
# PSD implementation

We have a finite discrete signal  
→ it can be represented as  
Fourier series using DFT.

$$c_k = \frac{1}{N} \sum_{j=0}^{N-1} x_j e^{-ijk2\pi/N} \quad (1)$$

Where  $k = 0 \dots N - 1$ ,  $x_j$  is a signal sample j,  $c_k$  is a FFT coefficient.

And PSD is just a square of magnitude of FFT (and some tricks)!



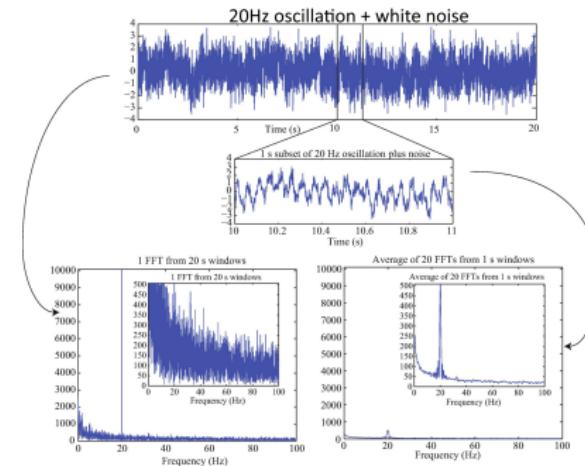
# PSD properties

Pros:

- Shows general properties
- As simple as it could be
- Fast to compute

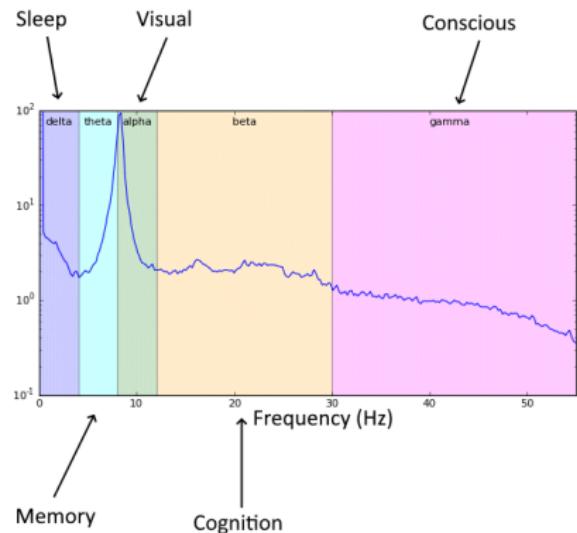
Cons:

- Filtering artefacts
- Impossible to compare raw values
- No time-domain



## PSD example: information processing

We can correlate loading in a frequency with some cognitive activity to find its functional relevance.

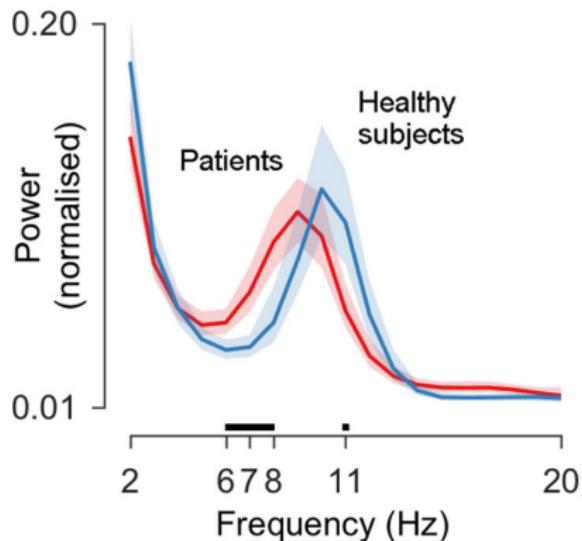


## PSD example: epilepsy

Phenomena: epilepsy zones tend to have slower alpha-oscillations.

Possible explanation: degeneration of processing neurons.

