Introduction to Computational Neuroscience

Lecture 4: Data analysis I

Lesson	Title
1	Introduction
2	Structure and Function of the NS
3	Windows to the Brain
4	Data analysis
5	Data analysis II
6	Single neuron models
7	Network models
8	Artificial neural networks
9	Learning and memory
10	Perception
11	Attention & decision making
12	Brain-Computer interface
13	Neuroscience and society
14	Future and outlook: AI
15	Projects presentations
16	Projects presentations

Basics

Analyses

Models

Cognitive

Applications

http://www.psychology.ut.ee/en/about-us/laboratory-experimental-psychology

http://www.psychology.ut.ee/en/about-us/location

Neuroimaging

Structural brain imaging techniques are used to resolve the anatomy of the brain in a living subject without physically penetrating the skull

* Measure anatomical changes over time
* Diagnose diseases such as tumors or vascular disorders

Functional brain imaging techniques are used to measure neural activity without physically penetrating the skull

* Which neural structures are active during certain mental operations?

Functional brain imaging

Non-invasive recording from human brain (Functional brain imaging)

Hemodynamic techniques

Positron emission tomography (PET)

Functional magnetic resonance imaging (fMRI)

Excellent spatial resolution (~1-2mm)
Poor temporal resolution (~1sec)

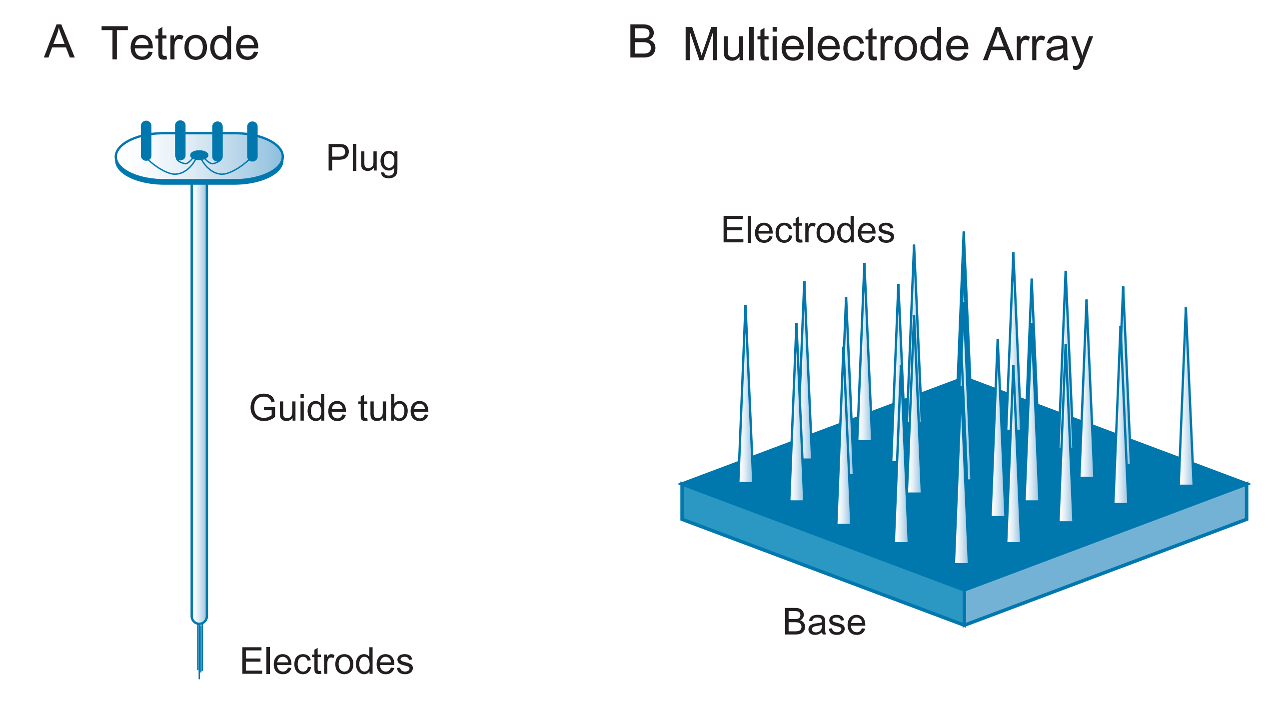
Electro-magnetic techniques

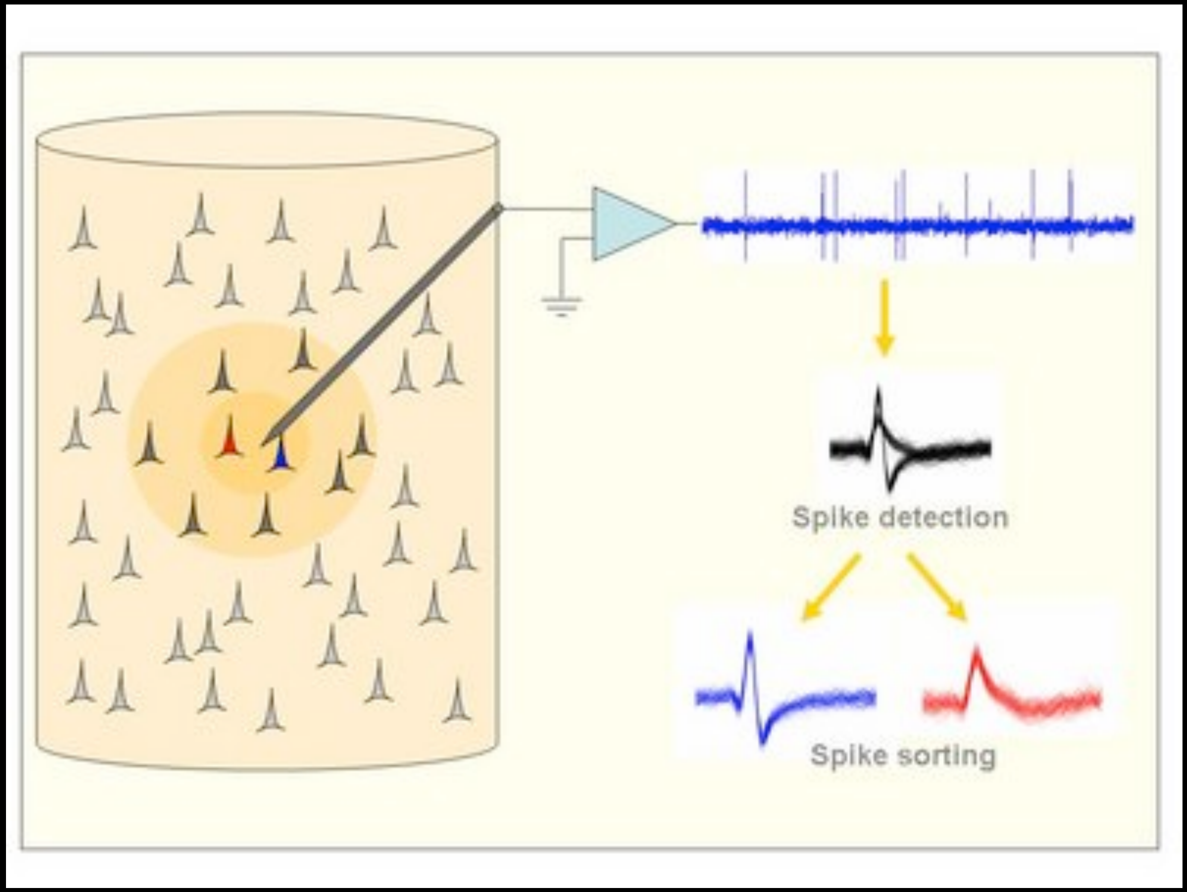
Electro-encephalography (EEG)

Magneto-encephalography (MEG)

Poor spatial resolution (esp. EEG)
Excellent temporal resolution (<1msec)

Extracellular recordings





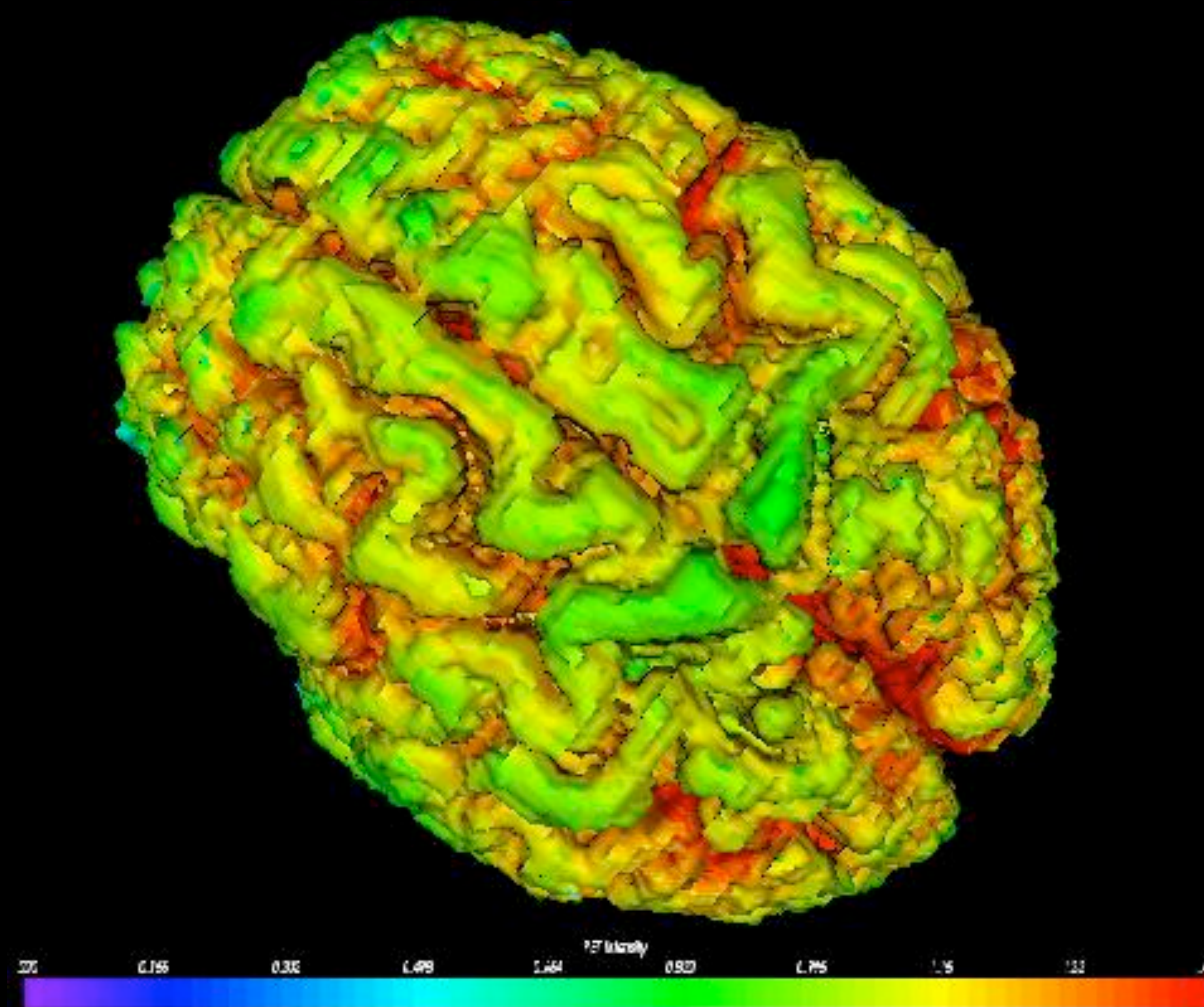
Easier than intracellular in vivo

Records a few tens up to hundreds neurons

Requires spike sorting to identify which cell fire which a.p.

Summary

- Structural (functional) brain imaging capture the anatomy (activation) of different brain regions
- MRI (fMRI) technique of choice for good spatial resolution
- EEG and MEG have excellent temporal resolution
- Electrophysiology techniques measure activity at the neuron level
- No perfect technique allows yet to monitor extensive regions of brain circuits with a single-neuron resolution



Analysis is what lies between data and results

Learning objectives

- Understand the basic analyses for continuous and spiking electrophysiology data

Continuous signals

Spikes

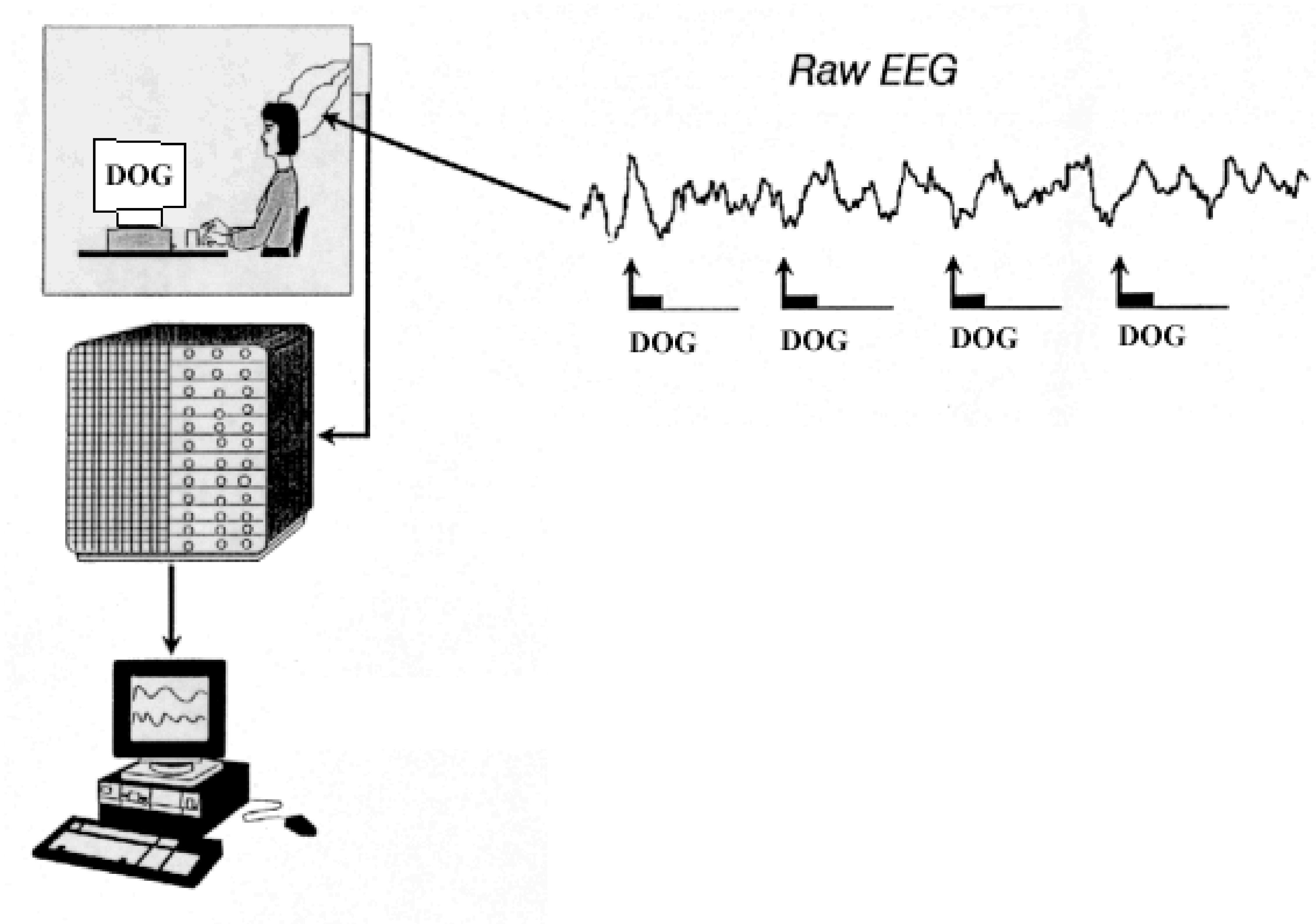
Continuous signals

Event Related Potentials (ERPs)

Analysis of rhythmic data (power spectrum)

Association measures (networks)

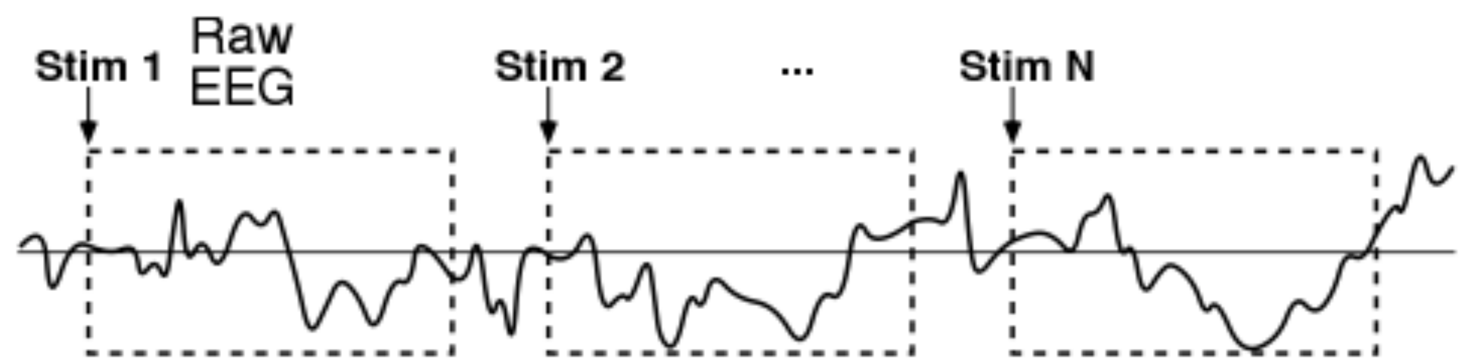
Event Related Potential



In many experiments we are interested in the activity generated by some event... (ex., sensory stimulus or behavior)

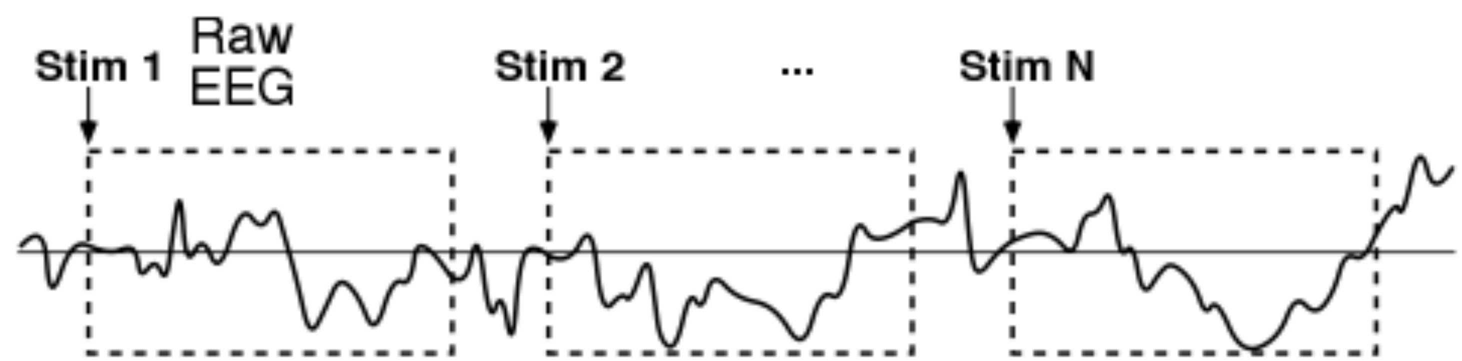
Event Related Potential

Individual responses are highly variable...



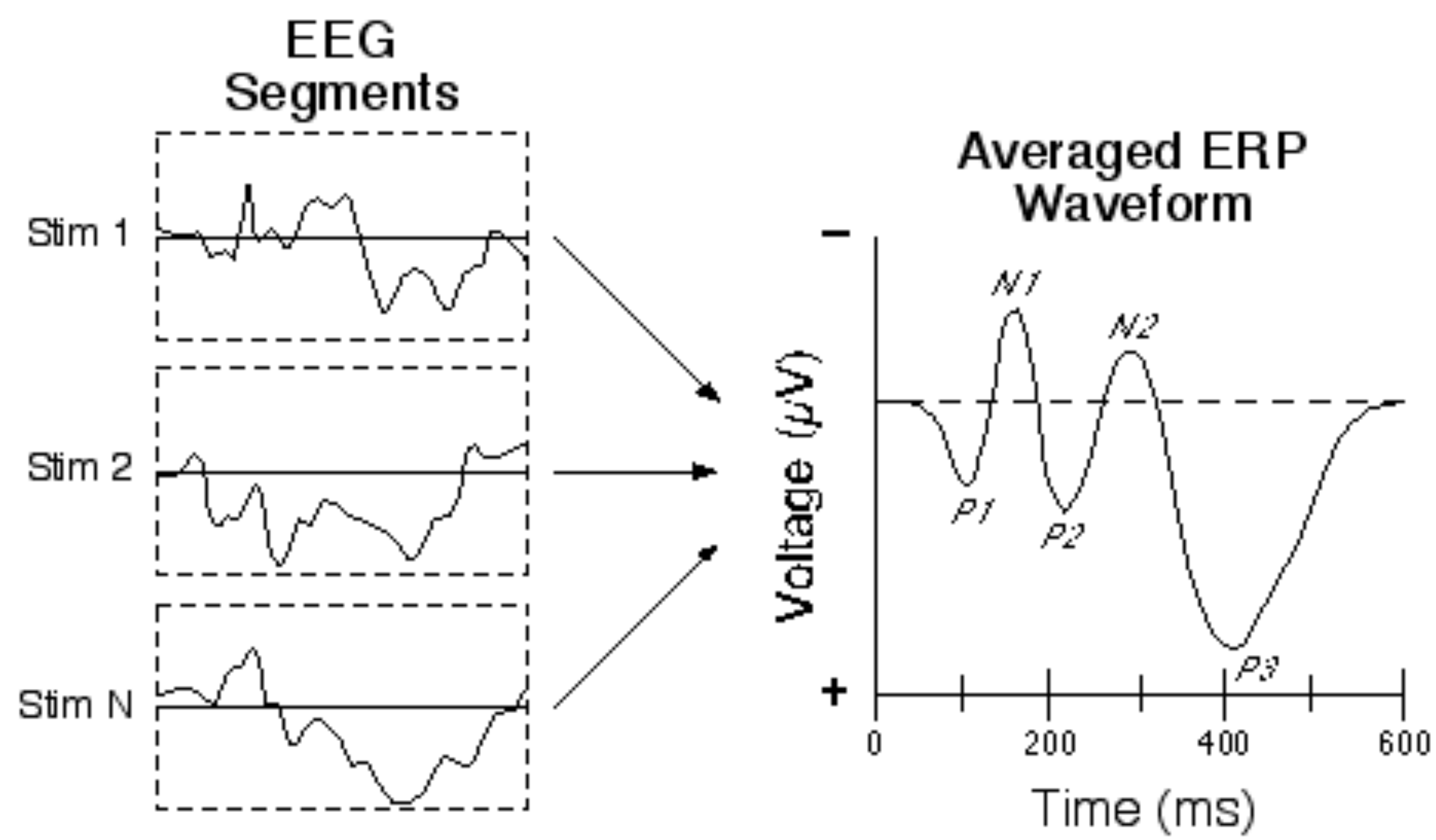
Event Related Potential

Individual responses are highly variable...