Usage: generic indicator of seizure liability

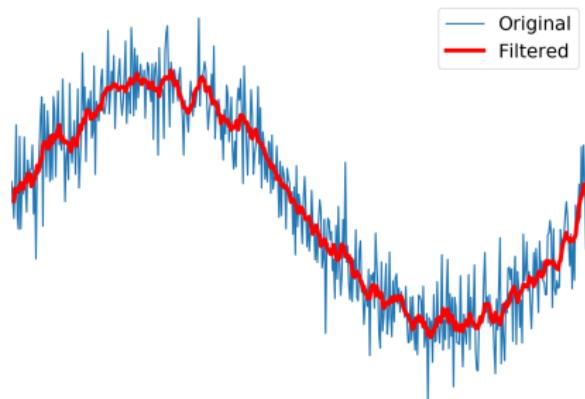


# Filtering

To have a look on particular frequency (range of them) we can *filter* a signal.

It allows:

- Reduce noise
- Remove artefacts
- Dive into frequency domain!

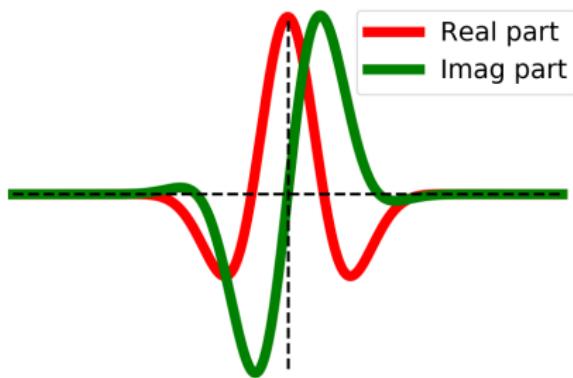


# Wavelets

Wavelets are complex functions which represent a single "heart-beat" of an oscillation in time-frequency domain.

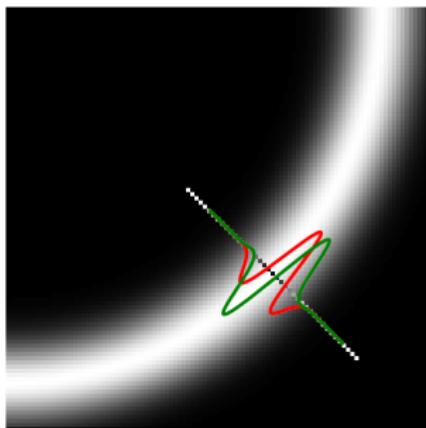
Pros:

- Simple implementations
- Fast (especially with GPU)
- Natural transition to frequency domain

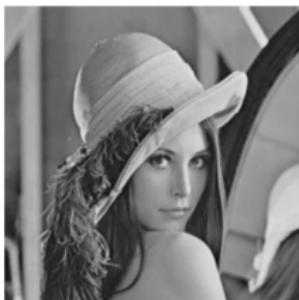


## Example in image processing

Images can be filtered to extract local changes in frequency (e.g. edges or gradients).



Original



Edges

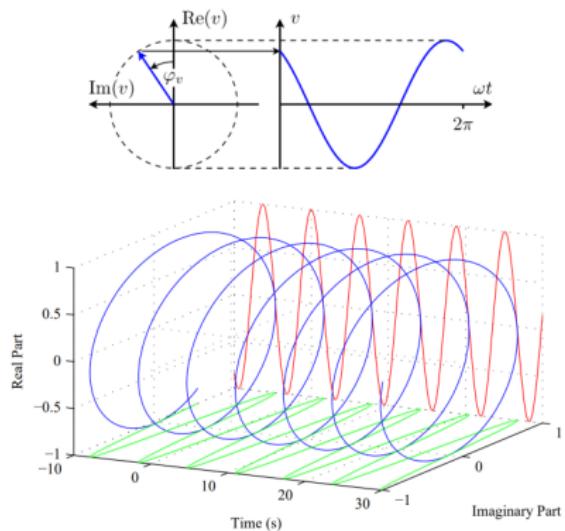


# Frequency domain

After the wavelet transformation a signal moves to time-frequency domain and obtains an addition "frequency dimension".

$$x[t] = x_{real}[t] + i * x_{imag}[t]$$

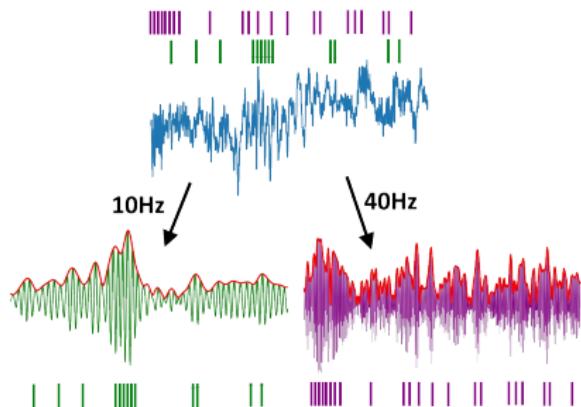
And phase is angle of a sample on complex plane.



## Example: neural separation

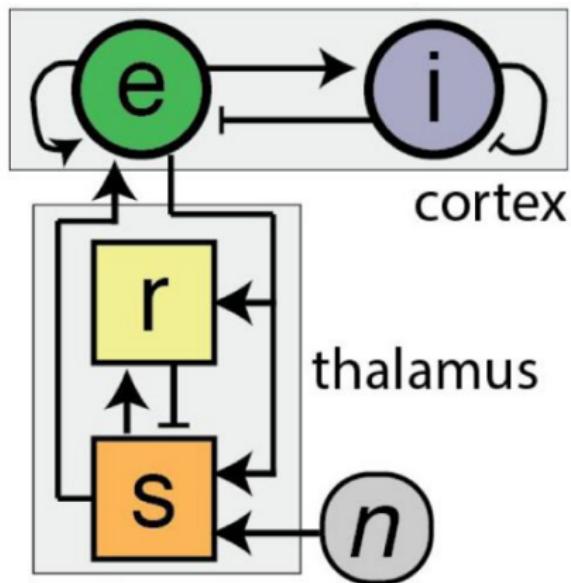
Complex signal has several important properties:

- Envelope (absolute value) represents "activity" in a certain band
- Separates activity of processes with different frequencies.
- We can compare phases

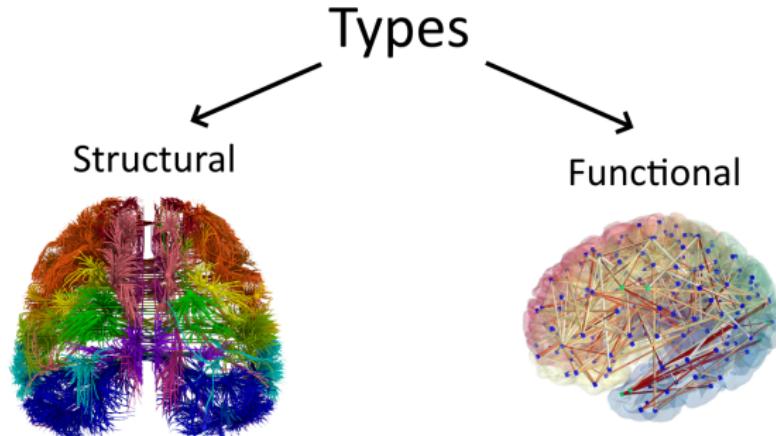


## Bivariate metrics

Neural activity is characterized by permanent communication between neuronal populations. One can use bivariate metrics to build connectome - map of pairwise interactions.



# Connectome



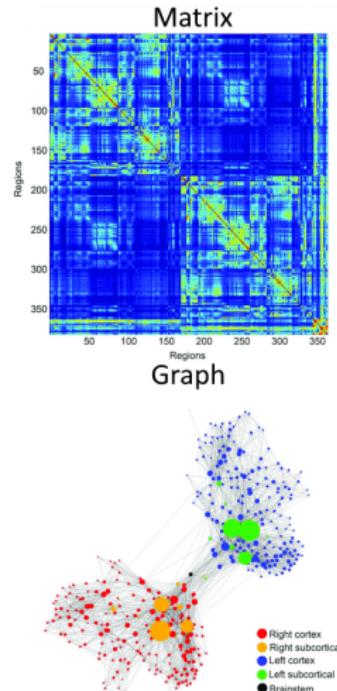
- Represents density of axons
- Fixed in time
- Measured with DTI
- Represents some functional similarity
- Vary in time
- Measured with EEG, MEG, e.t.c.

# Correlation

To measure similarity between two timeseries we can simply compute correlation (Pearson for instance).

Cons:

- Broadband is mix of everything
- No time-lag!