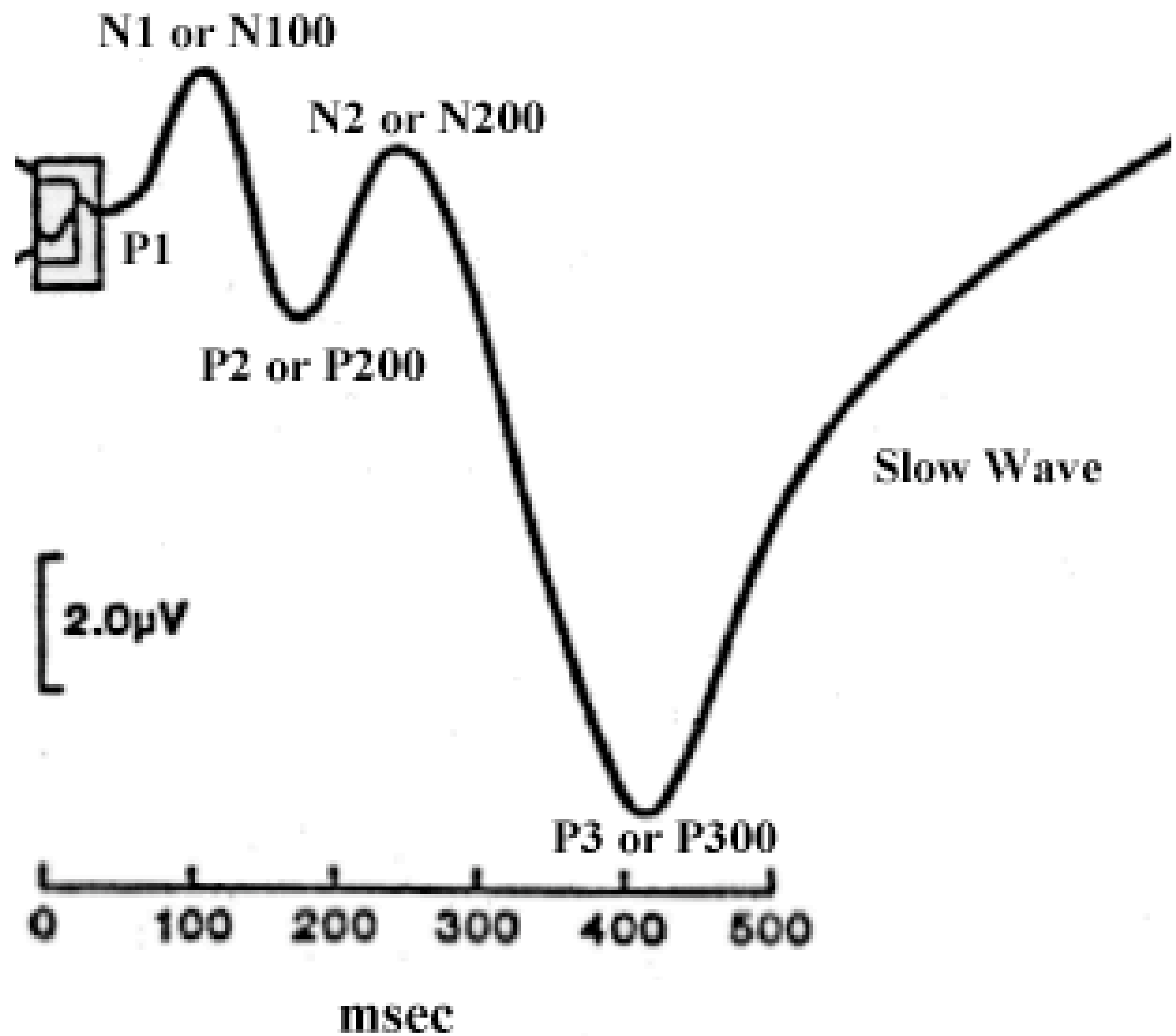
To reveal the activity temporally locked to some event:

align and average many repetitions (signal-to-noise ratio↑)



= ERP

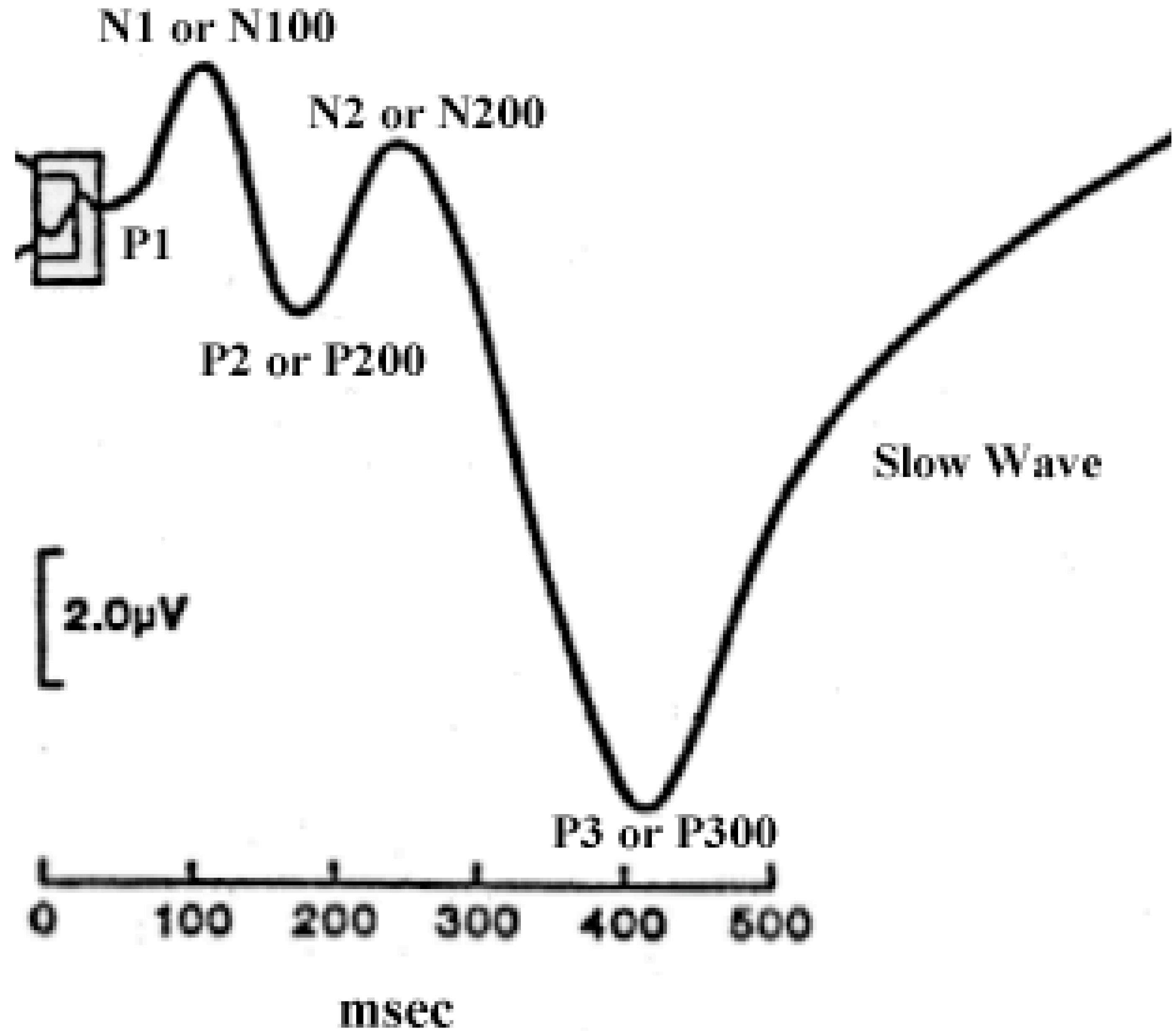
ERP (nomenclature)



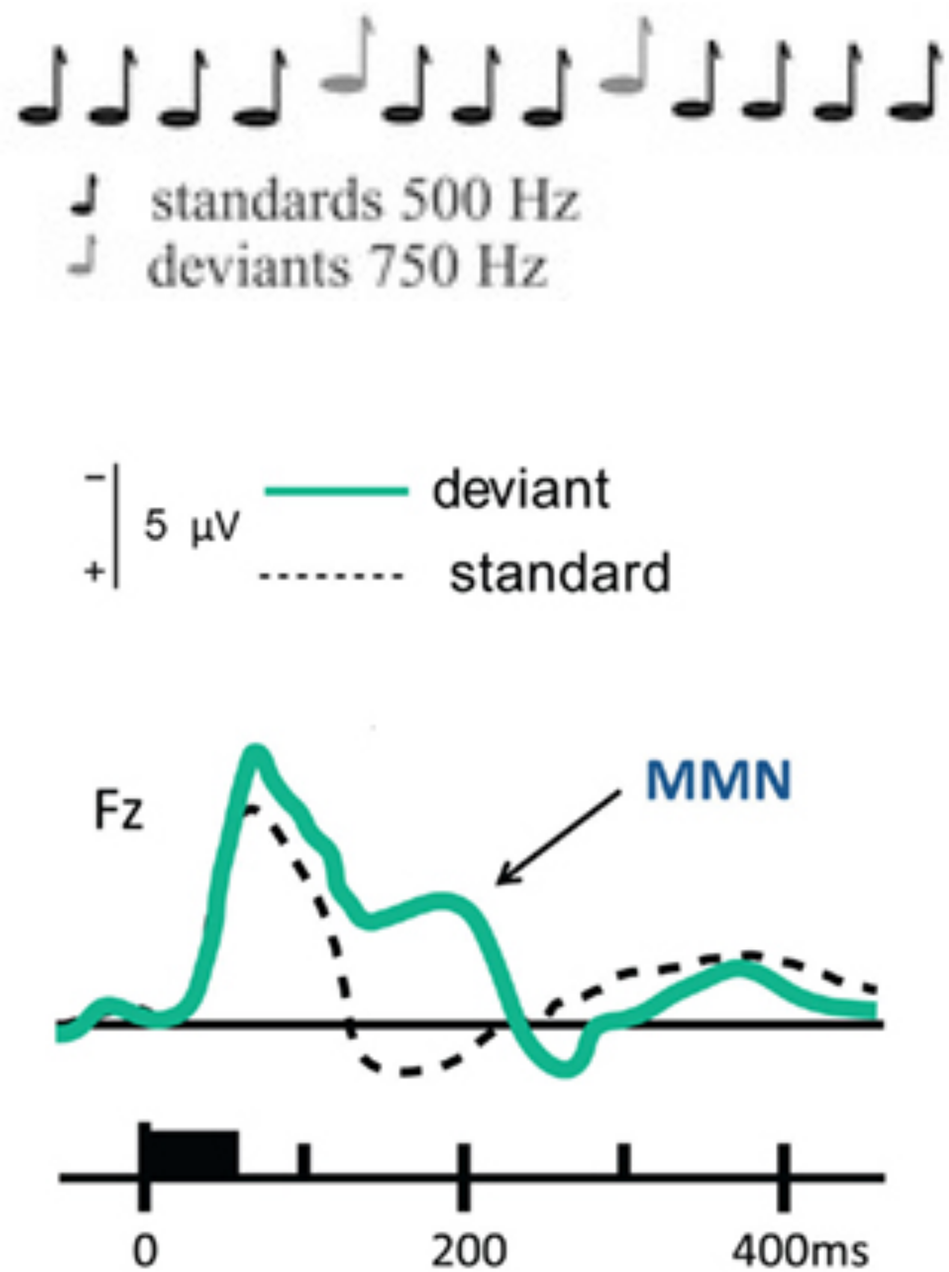
ERP (nomenclature)

P or N depending on the polarity (traditionally, negative is plotted up)

Numbers after the letter indicate the approximate peak latency (1, 2, 3 are short for 100 ms, 200 ms, 300 ms...)

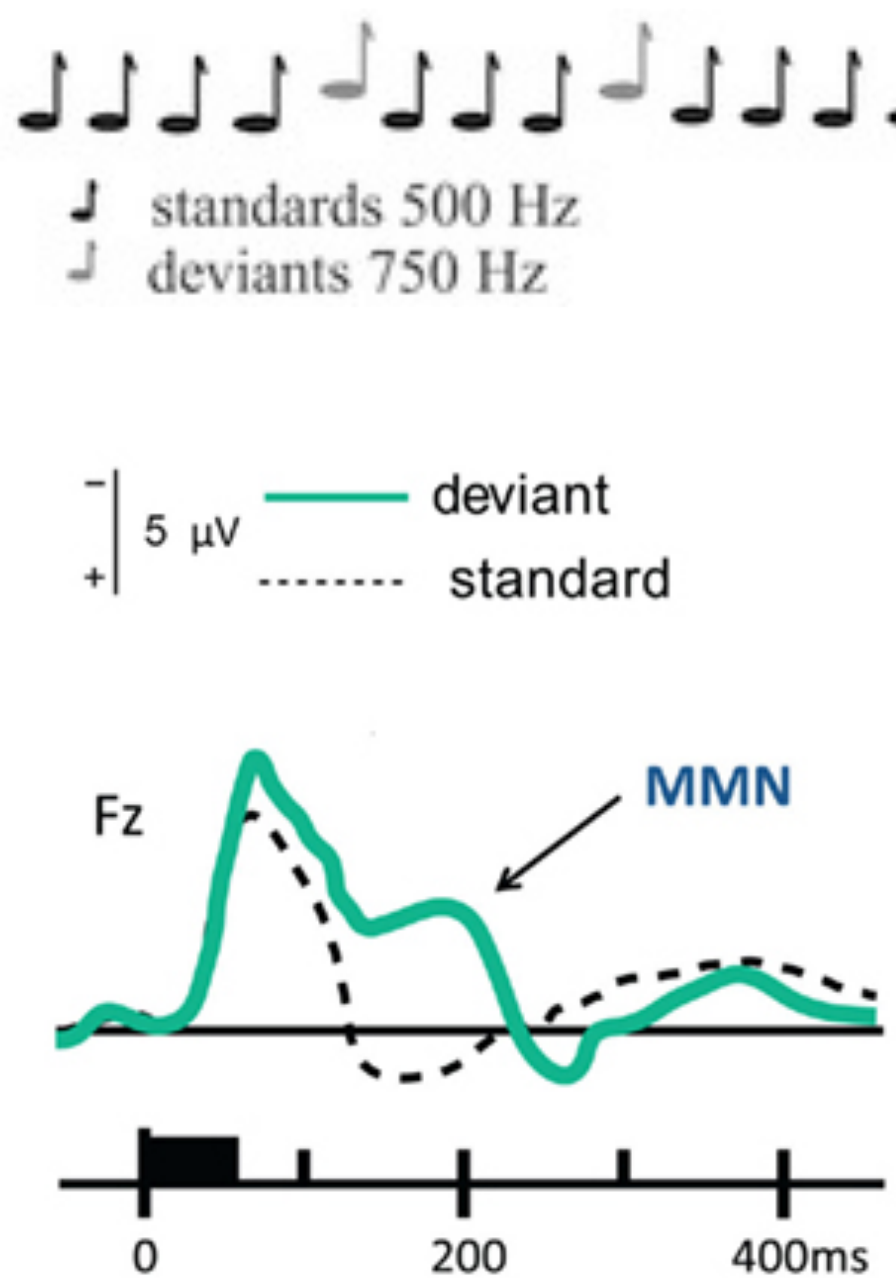


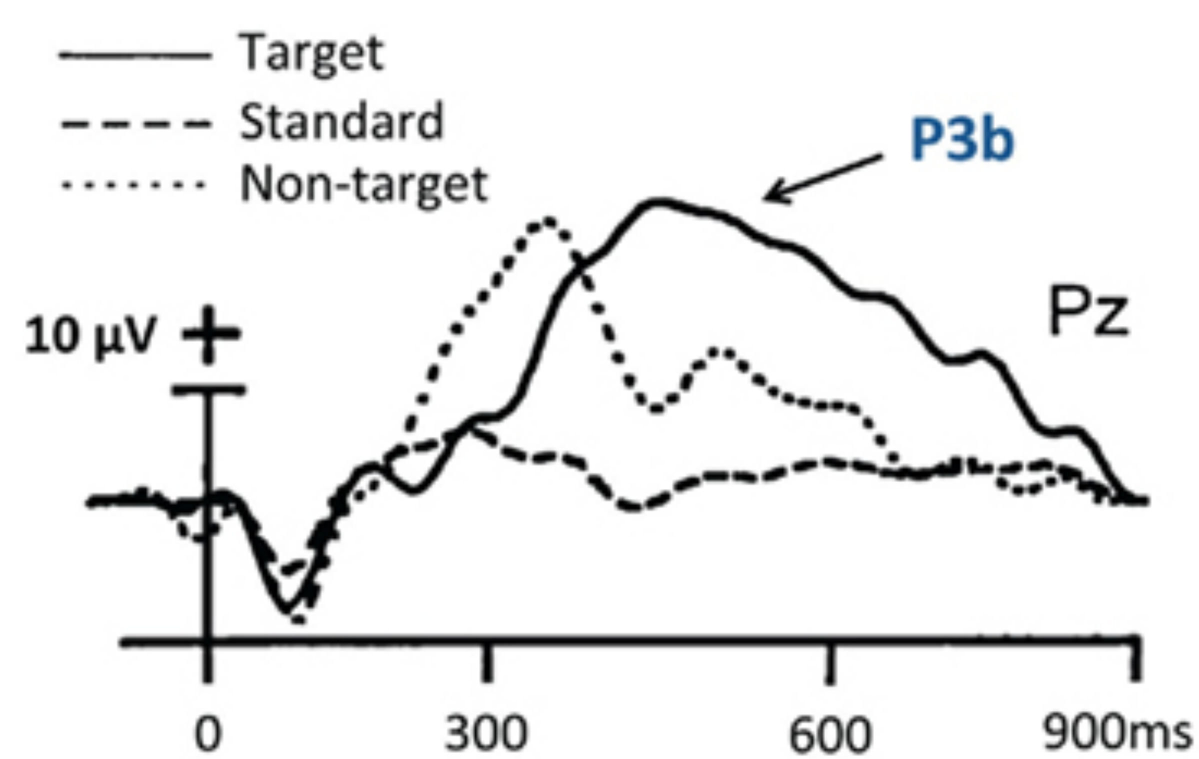
ERP (examples)



MMN

ERP (examples)





MMN

P300

Analysis of rhythmic data

Über das Elektrenkephalogramm des Menschen.

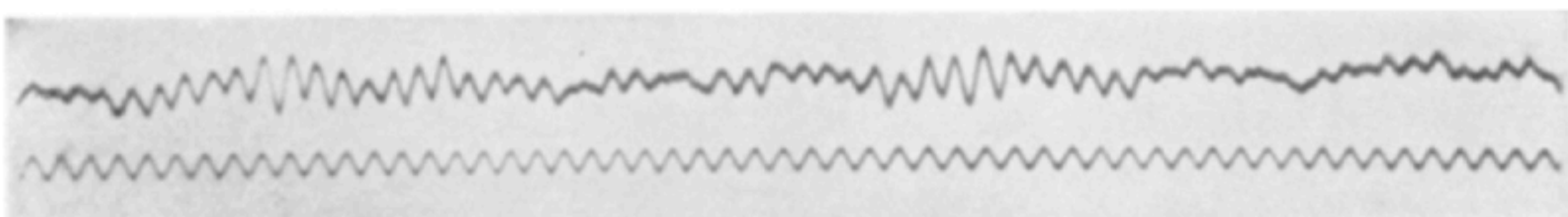
Von

Professor Dr. **Hans Berger**, Jena.

(Mit 17 Textabbildungen.)