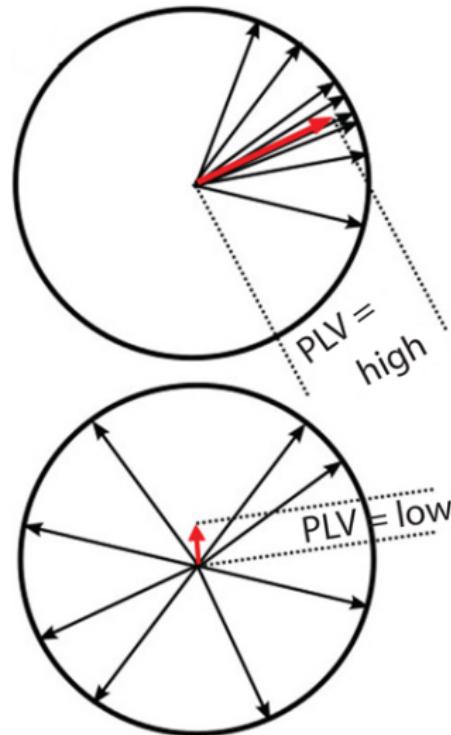


## Phase-locking

For similarity in time-frequency domain we need to measure phase coherence, or phase-locking value.

$$cPLV = \frac{1}{N} \sum_{t=1}^N e^{i*x_t * y_t^*}$$

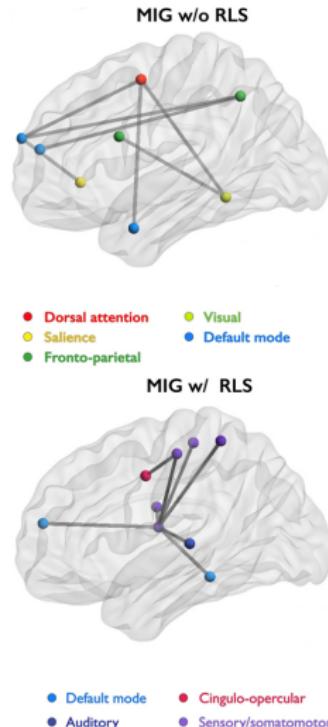
Where  $x_t$  and  $y_t^*$  are original and conj part of complex signals.



## Example: migraine

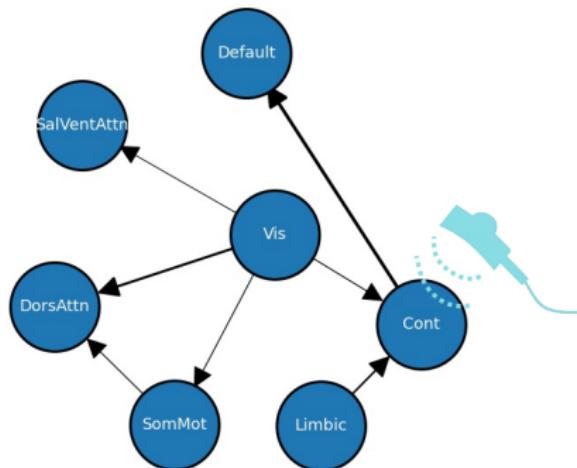
Connectome may serve as biomarker of cognitive impairment or help to explain the reason of it.

For instance, patients with Restless Legs Syndrome in migraine show stronger connections with sensory & somatomotor areas.



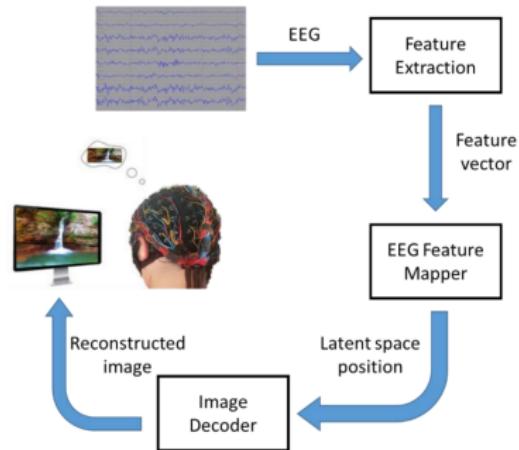
## Example: controllability

Several methods of brain stimulation are used for therapy. Connectomes help to find key areas to stimulate if one want to break coupling or force it.



# Mind reading

Apart of classical statistics, one can try to use neural recordings to read mind (in theory).



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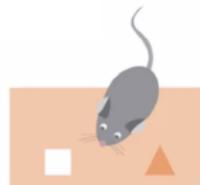
<sup>1</sup><https://www.biorxiv.org/content/10.1101/787101v2.full.pdf>

# Modeling

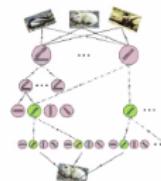
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# Three levels of understanding the brain

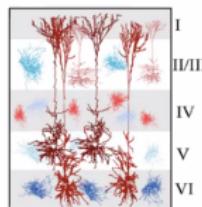
**COMPUTATIONAL**



**ALGORITHMIC**

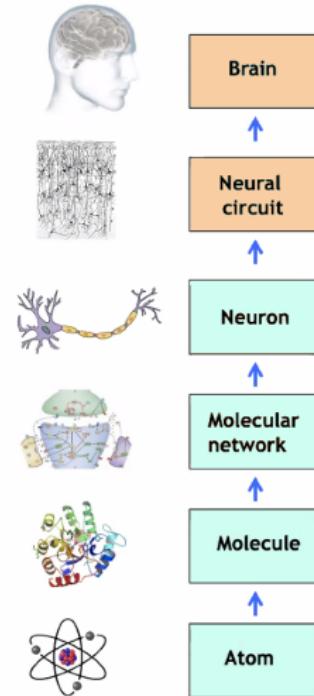


**PHYSICAL**



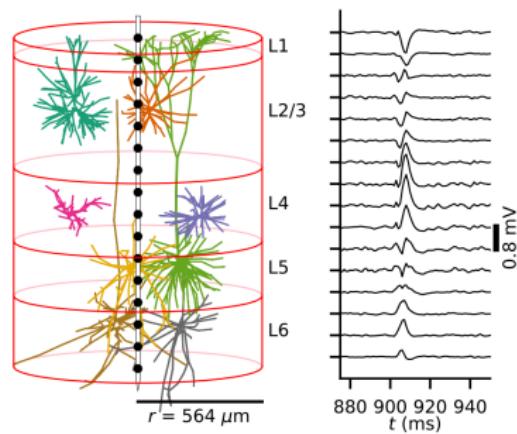
# Model levels

There is no single-bullet to perform simulation of every possible level of detailization and multiple models exist to fulfil those gaps.



# Biophysical models

One may utilize the concept of physical models of single neuron and combine it to a huge neural network/tissue and compute LFP using physical laws.



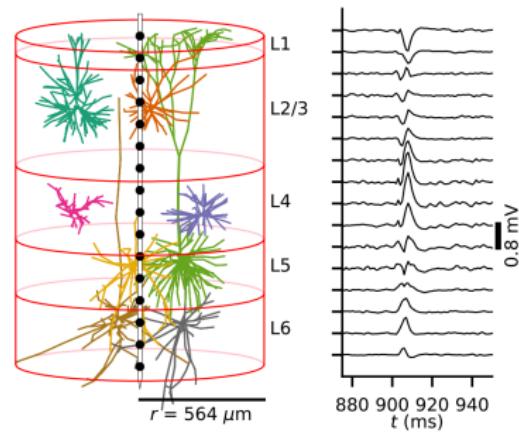
# Biophysical models

Pros:

- Precision
- Every possible parameter

Cons:

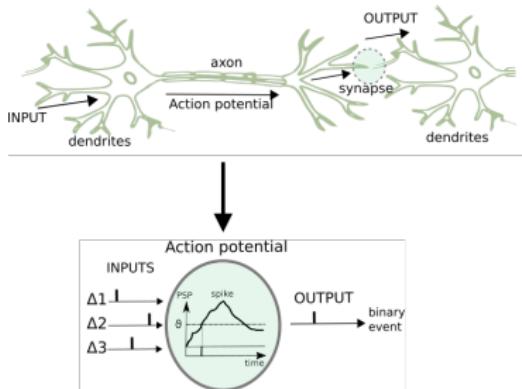
- Slow
- We dont know everything
- Hard to tune



# Spiking networks

We can reduce model complexity and make it simpler.  
Properties of SNN:

- Neurons are represented as nodes
- Information is transmitted with spikes
- Has time and space