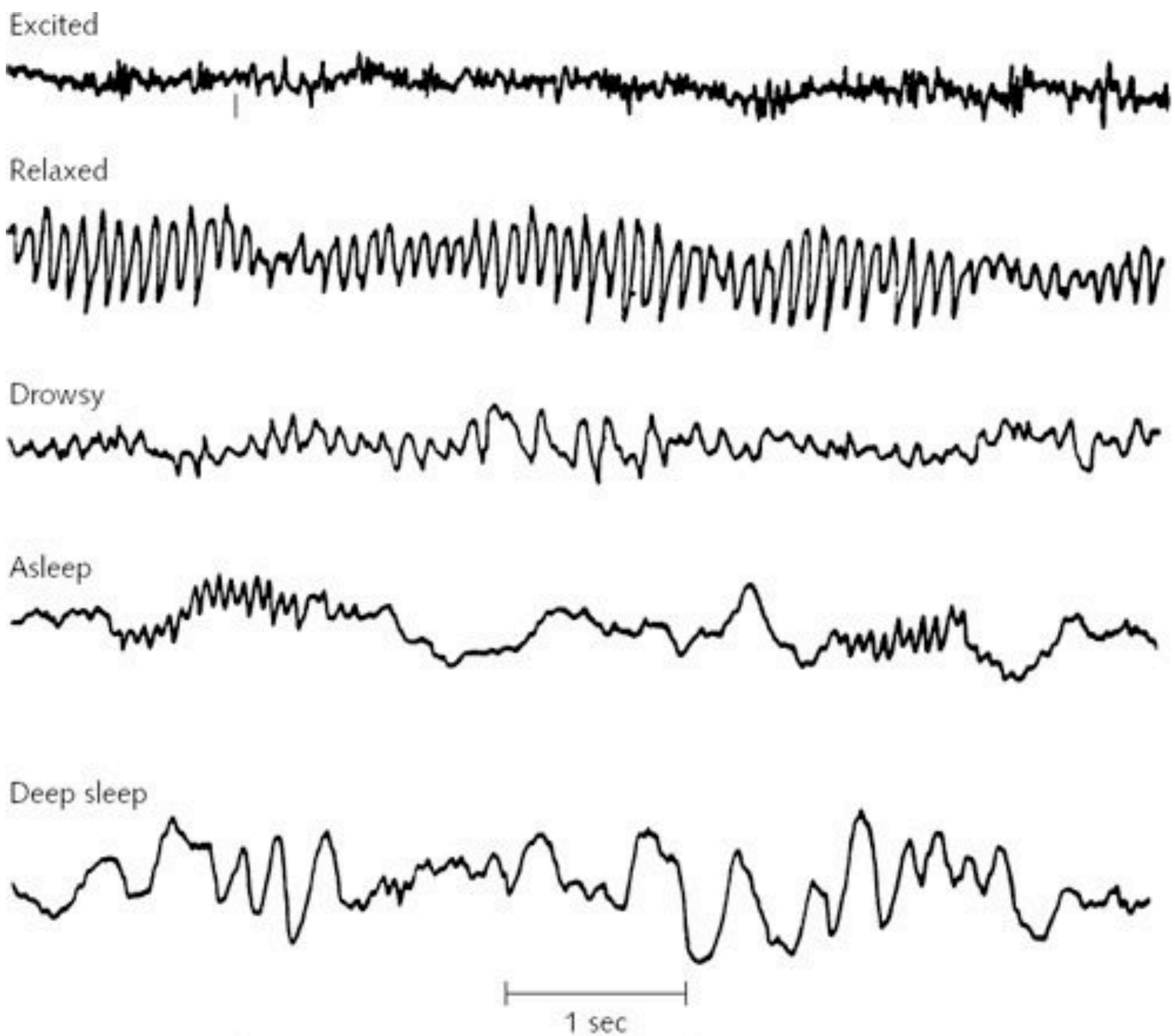
(Eingegangen am 22. April 1929.)

"Berger's wave"



...one can distinguish larger first order waves with an average duration of 90 milliseconds and smaller second waves with an average duration of 35 milliseconds.

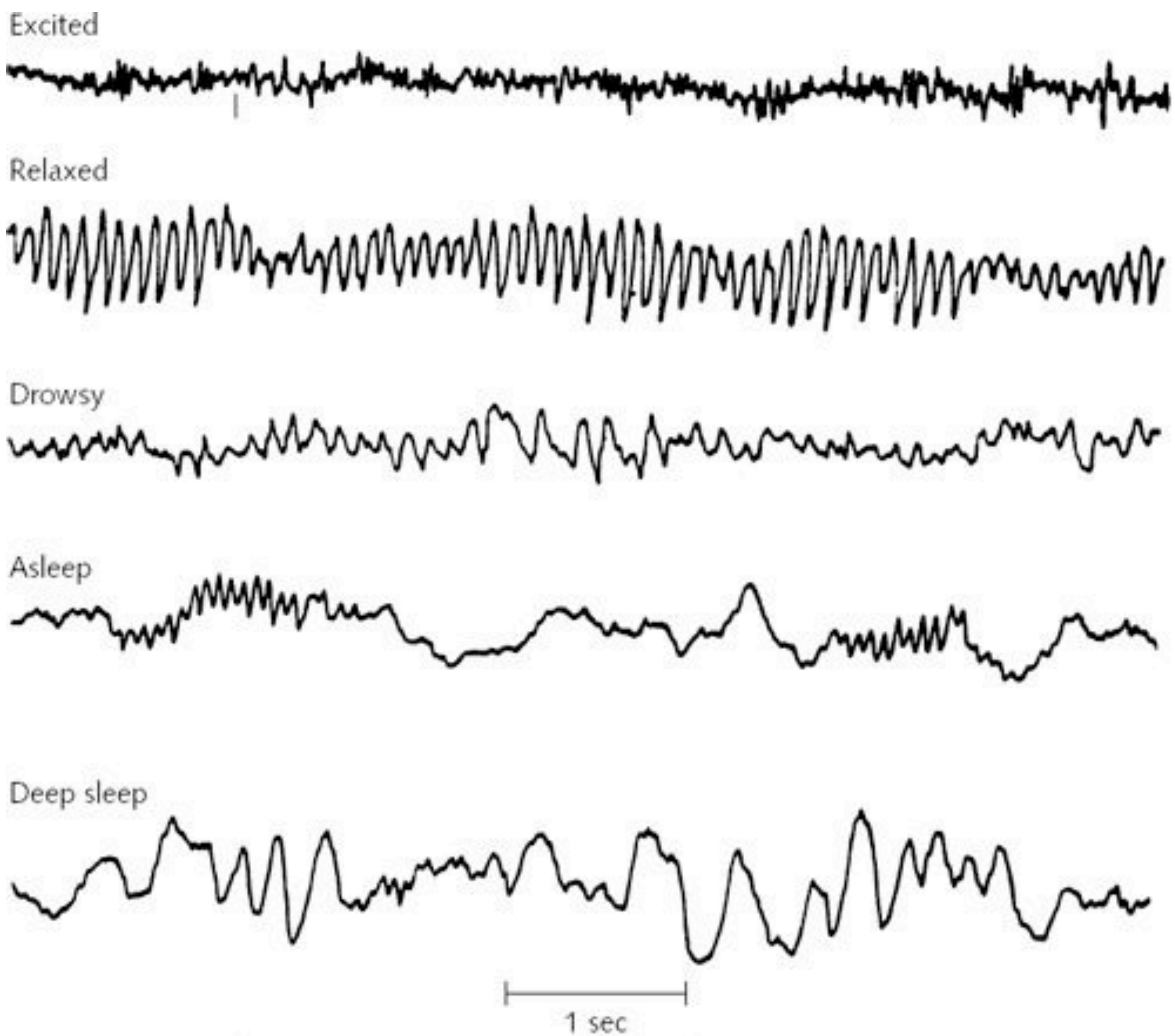
Why?



Quantifying brain waves is a great tool for the clinics:

* epilepsy
* coma/anesthesia
* sleep
* encephalopathies
* brain death
* BCI

Why?



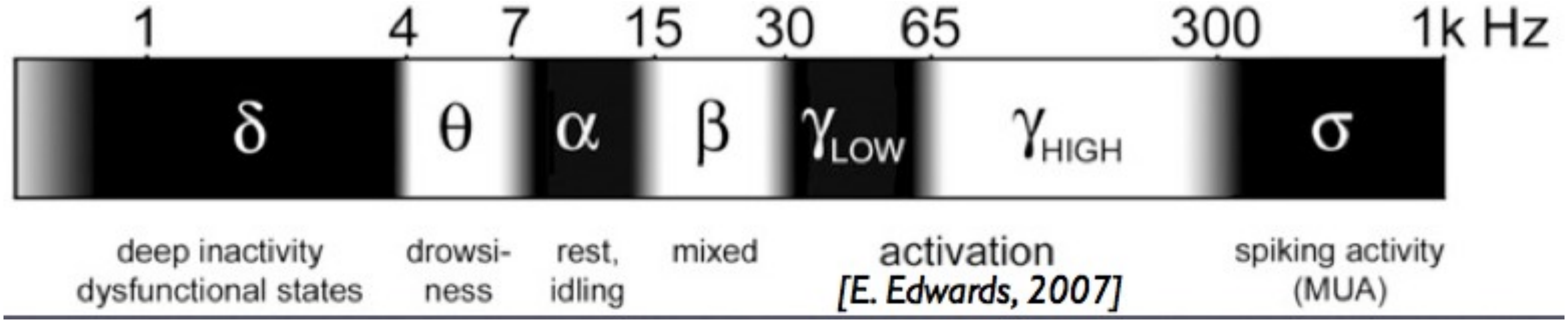
Why?

* More prominent and regular oscillations during sleep

Why?

* More prominent and regular oscillations during sleep

* 3 orders of magnitude

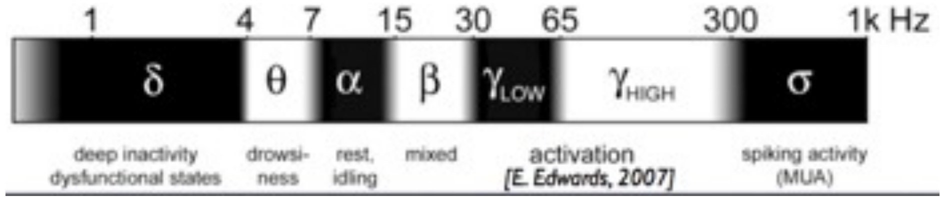


[E. Edwards, 2007]

Why?

* More prominent and regular oscillations during sleep

* 3 orders of magnitude

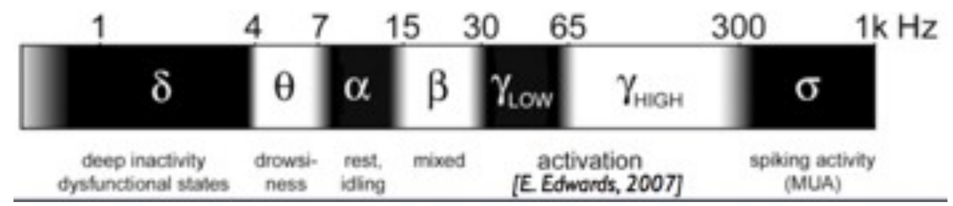


* Phylogenetically conserved

Why?

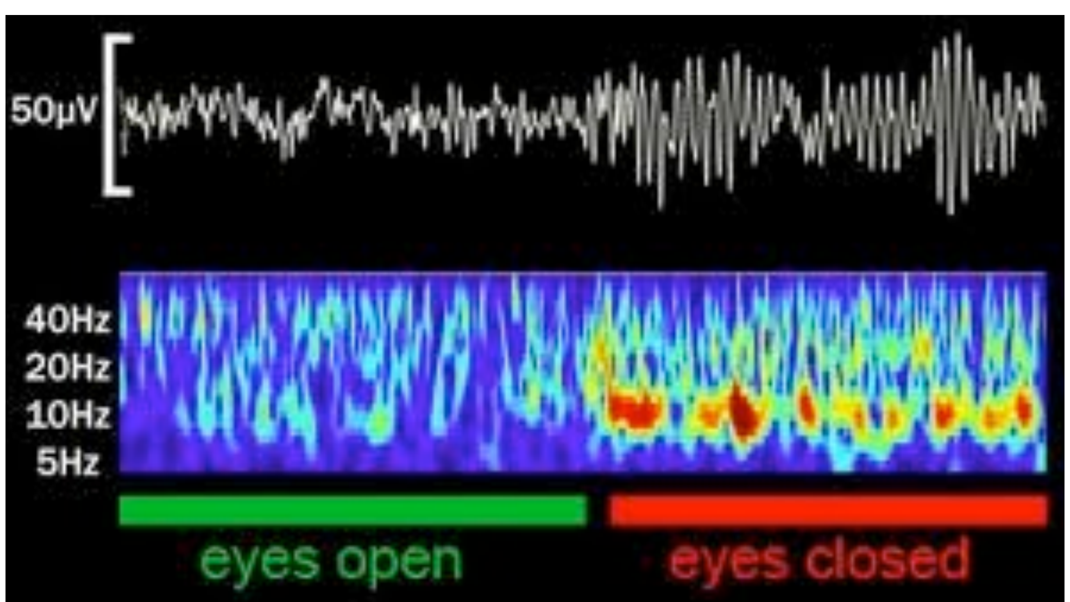
* More prominent and regular oscillations during sleep

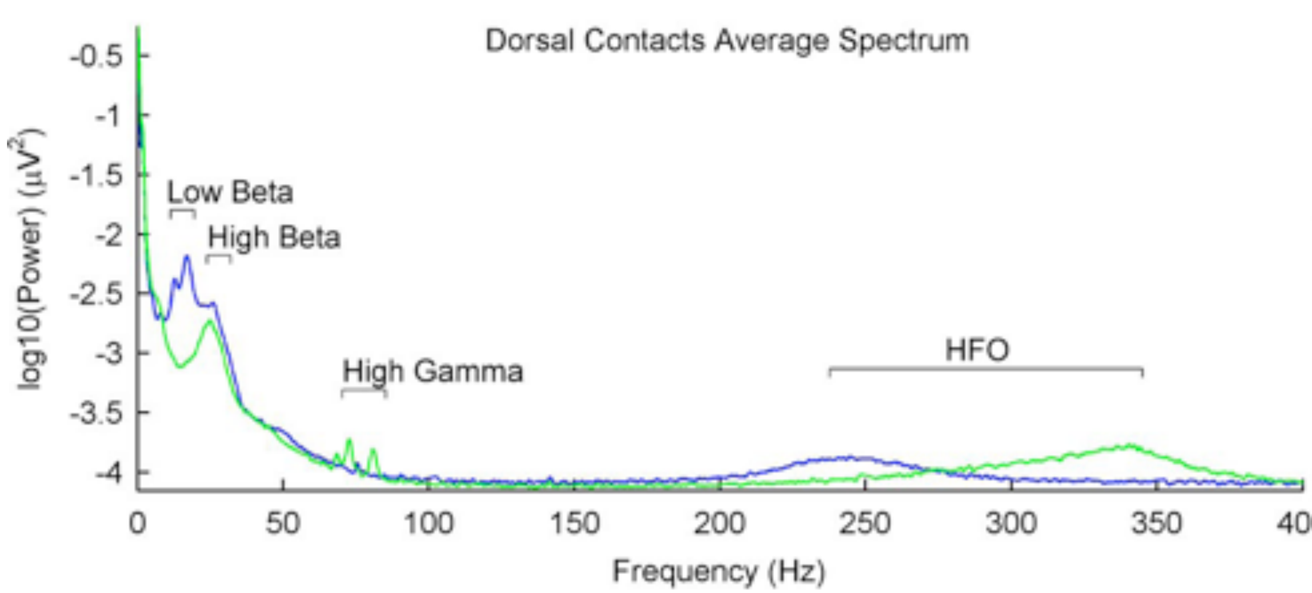
* 3 orders of magnitude



* Phylogenetically conserved

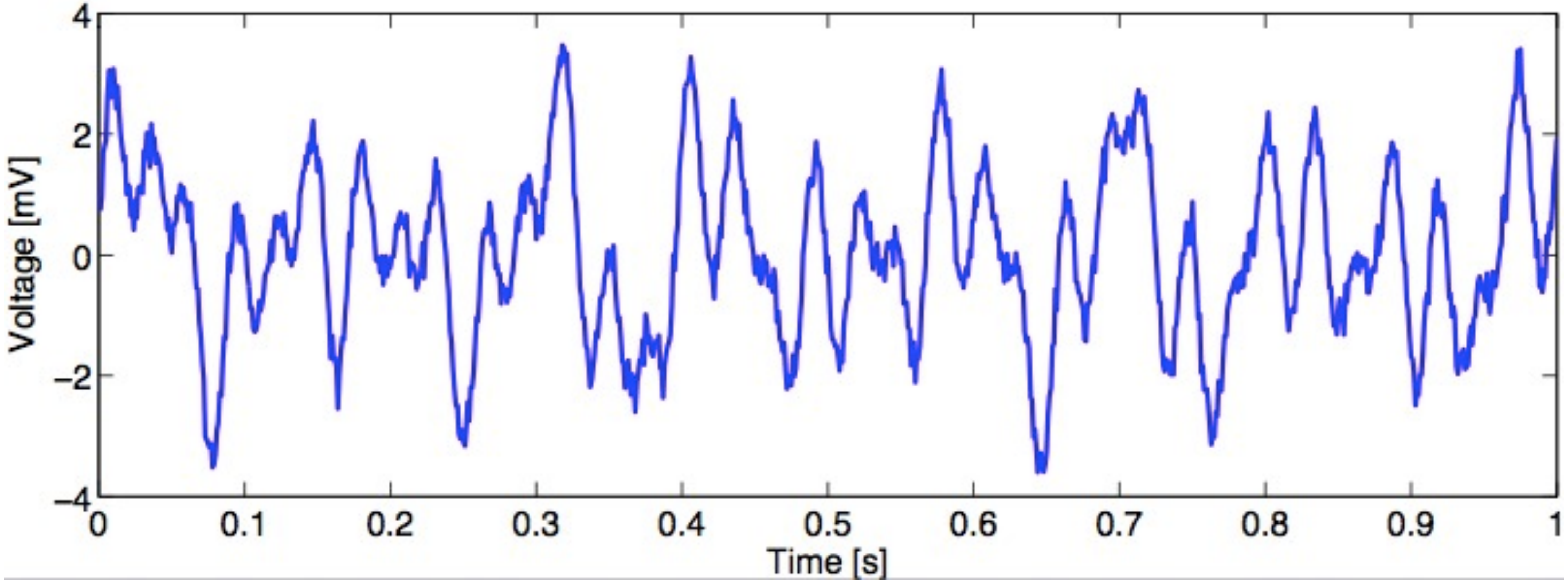
* Change with stimulus, behavior, or disease





Visual inspection

EEG

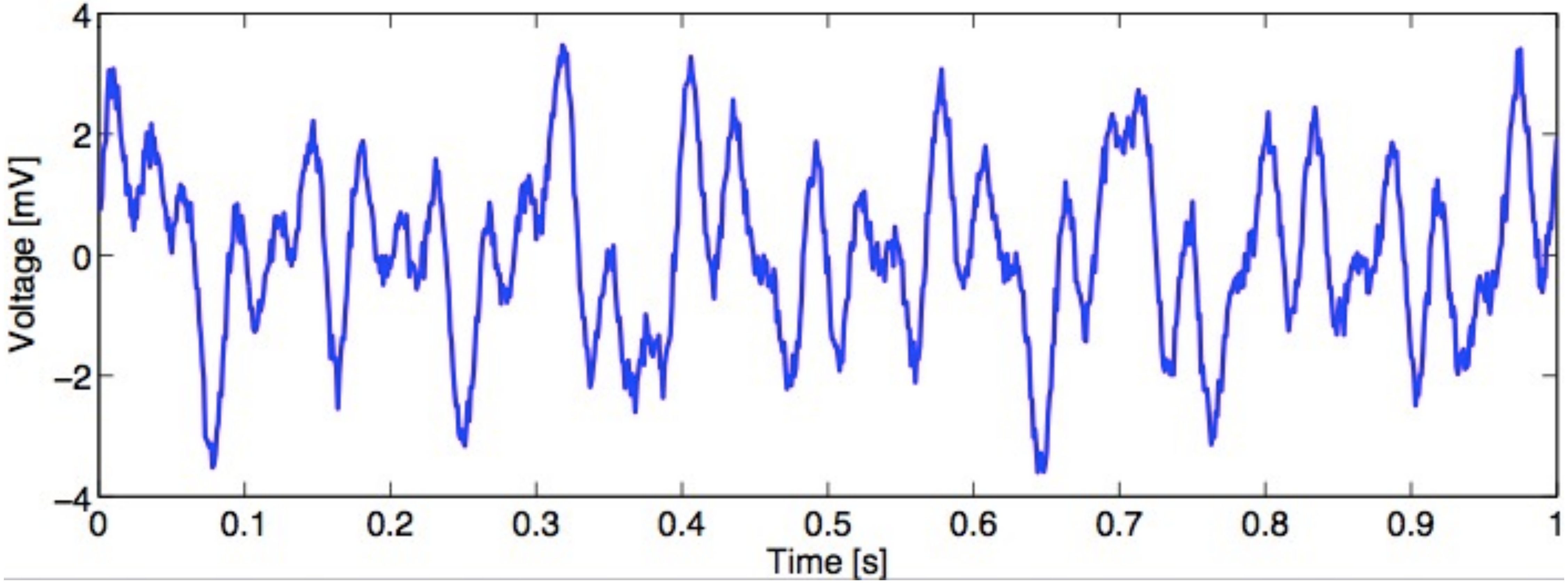


Visual inspection: looks rhythmic but very complicated

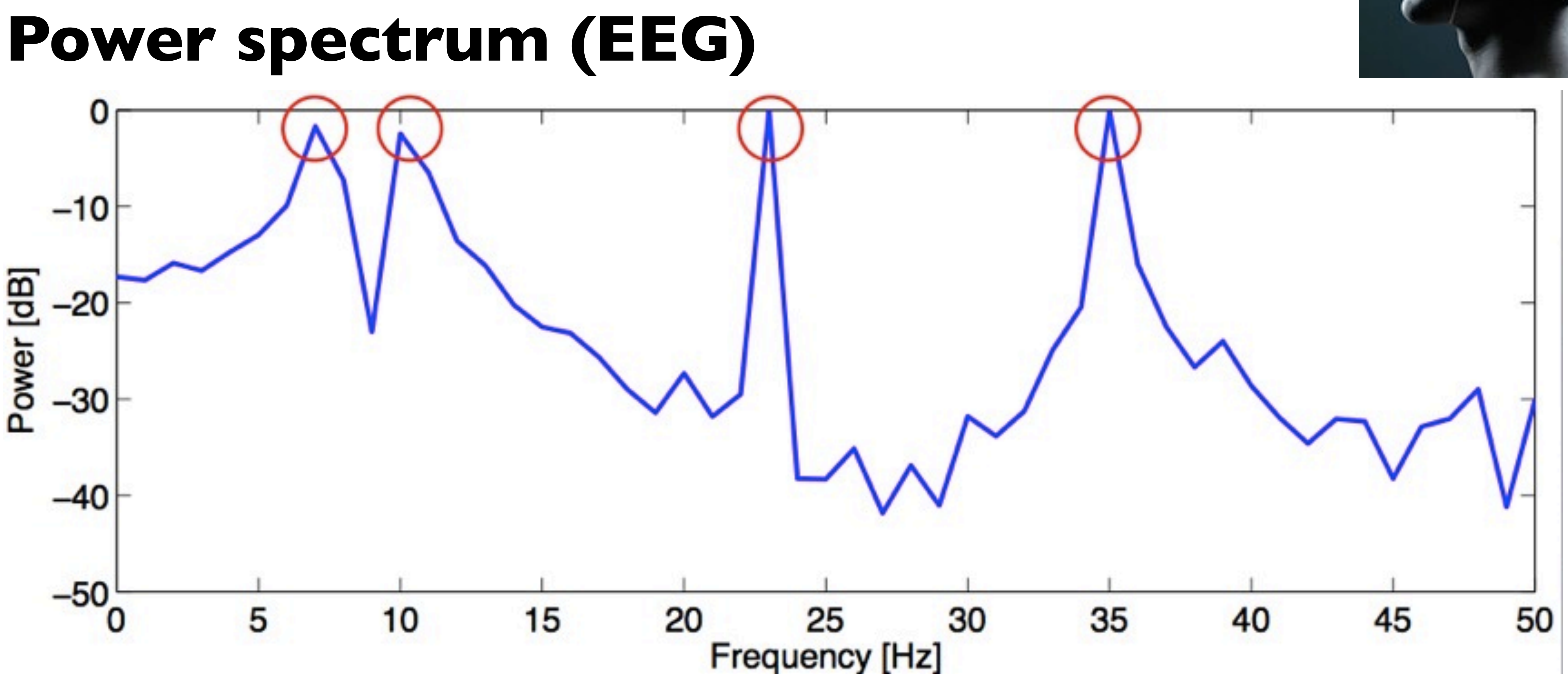
How can we simplify?