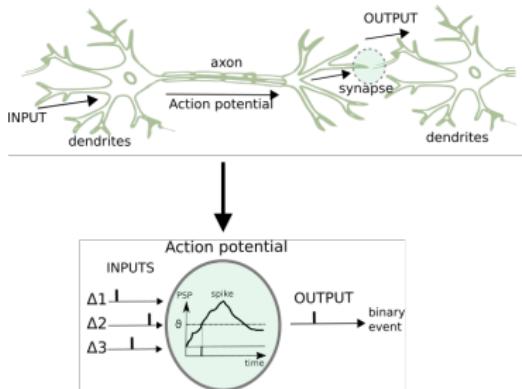
# Spiking networks

## Pros:

- Relatively fast
- Follow laws of physiology\*
- Can be trained

## Cons:

- Loss of information
- Training is hard

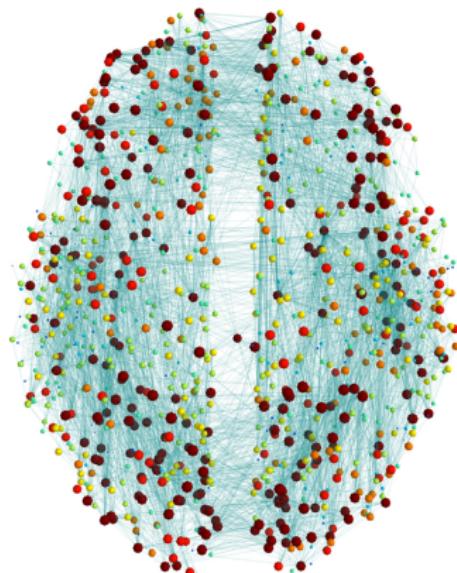


# System-level models

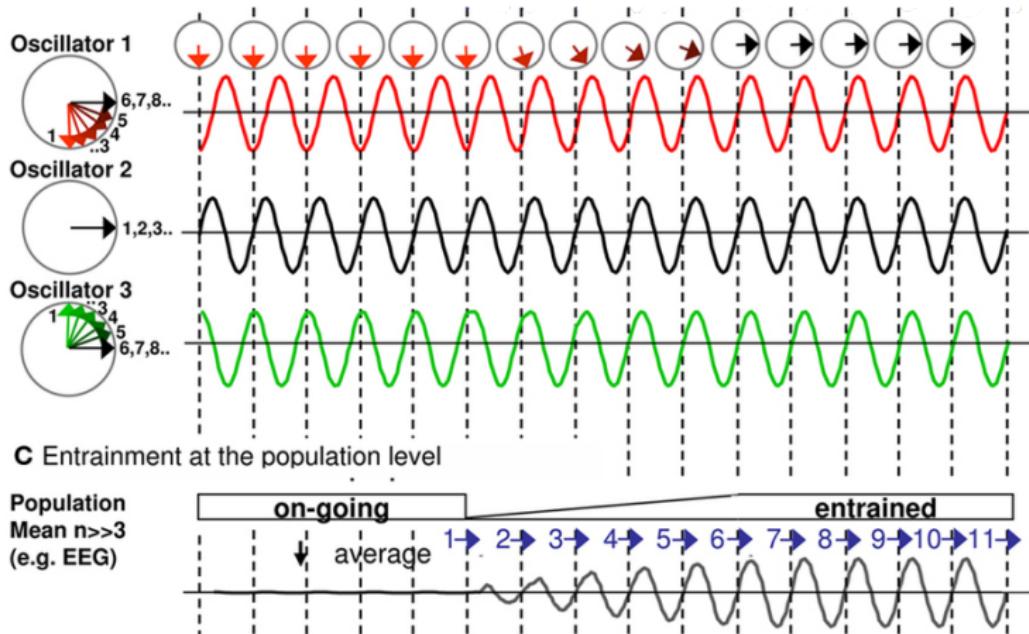
Problems:

- Too much neurons are involved in cognitive processes to be modeled
- We don't have precise information about cell-level interactions

Solution: reduce resolution from a neuron-level to population.