Visual inspection

EEG



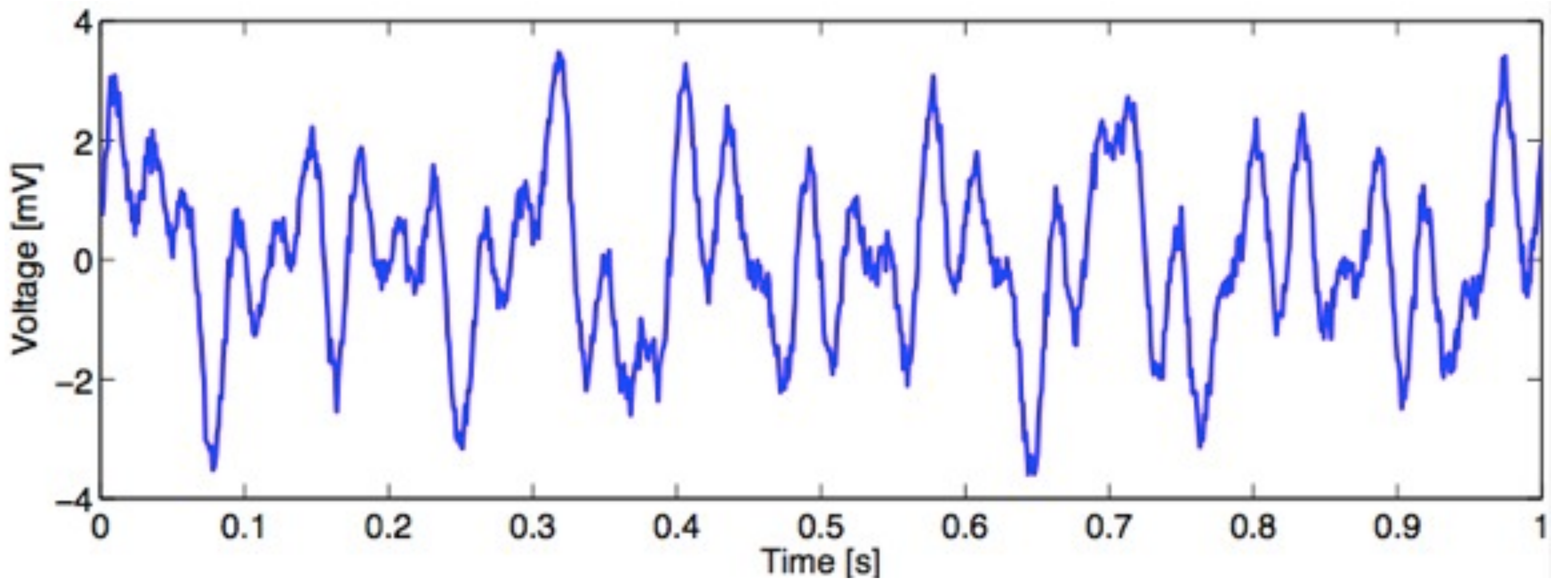
Power spectrum



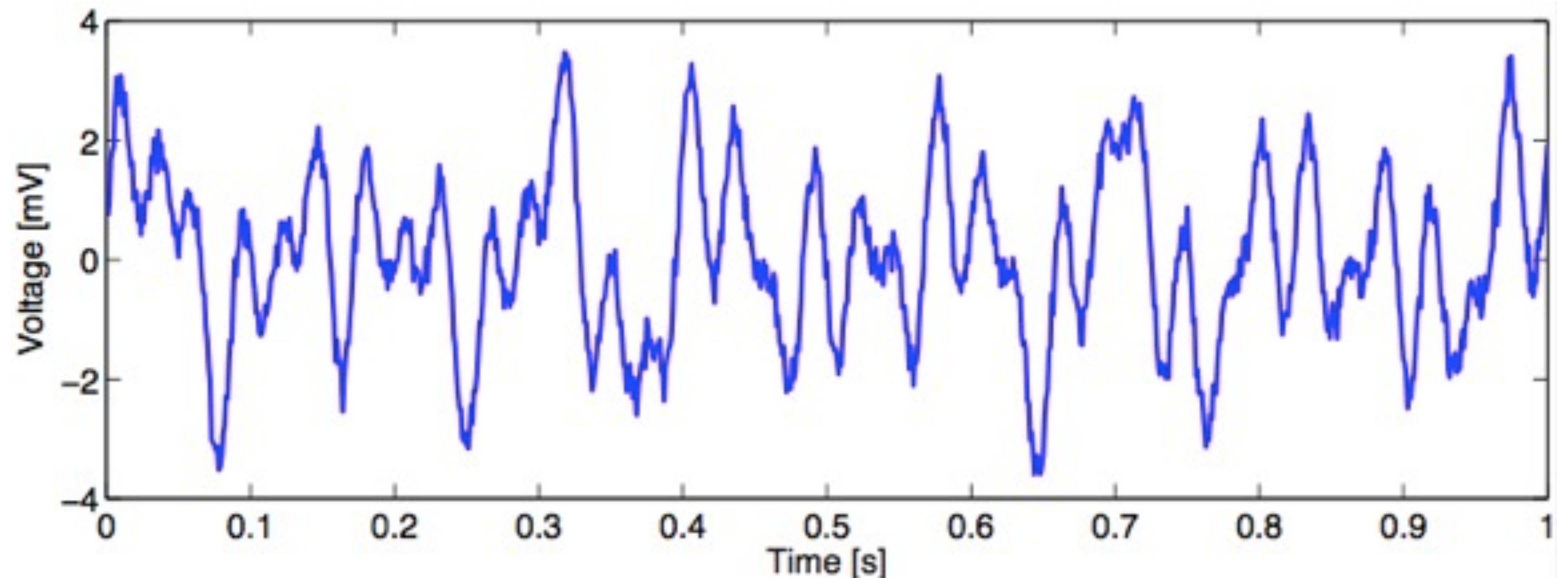
Axes: Power (dB) vs Frequency (Hz)

Simpler representation in frequency domain. Four peaks at {7, 10, 23, 35} Hz

Idea

v = 

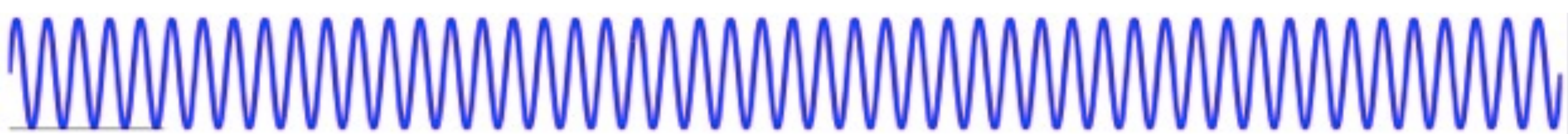
Idea

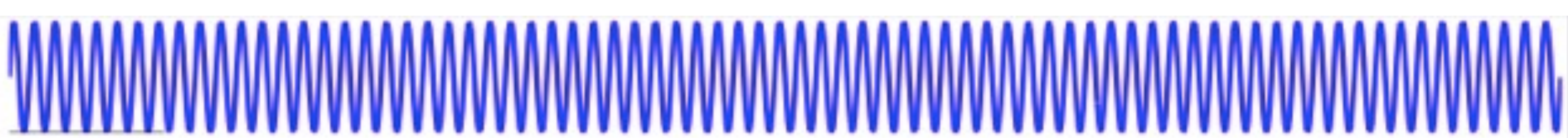
v = 

Separate the signal into oscillations at different frequencies

v = 

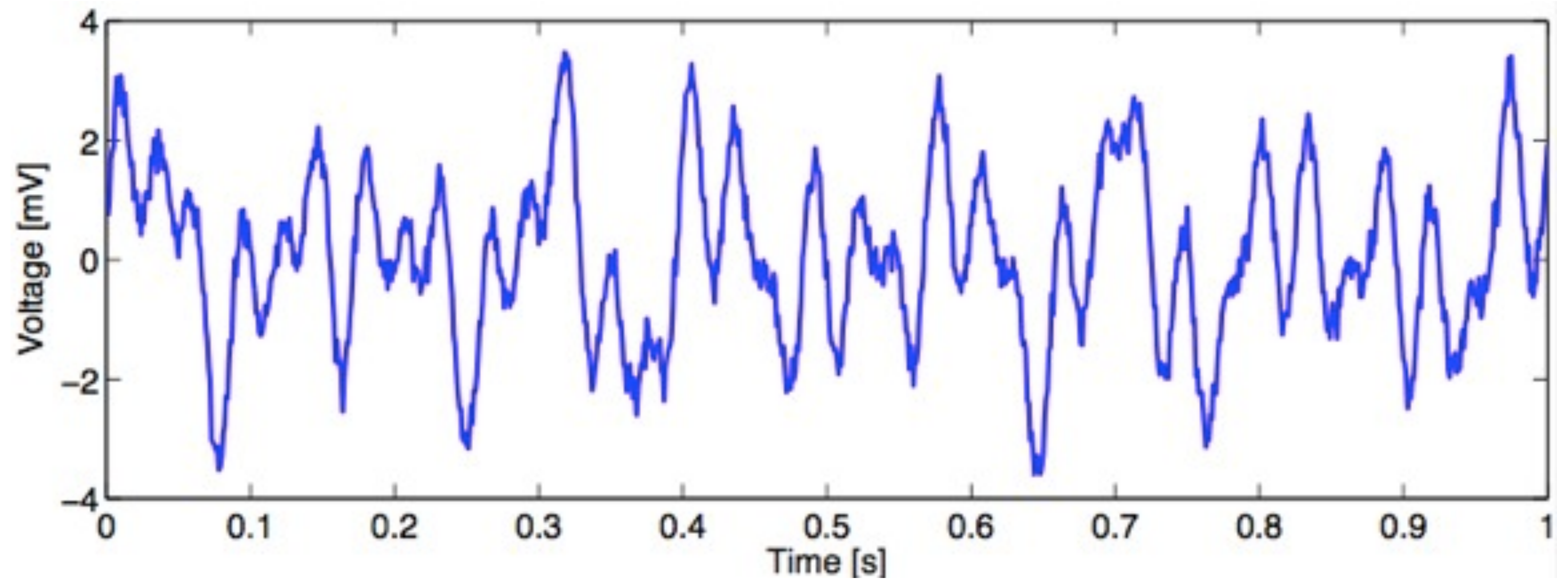
+ 

+ 

+ 

+ ...

Idea

V = 

Separate the signal into oscillations at different frequencies

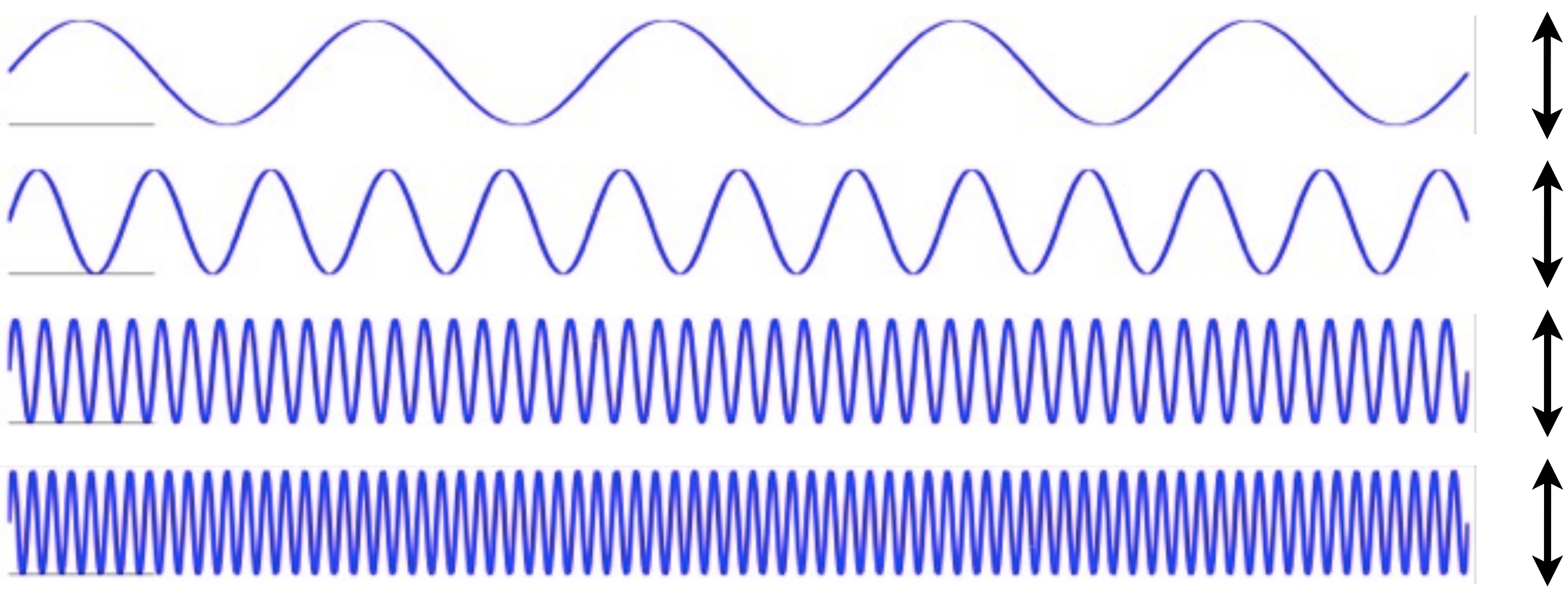
V =

+

+

+

+ ...



$\mathbf{A_1}$ $\mathbf{f_1}$

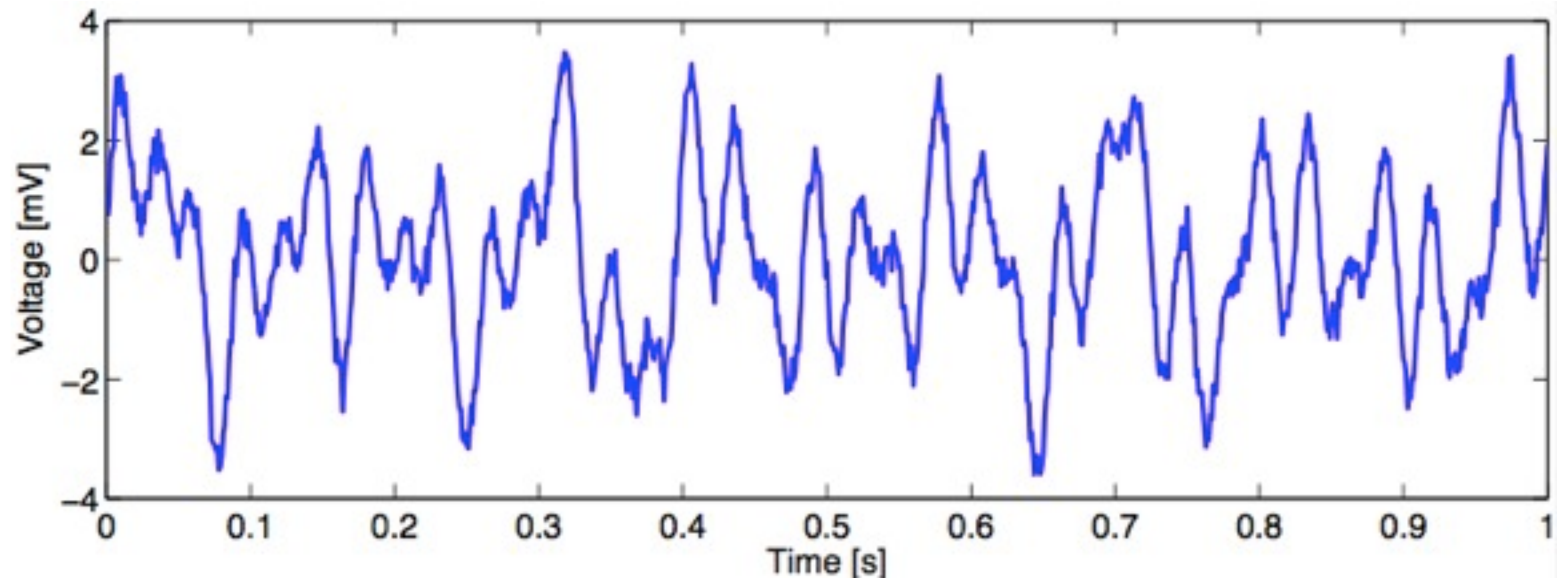
$\mathbf{A_2}$ $\mathbf{f_2}$

$\mathbf{A_3}$ $\mathbf{f_3}$

$\mathbf{A_4}$ $\mathbf{f_4}$

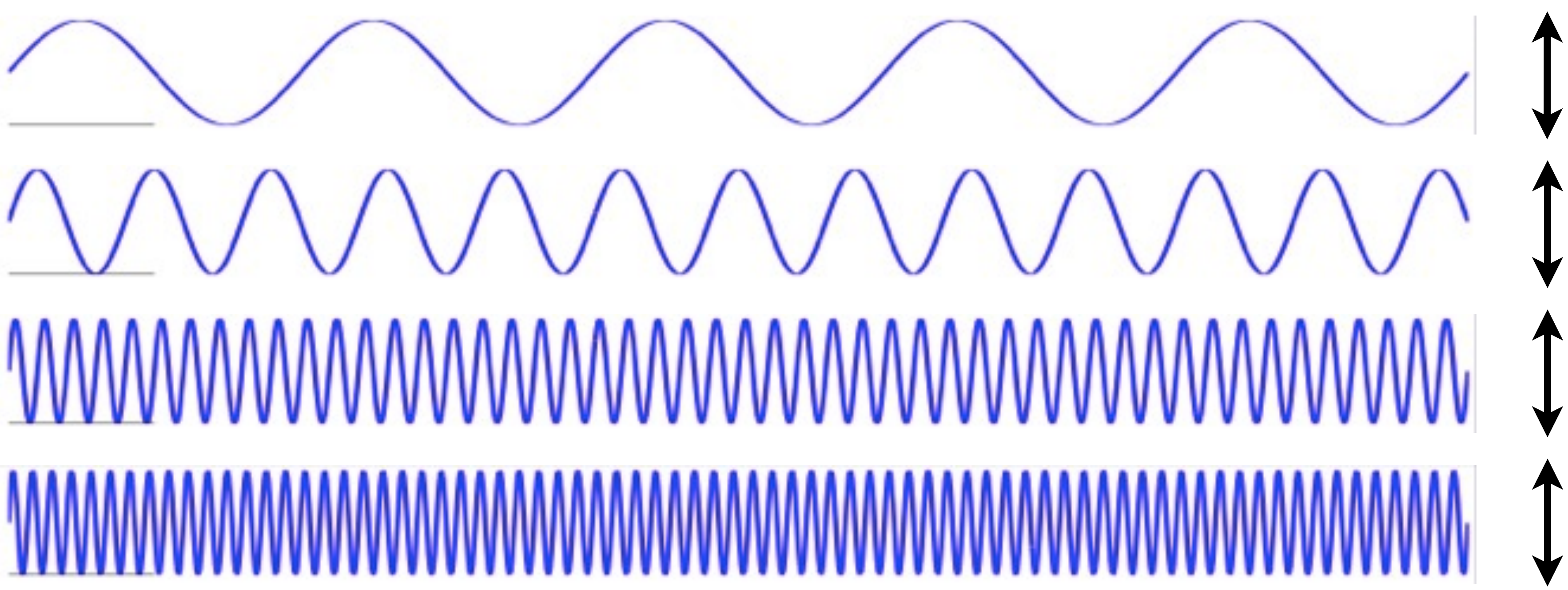
Idea

V =



Separate the signal into oscillations at different frequencies

V =



A_1 f_1

\+ A_2 f_2

\+ A_3 f_3

\+ A_4 f_4

\+ ...

Represent V as a sum of sinusoids (e.g., part 7 Hz, part 10 Hz,...)