# Oscillatory models

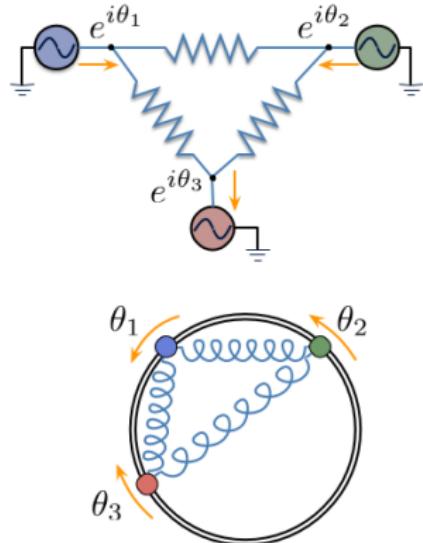


## Kuramoto model

To model simple synchronous oscillatory behaviour kuramoto model could be used.

$$\frac{\Delta\phi_i}{\Delta t} = \omega_i + \frac{K}{N} \sum_{j=1}^N \sin(\phi_i - \phi_j)$$

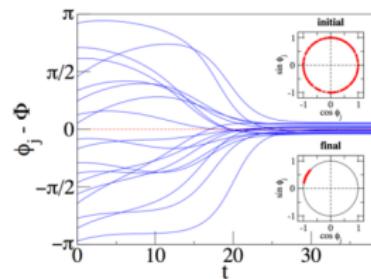
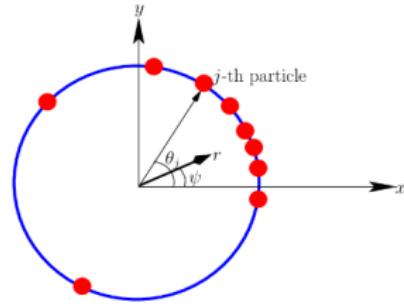
Where  $\phi_i$  is phase of i'th node and K is a *coupling* parameter (usually around 1-2).



# Kuramoto properties

Even with its simplicity,  
kuramoto has useful  
properties:

- Self-synchronous
- Connectome to control it
- Criticality

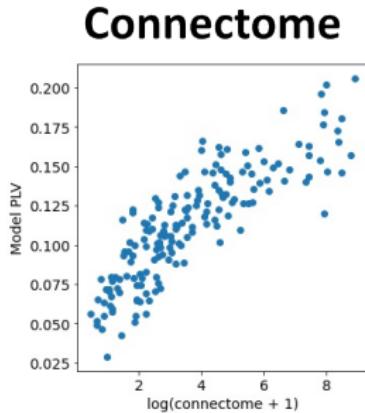


## Example: kuramoto stimulus

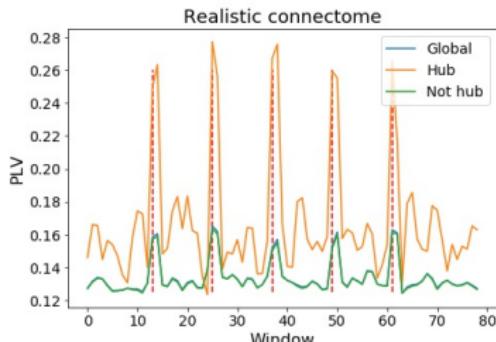
It is possible to study functional connectome using kuramoto.

Hypothesis: stimulation of hub & non-hub nodes force synchrony of different magnitudes.

Results: stimulation of hubs force a model nodes to work in the same regime.



### Effect of stimulus



## Homework

You will have a short python notebook with some practical clarifications.

- Implement kuramoto model (4pts)
- Simulate 20 signals: 10 with 10Hz, 5 with 15Hz and 5 with 25Hz. (1pts)
- Compute, plot and compare PSD for those signals (1pts)
- Compute synchrony and correlation for those signals (1pts)
- Using the same model, simulate a signal with 10Hz during the first 0-60s, 15Hz during 60-120s, 25 during 120-180s and 15 during 180-240s (1pts)
- Compute and plot time-resolved spectrum for this signal (1pts)

## Additional reading:

- The origin of extracellular fields and currents — EEG, ECoG, LFP and spikes
- Neuronal Dynamics: From Single Neurons to Networks and Models of Cognition
- Biophysical modeling of the neural origin of EEG and MEG signals
- Modelling and analysis of local field potentials for studying the function of cortical circuits
- Physiologically motivated multiplex Kuramoto model describes phase diagram of cortical activity
- Human Brain Oscillations: From Physiological Mechanisms to Analysis and Cognition
- Predicting the effects of deep brain stimulation using a reduced coupled oscillator model