Idea

We want to decompose data V(t) into sinusoids

We need to find the coefficients:

Complex coefficients

$$V[f] = \int_0^1 \underbrace{\boxed{v[t]}}_{\text{Data}} \underbrace{\boxed{e^{-2\pi i f t}}}_{\text{Sinusoids}} dt$$

Fourier transform

$$P[f] \sim |V[f]|^2$$

Power (complex coefficients squared)

Sinusoids with better match to V(t) will have larger power

In practice

$$V[f] = \int_0^1 \underbrace{\boxed{v[t]}}_{\text{Data}} \underbrace{\boxed{e^{-2\pi i f t}}}_{\text{Sinusoids}} dt$$

Fourier transform

$$P[f] \sim |V[f]|^2$$

Power (complex coefficients squared)

To compute the power spectrum in MATLAB use command

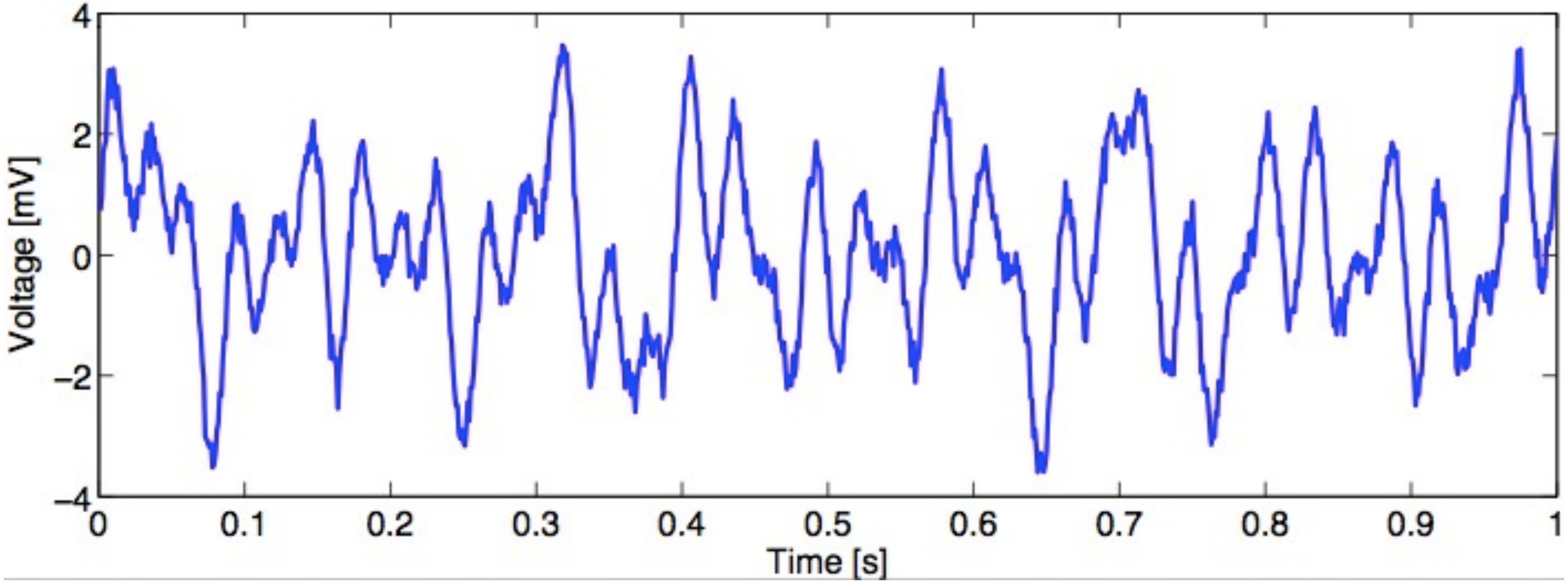
```
fft
```

```
>> pow = abs(fft(v)).^2*2/length(v);
```

Example

EEG

V =



T = 1 s

dt = 1 ms

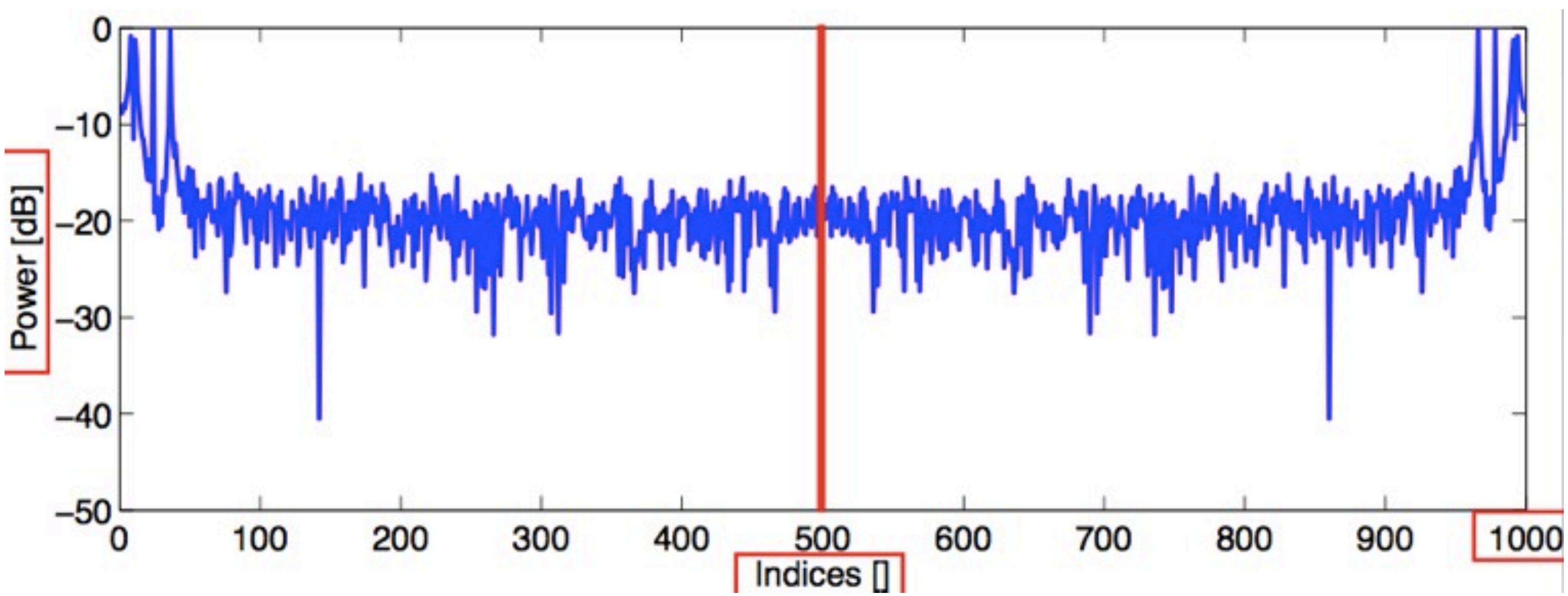
length(V) = 1000

Example

MATLAB code

1000 data pts

```
>> pow = abs(fft(v)).^2*2/length(v);
>> pow = 10*log10(pow);
>> plot(pow)
```



Matches length of v

Incomplete: Must label x-axis?

Power spectrum x-axis

Indices and frequencies are related in a funny way...

Examine vector **pow**:

1000

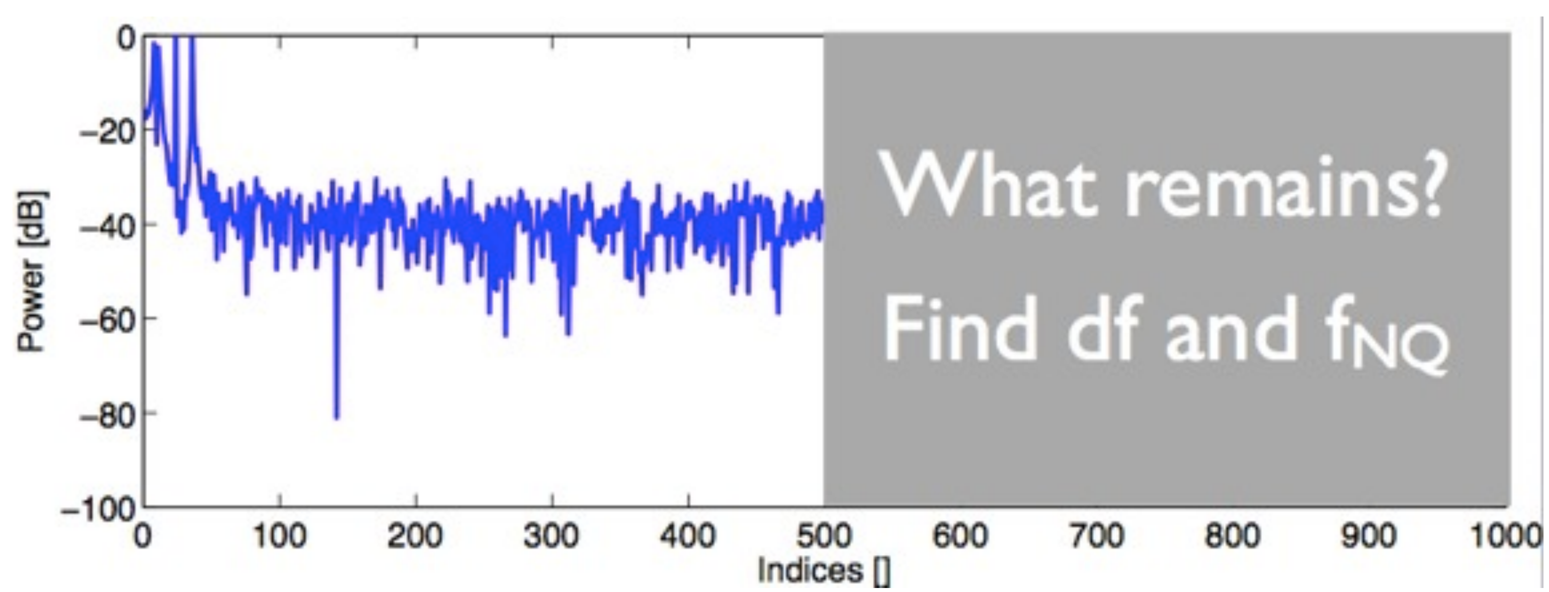
Freq	0	df	2df	...	f_{NQ} - df	f_{NQ}	
Index	1	2	3		500	501	

Frequency resolution (df)

f > 0

Nyquist frequency (f_{NQ})

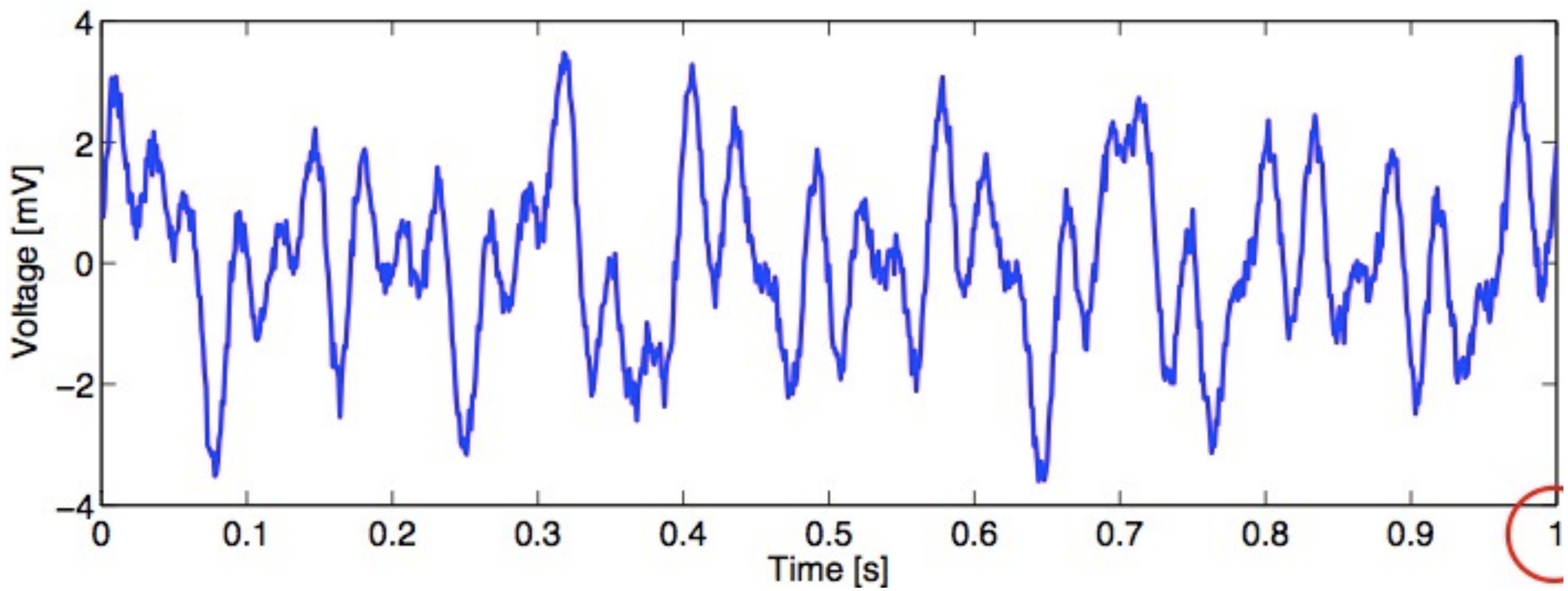
f < 0



Power spectrum x-axis

What is **df**? $$df = \frac{1}{T}$$ where **T** = Total time of recording

V =



T = 1 s
df = 1 Hz

Q: How do we improve frequency resolution?

A: Increase **T** (record for longer time)

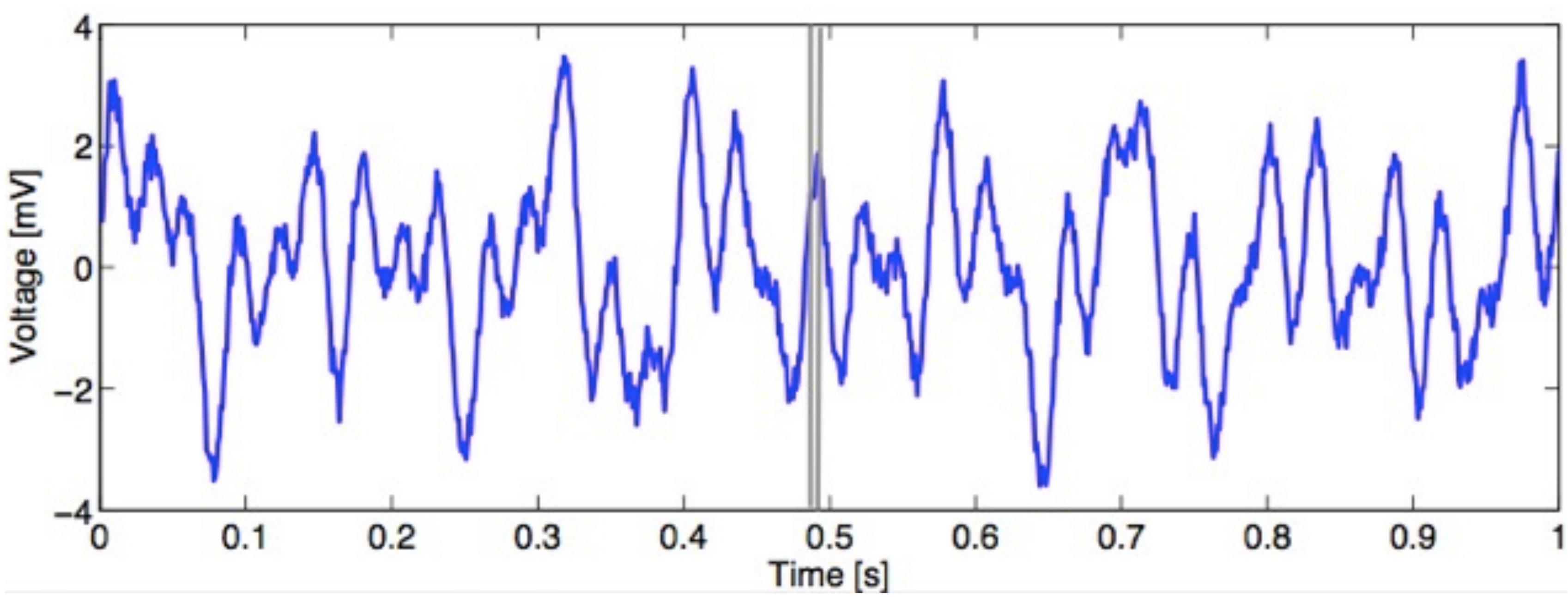
Power spectrum x-axis

What is f_{NQ}? $$f_{\mathrm{NQ}} = \frac{f_0}{2}$$ where f_0 = sampling frequency

The Nyquist frequency f_{NQ} is the highest frequency we can observe in the data

dt = 1 ms

V =



f_0 = 1/dt

f_0 = 1000 Hz

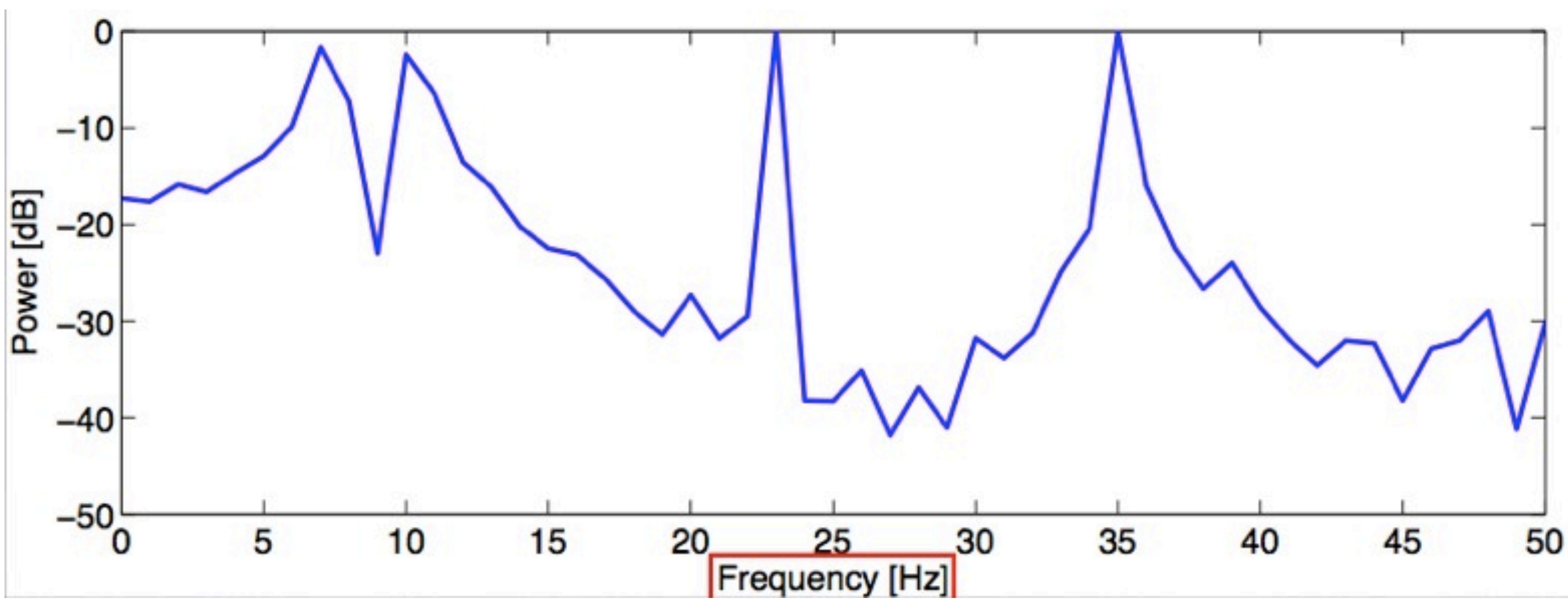
f_{NQ} = 500 Hz

Q: How do we increase the Nyquist frequency?

A: Increase the sampling rate f_0 (hardware)

Example (MATLAB code)

```
>> pow = abs(fft(v)).^2*2/length(v);
>> pow = 10*log10(pow);
>> pow = pow(1:length(v)/2+1);        % First half of pow
>> df = 1/max(t);  fNQ = 1/dt/2;      % Define df & fNQ
>> faxis = (0:df:fNQ);                % Frequency axis
>> plot(faxis,pow);  xlim([0 50]);
```



Summary

```
>> pow = abs(fft(v)).^2*2/length(v);
```

Frequency resolution $df = \frac{1}{T}$

Nyquist frequency $f_{\mathrm{NQ}} = \frac{f_0}{2}$

For finer frequency resolution: use more data

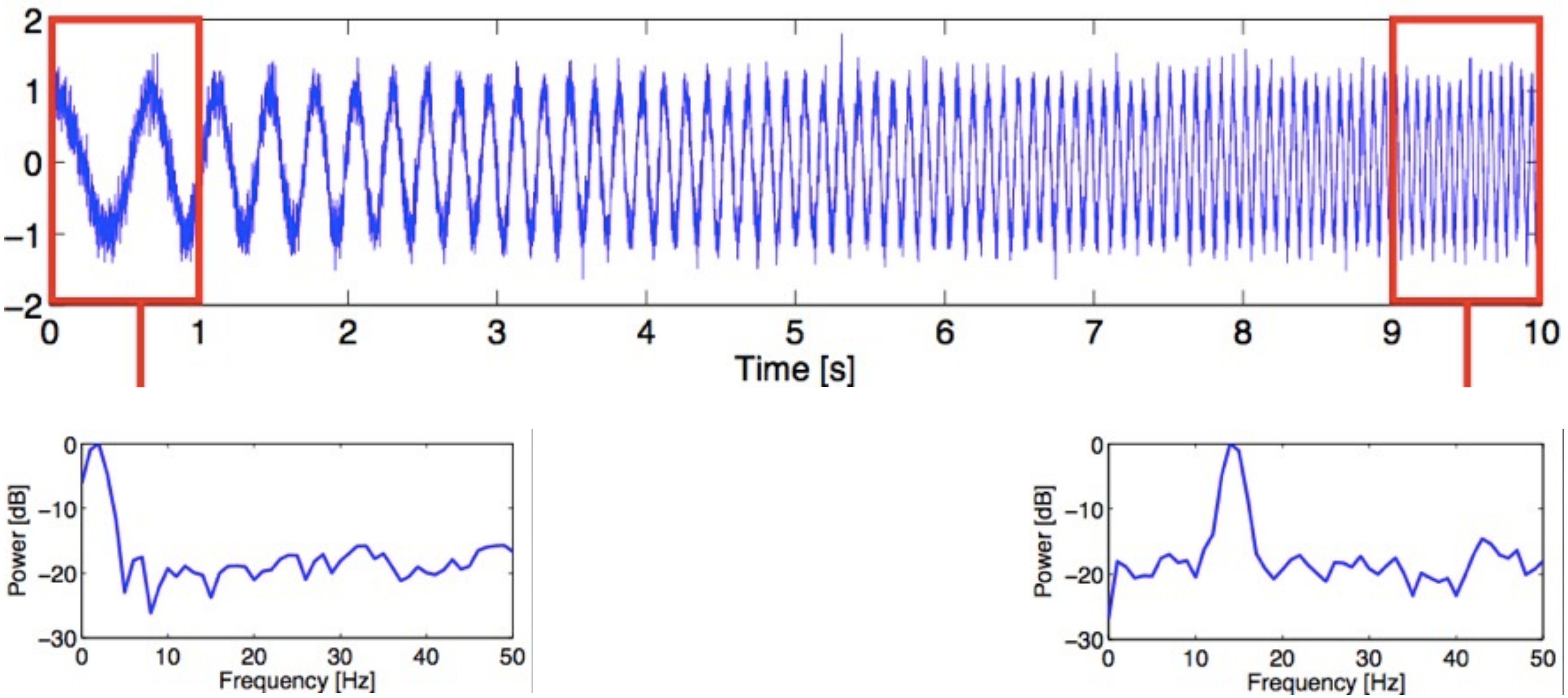
To observe higher frequencies: increase sampling rate

Built-in routines: `>> periodogram(...)`

Many subtleties....

Spectrogram

What if signal characteristics change in time?



Different spectra at beginning and end of signal

Idea: split up data into windows & compute spectrum in each

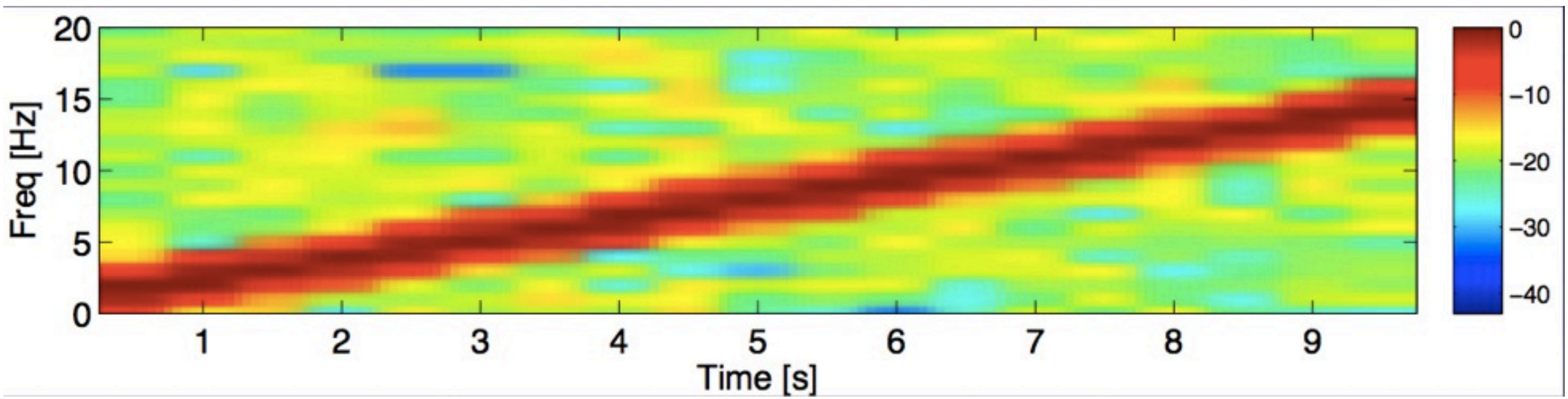
Example (MATLAB code)

window padding

```
>> [S,F,T] = spectrogram(v,1,0.5,1,1000);
>> S = abs(S);
```

overlap f_0

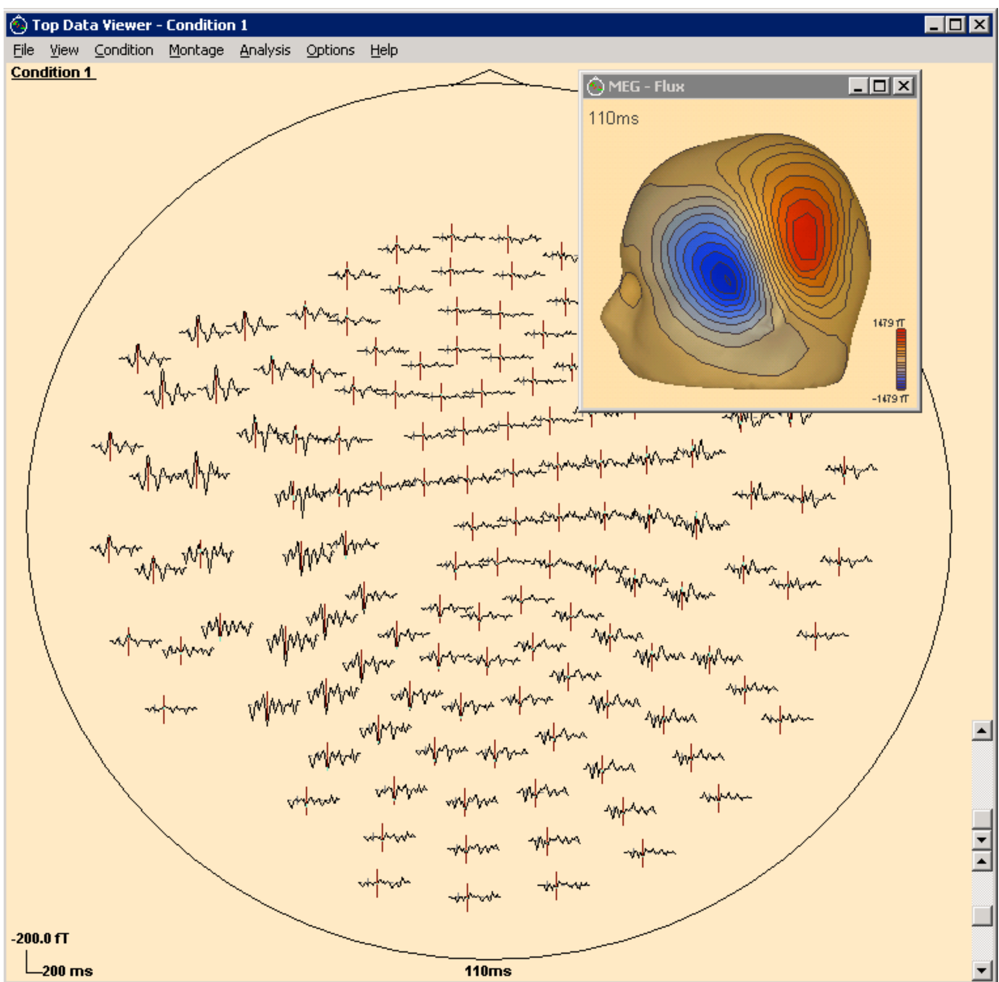
```
>> imagesc(T,F,10*log10(S/max(S(:))));
```

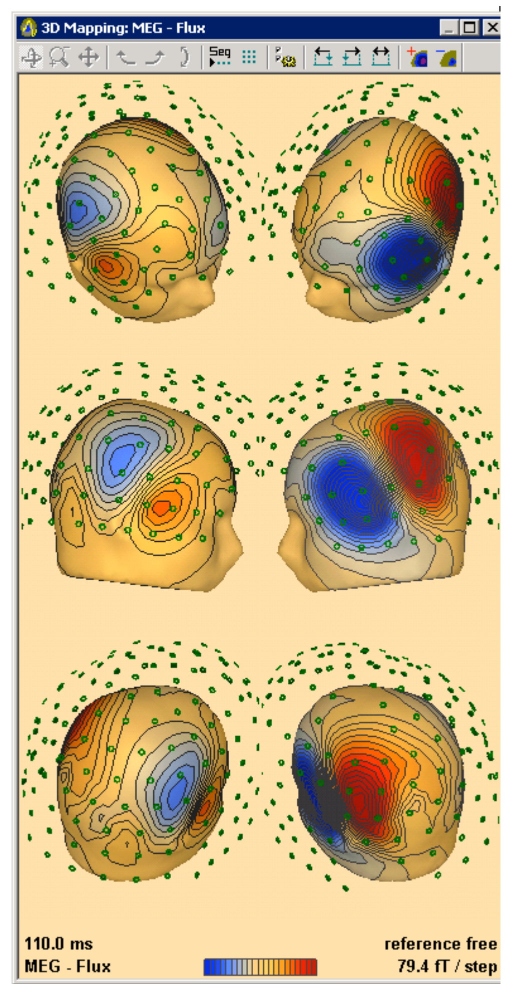


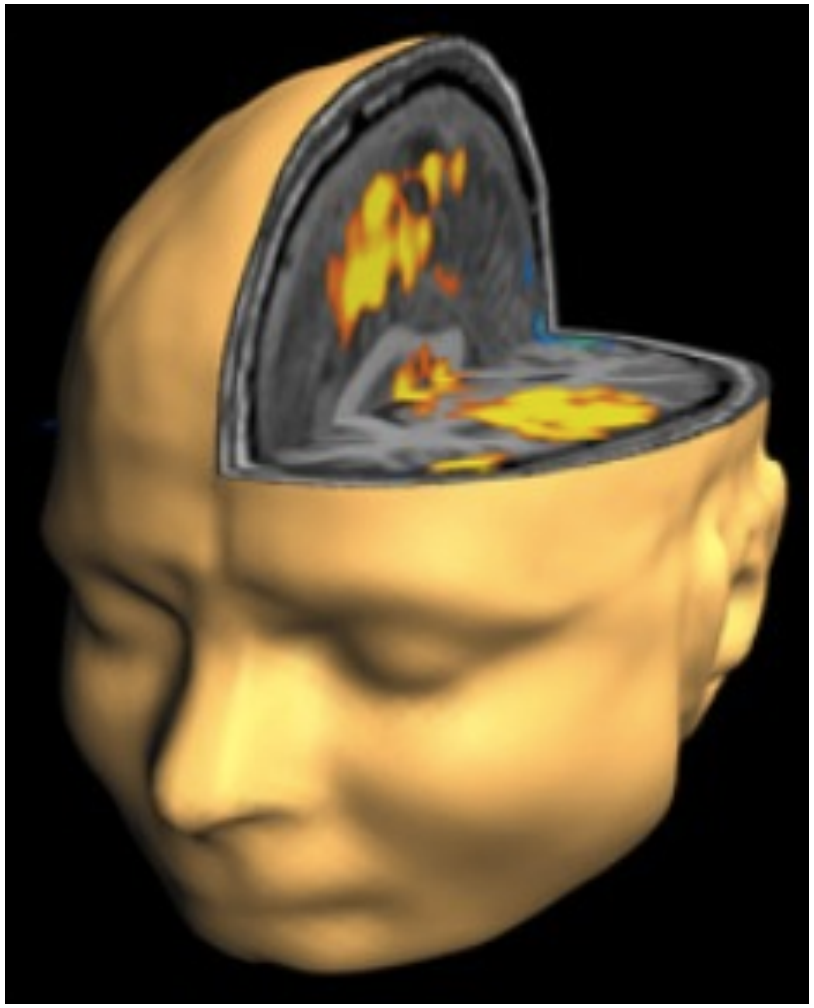
Plot of power (color) vs frequency and time

A better representation of data

Network analysis







In many experiments we collect tens or hundreds of channels

How are the activities of different channels related?

Association measures

Association measures quantify some degree of interdependence between two or more time series:

Correlation (cross-correlation)

Synchronization

Granger causality

Mutual information

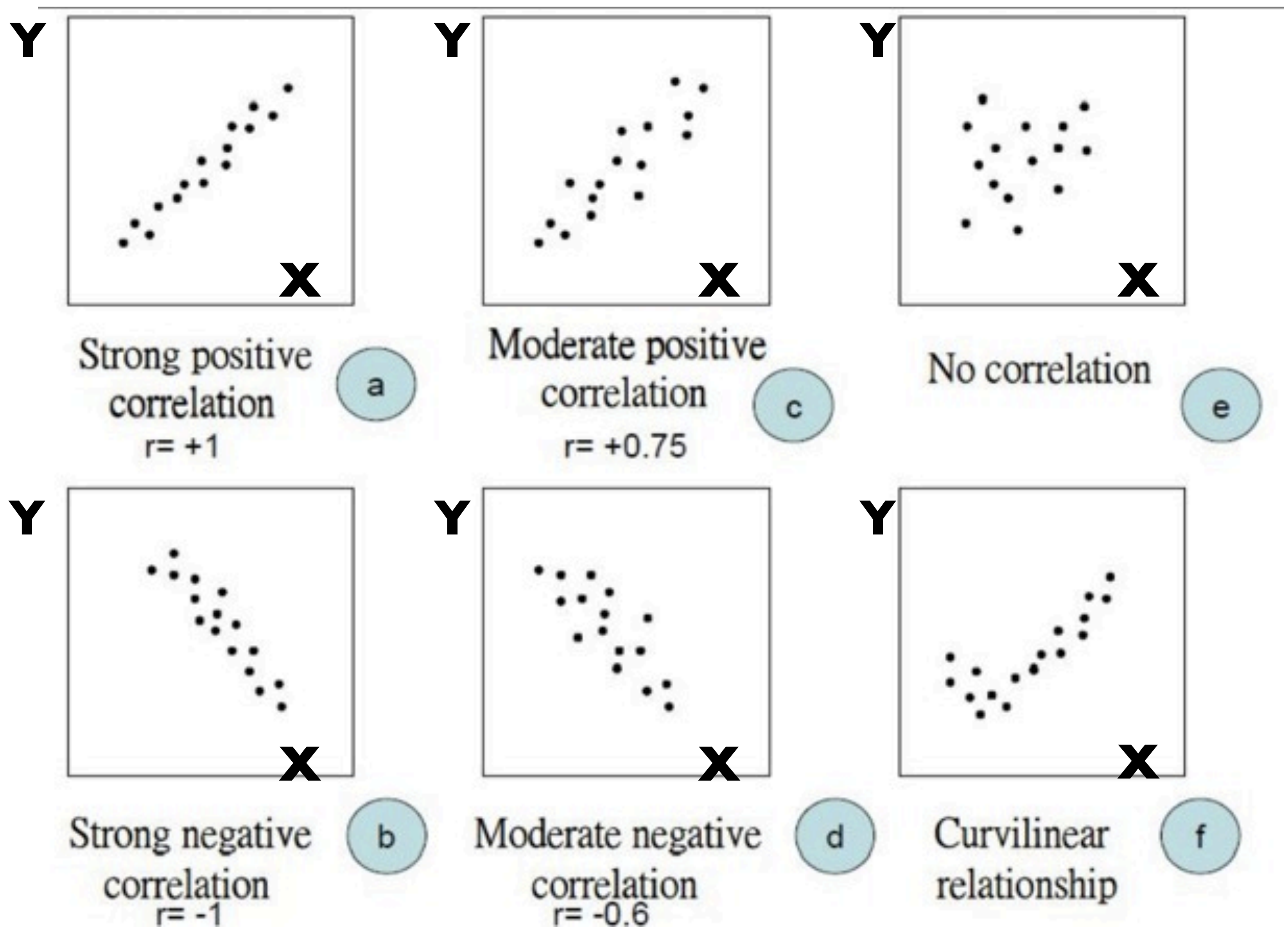
...

Correlation

Given two time series: **X** = {$x_1, x_2, x_3, \ldots, x_n$} & **Y** = {$y_1, y_2, y_3, \ldots, y_n$}

the correlation coefficient ***r*** mesures the linear "similarity" between them

Y(t) = a*X(t) + w(t) ?

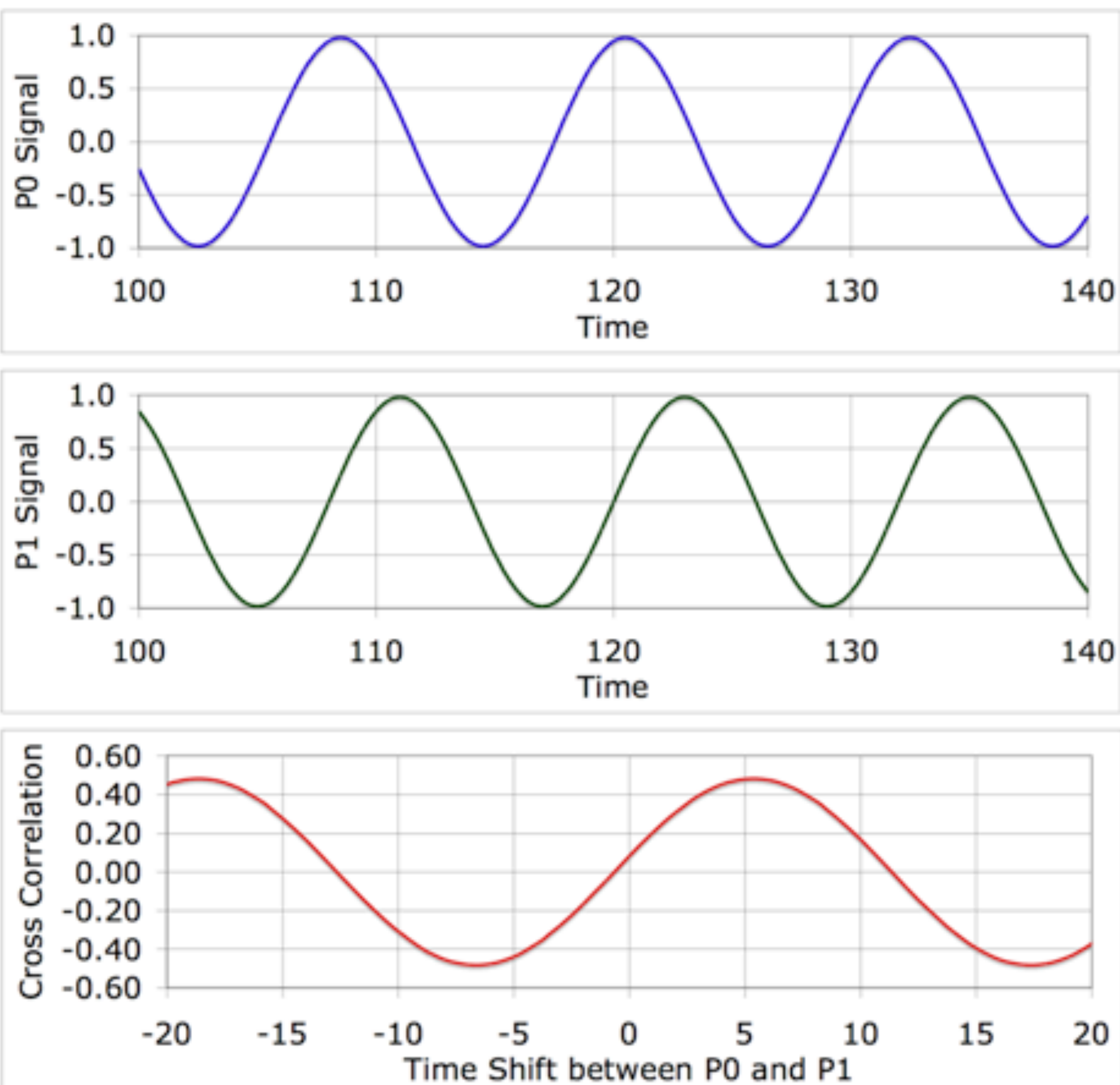


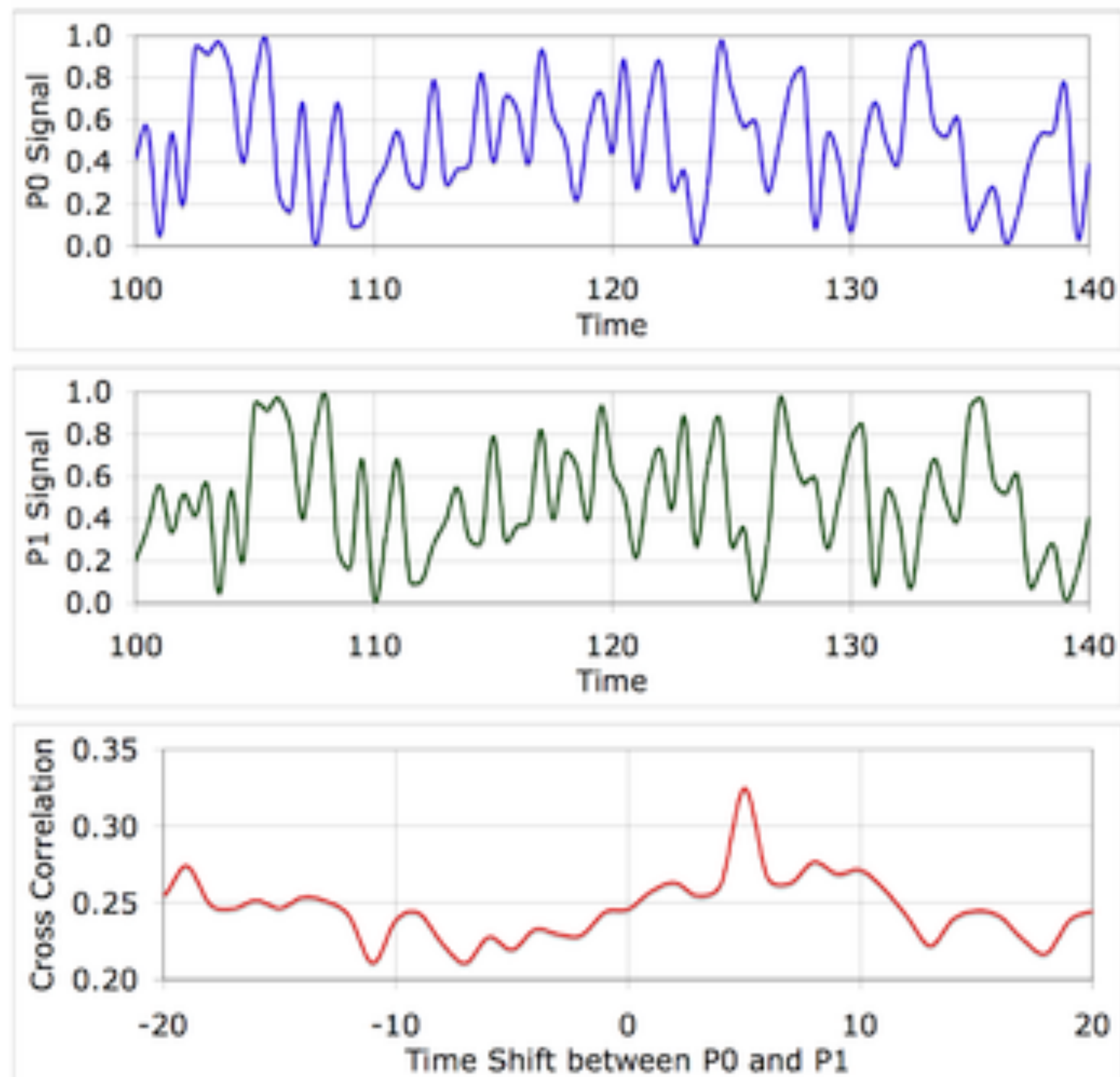
$$r = \frac{\sum_{i=1}^{n}\left(\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2 \sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}}$$

```
>> r =
corr(X,Y);
```

Cross-correlation

Cross-correlation measure the degree of linear similarity of two signals as a function of a time shift (lag)





Cross-correlation

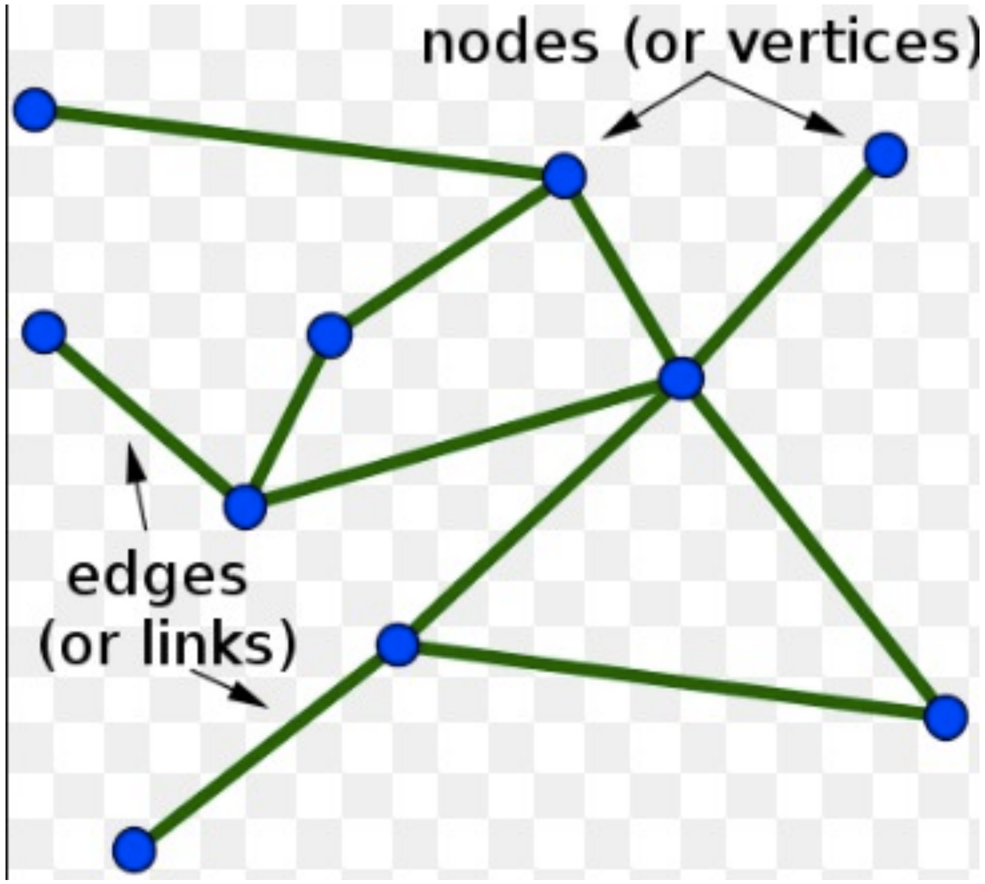
The value and position (lag) of the maximum of the cross-correlation function can give information about the strength and timing of interactions

Y(t) = a*X(t-d) + w(t) ?

$$r = \frac{\sum_i [(x_i - \bar{x})(y_{i-d} - \bar{y})]}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (y_{i-d} - \bar{y})^2}}$$

```
>> r =
xcorr(X,Y,maxlag);
```
% returns a vector ***r*** of length 2*maxlag + 1

Networks



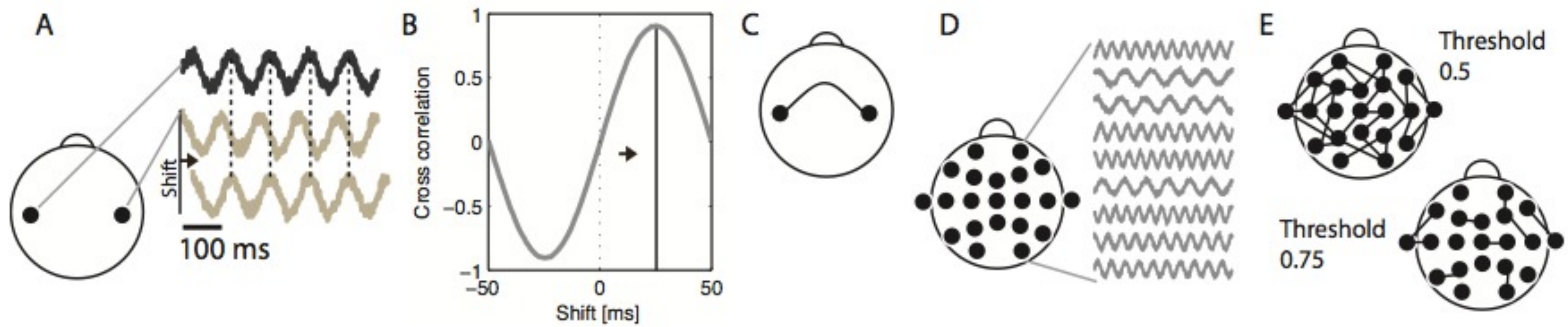
Set of nodes and edges

It allows to study a set of channels as a whole

In structural networks the edges represent physical connections between nodes (synapses or white matter tracts)

Functional networks rely on the co-activation or coupling of the dynamics of separate brain areas

Networks



1 Compute a measure of "coupling" between two channels (e.g. cross-correlation)

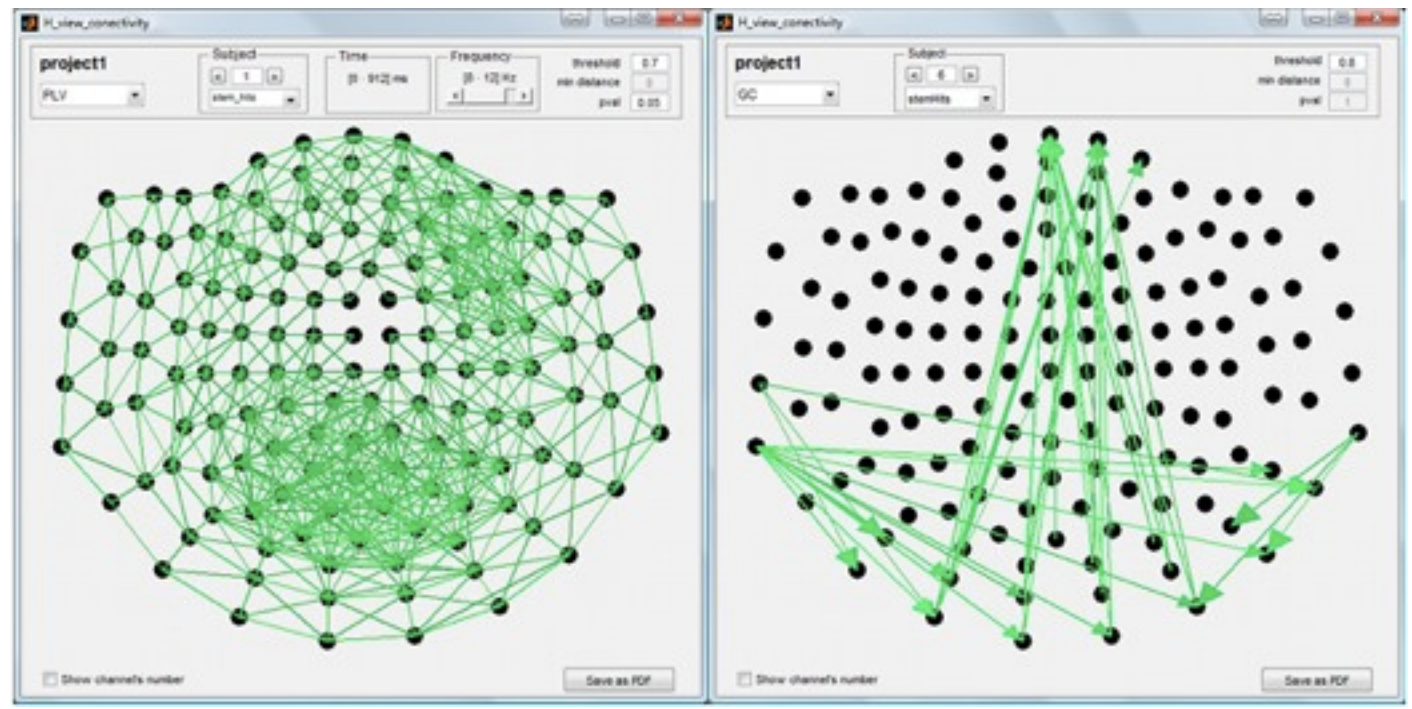
2 Draw and edge if the "coupling" > threshold

3 Repeat for all pairs of channels

Network ⟶ characterize its structure (degree, length, hubs, clusters,...)

Networks

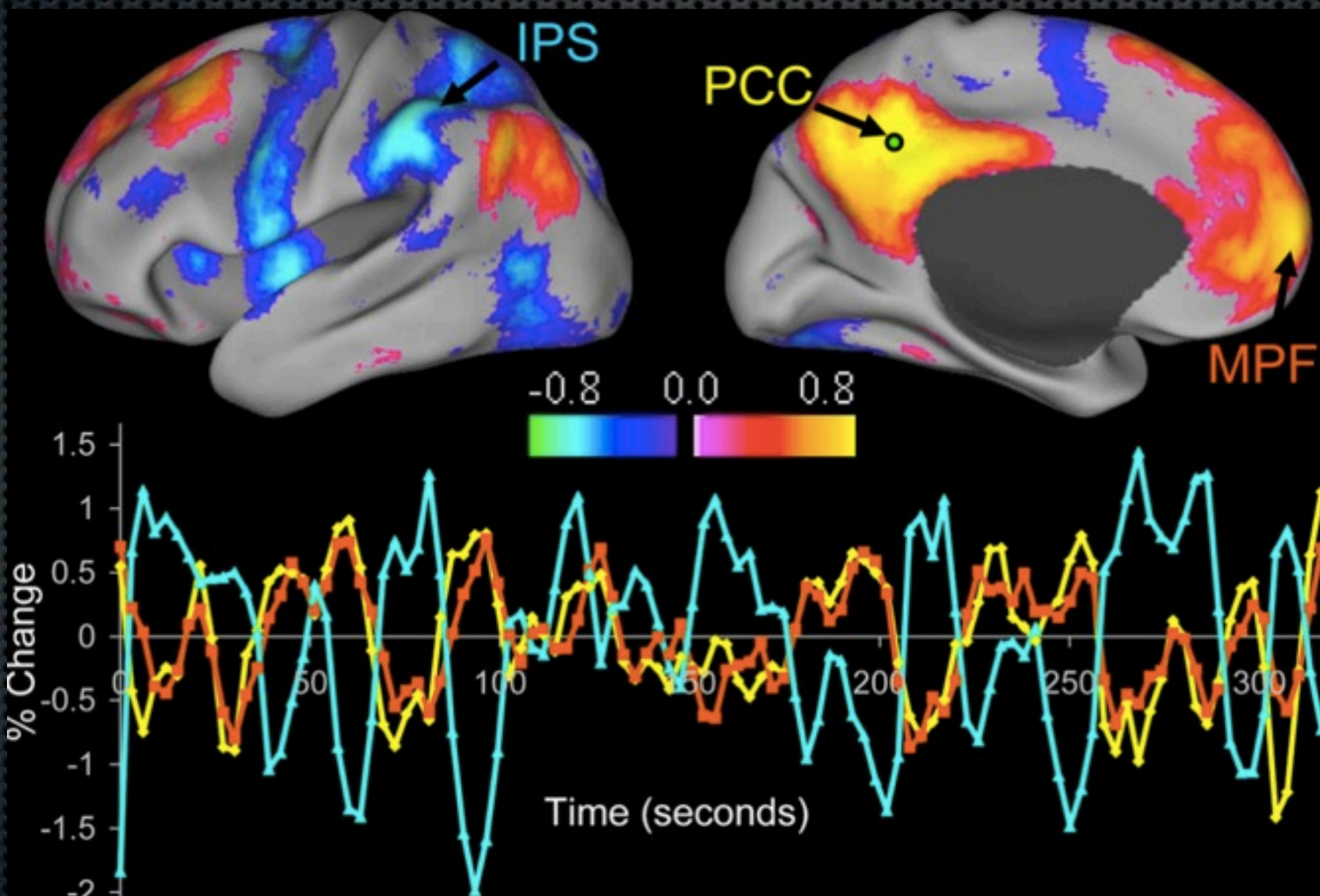
The easy way to estimate connectivity: HERMES toolbox



http://hermes.ctb.upm.es

Default Mode Network (DMN)

fMRI (BOLD) → **Spontaneous modulations during resting** → **Correlations (functional connectivity)**



Continuous signals

Spikes

Spikes

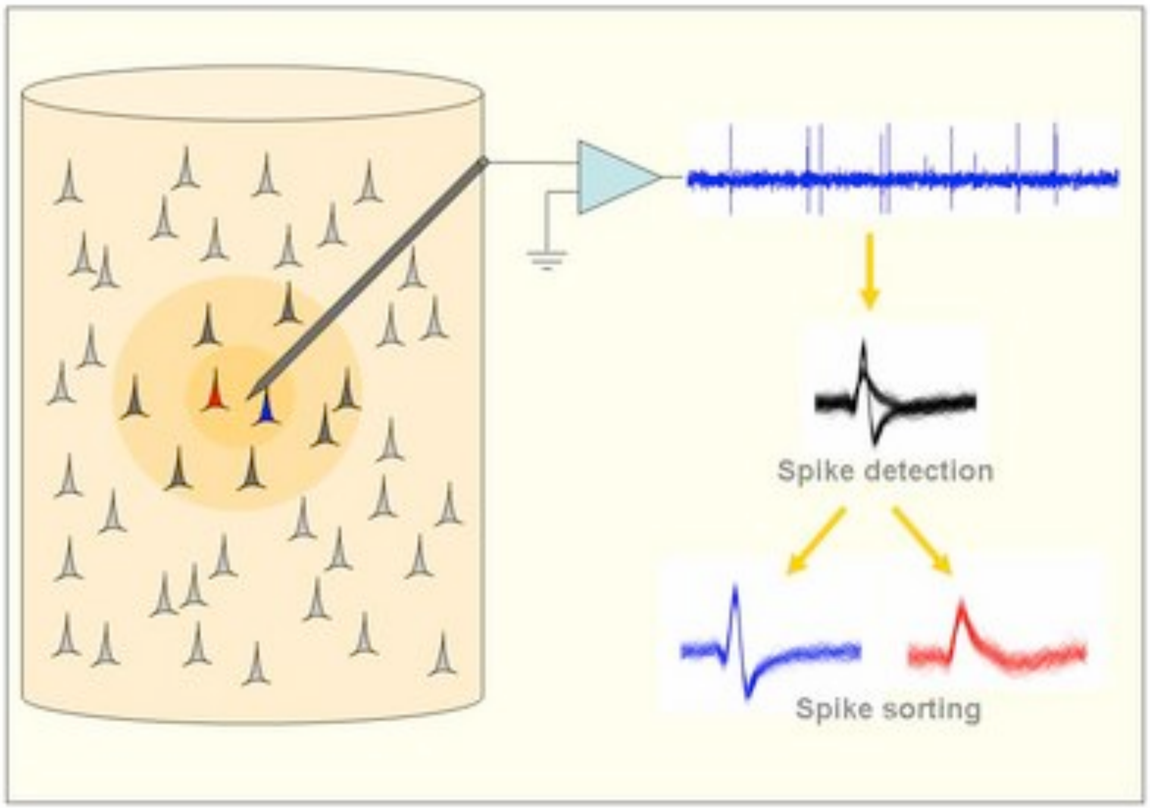
Raster plot

Post-stimulus time histogram

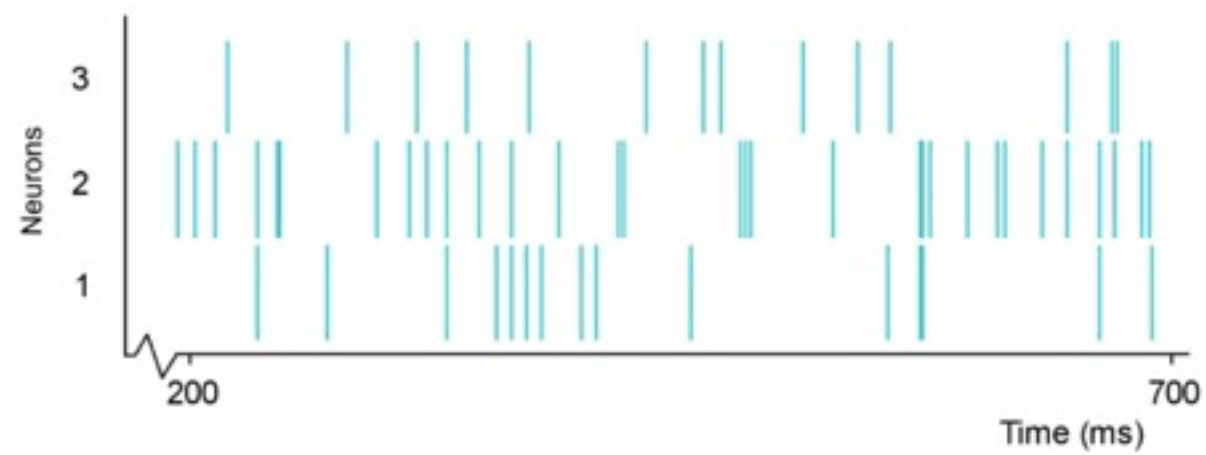
Receptive field

Spike triggered average

Spike trains (raster plot)



raster plot

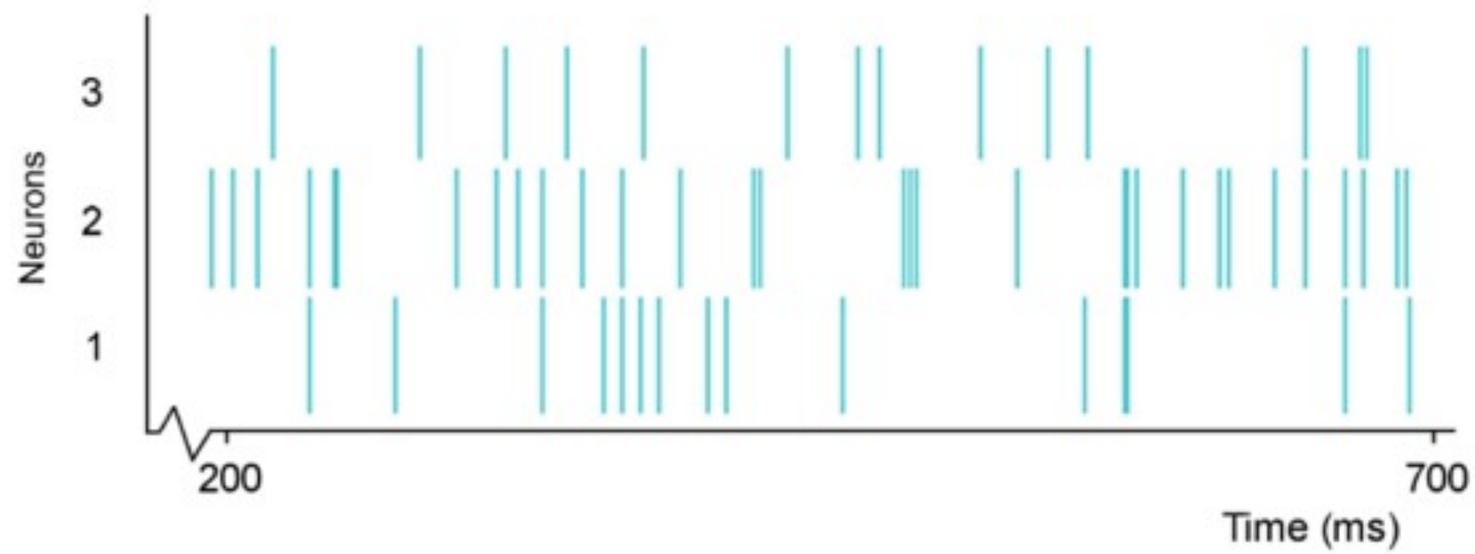


A spike train is a series of discrete action potentials from a neuron taken as a time series

A **raster plot** represents spike train along time in the x-axis and cell number (or trial number) in the y-axis

Spike trains (rate)

Each neuron can be characterized by its firing rate ***r***
r = average number of events per unit of time



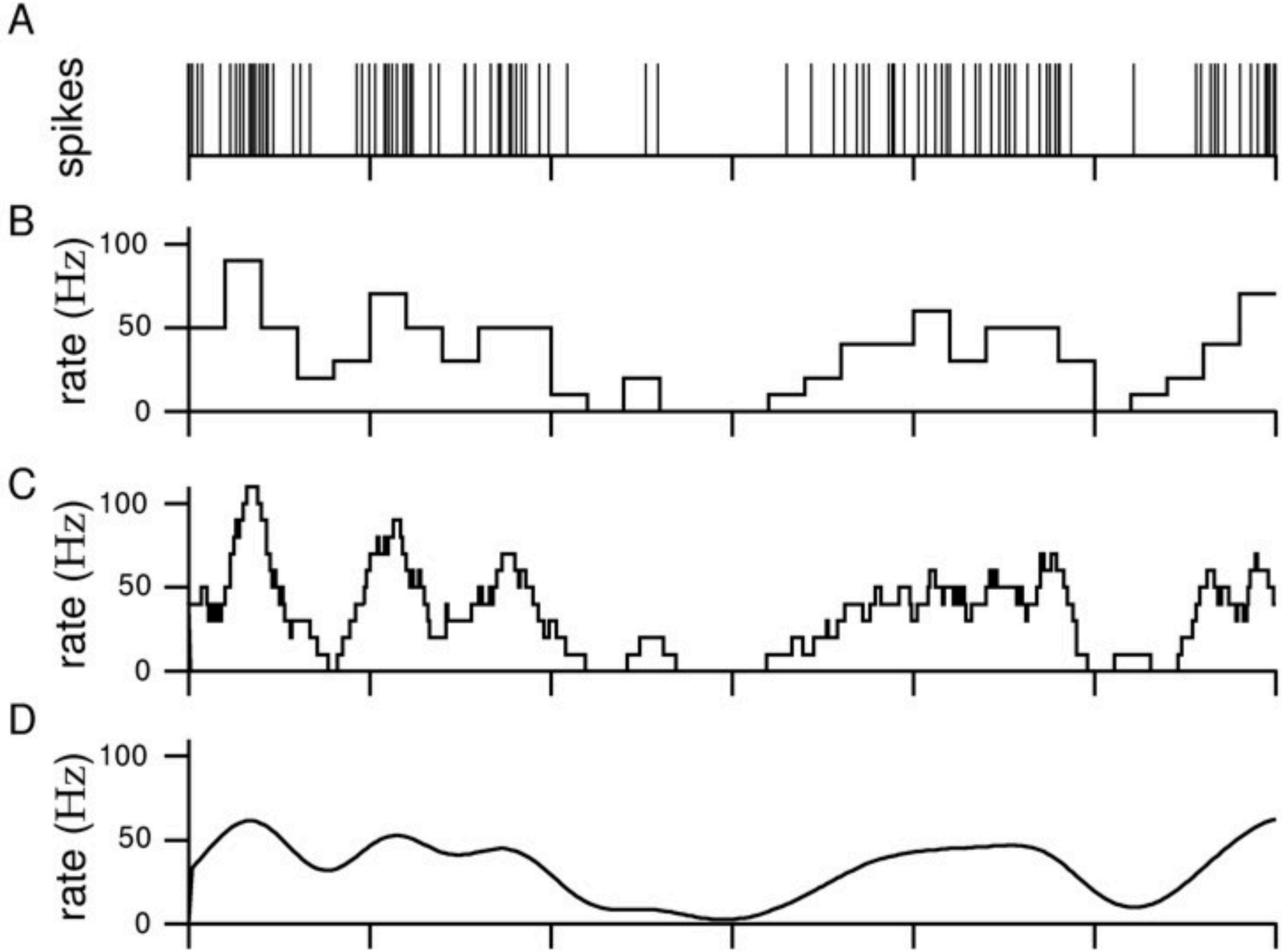
28 spikes/s

64 spikes/s

17 spikes/s

If properties change over time a more refined measure is the instantaneous rate ***r(t)***:
r(t)***dt = average number of events between t and t +dt**

Spike trains (rate)



IT neuron from monkey while watching video

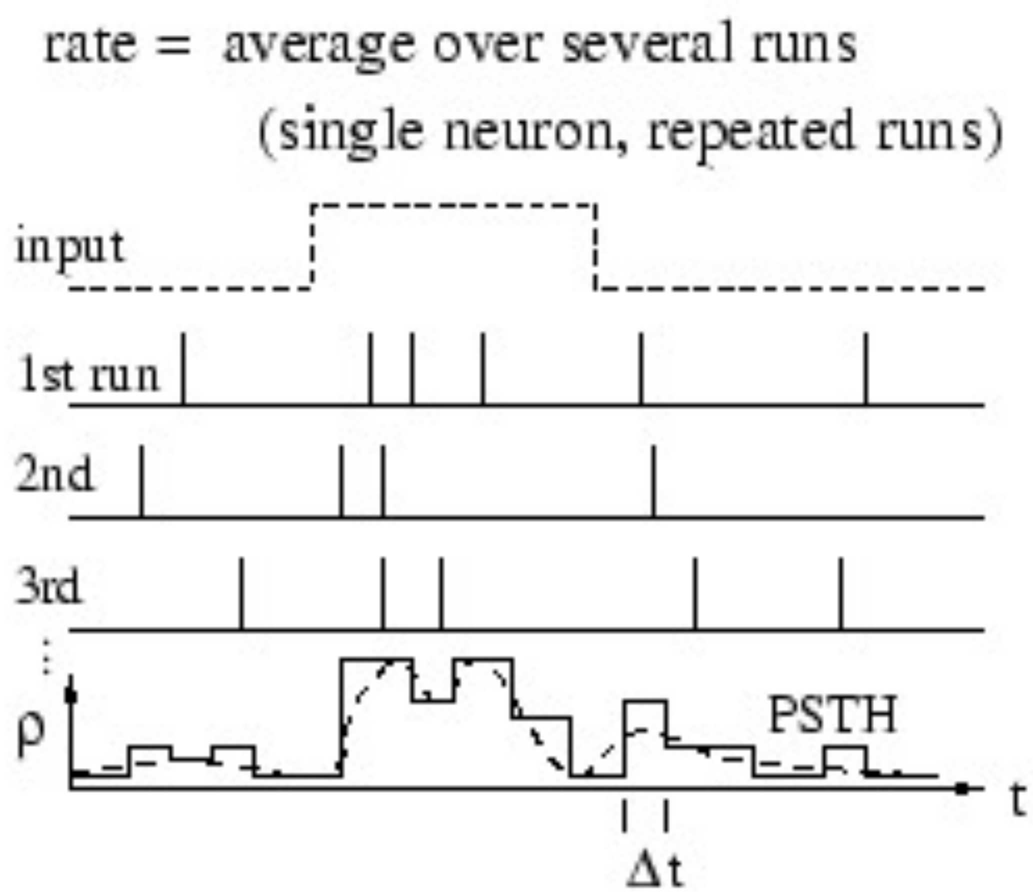
Binning
dt = 100 ms

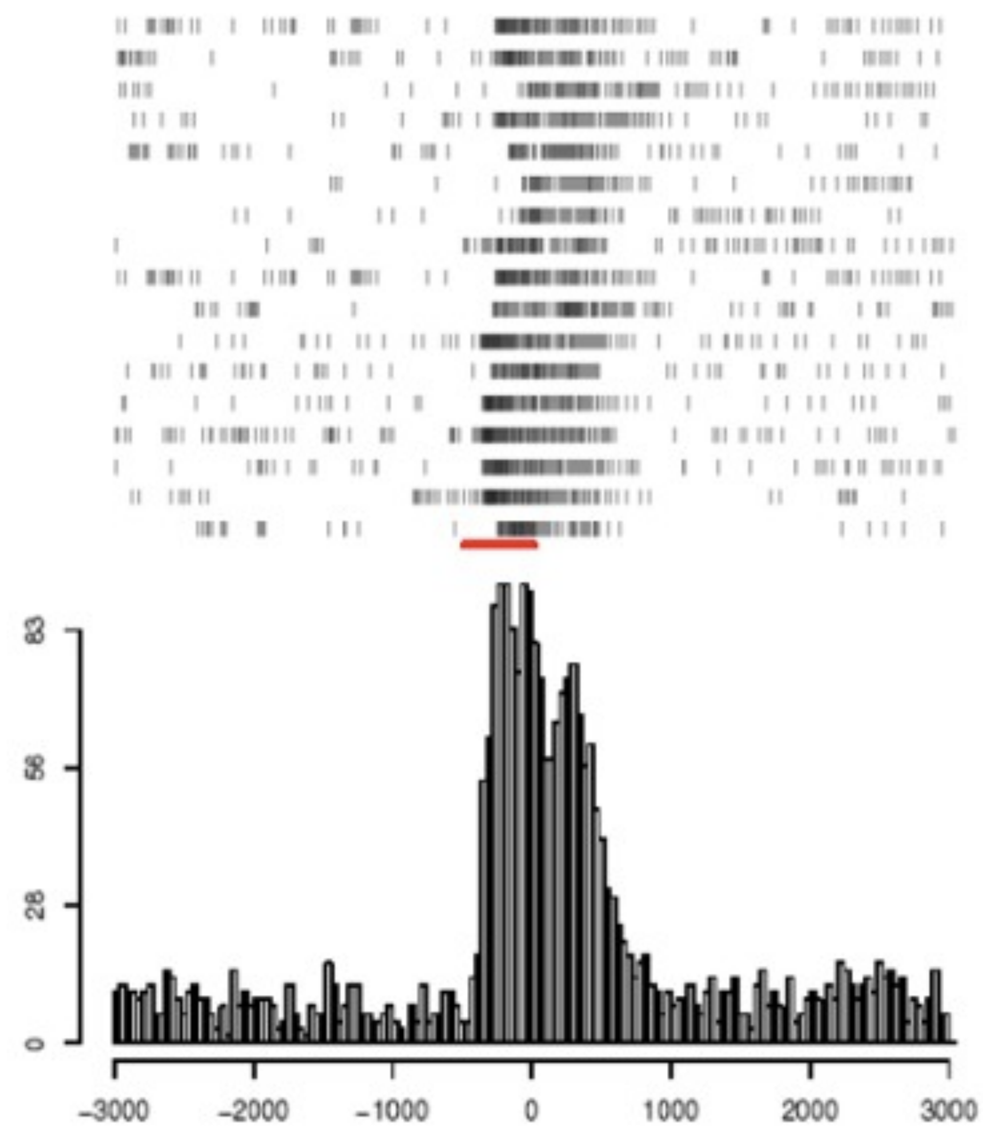
Rectangular window

Gaussian window

Post-Stimulus Time Histogram

PSTH is an histogram of the times at which neurons fire





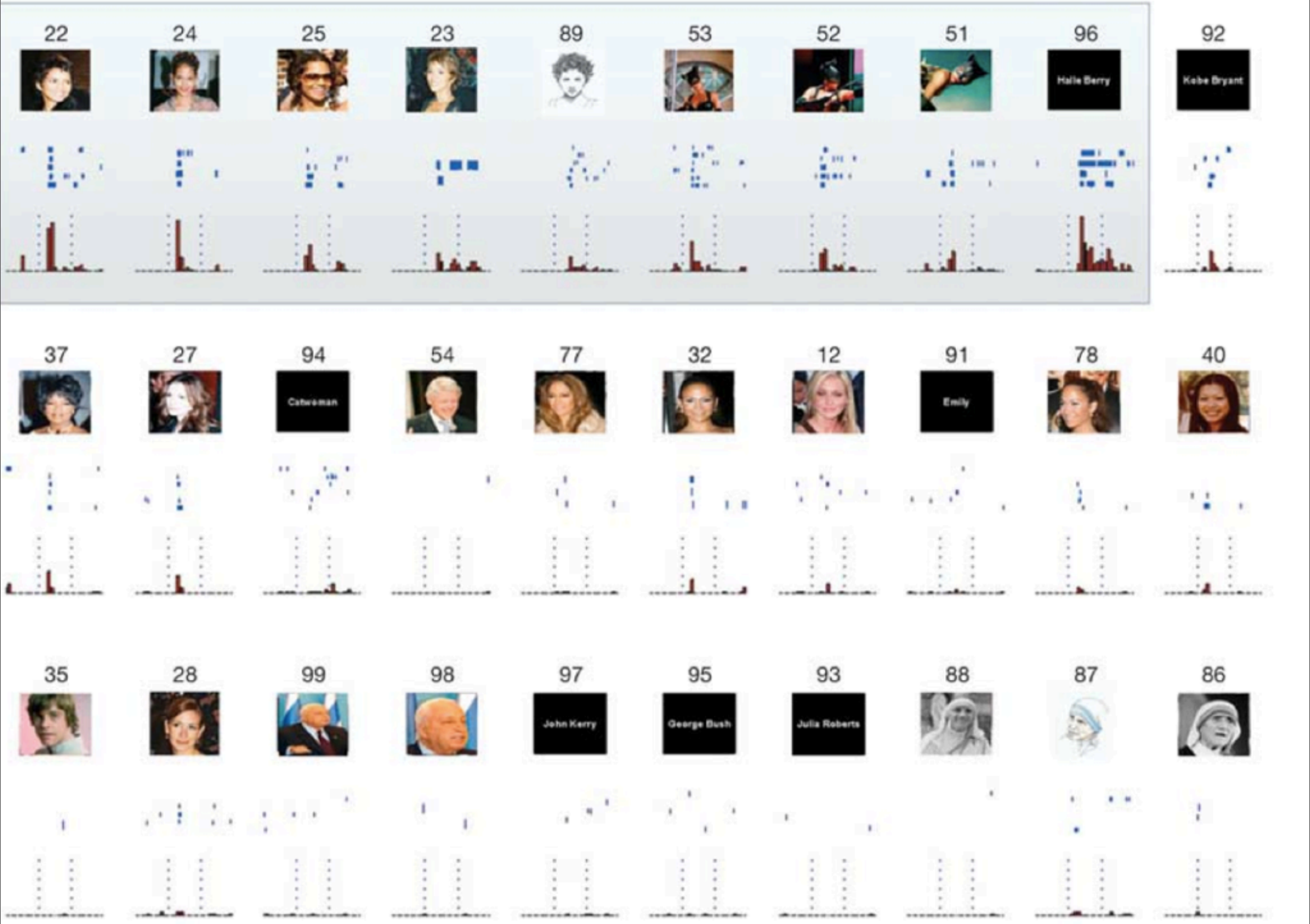
PSTH is used to visualize the rate and timing of spikes in relation to an external stimulus. **PSTH/#trials** ~ **r(t)**

Receptive field

The **receptive field** of a neuron is a region of space in which the presence of a stimulus will alter the firing of that neuron

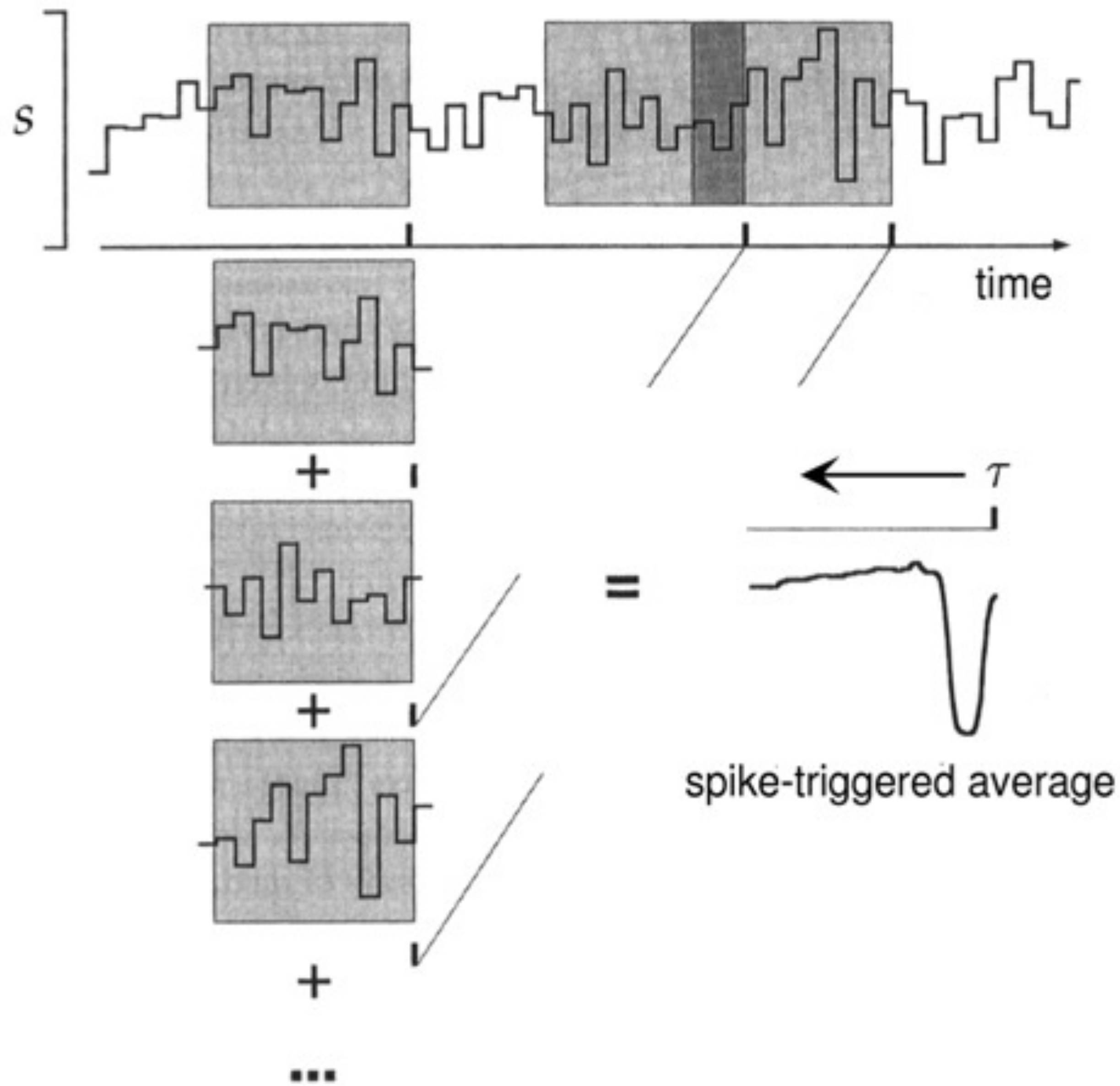
The space can be a region on an animal's body (somatosensory), a range of frequencies (auditory), a part of the visual field (visual system), or even a fixed location in the space surrounding an animal (place cells)

http://www.youtube.com/watch?v=8VdFf3egwfg


22 24 25 23 89 53 52 51 96 92
Halle Berry
Kobe Bryant
37 27 94 54 77 32 12 91 78 40
Catwoman
Emily
35 28 99 98 97 95 93 88 87 86
John Kerry
George Bush
Julia Roberts

Spike Triggered Average

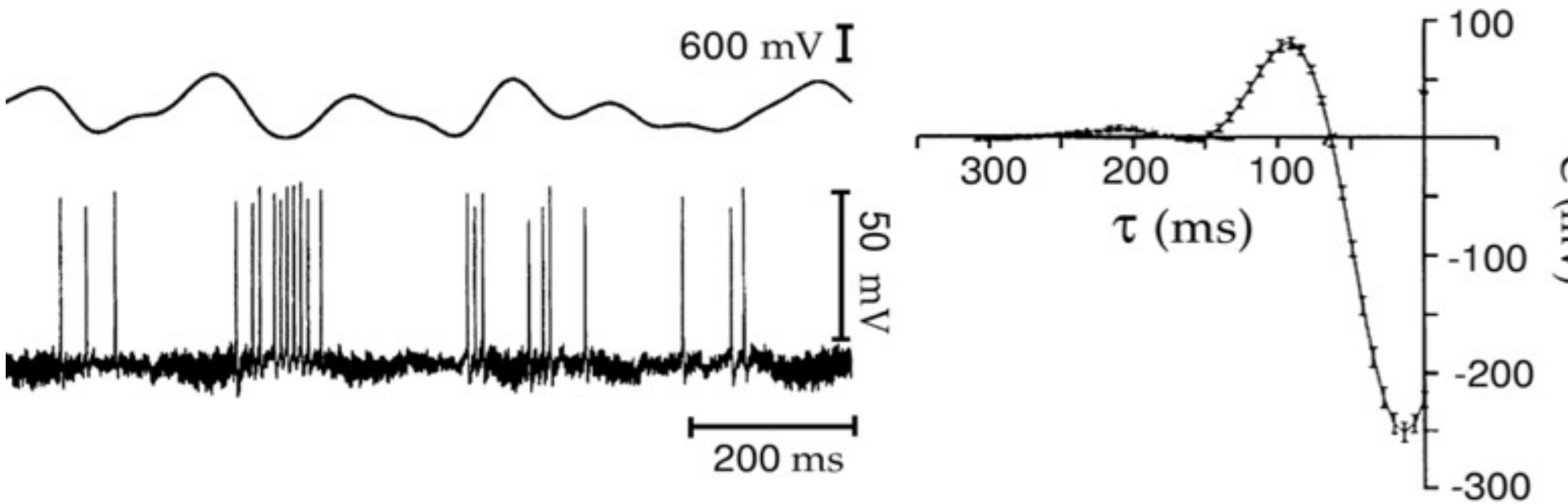
What makes a neuron fire?



The Spike Triggered Average (STA) is the **average stimulus** preceding a spike

Spike Triggered Average (Ex.)

Weakly electric fish (Eigenmannia)



STA from neuron in the electrosensory antennal lobe

Summary

- Event related potentials (ERPs) and post-time stimulus histograms (PSTH) average the neural responses near some event of interest
- Power spectrum can reveal the presence of rhythms or oscillations in recordings
- Functional networks are defined by the co-activation of separate brain areas
- Receptive fields describes what a neuron is sensitive to

Lesson	Title
1	Introduction
2	Structure and Function of the NS
3	Windows to the Brain
4	Data analysis
5	Data analysis II
6	Single neuron models
7	Network models
8	Artificial neural networks
9	Learning and memory
10	Perception
11	Attention & decision making
12	Brain-Computer interface
13	Neuroscience and society
14	Future and outlook: AI
15	Projects presentations
16	Projects presentations

Basics

Analyses

Models

Cognitive

Applications