BRAIN-COMPUTER INTERFACE

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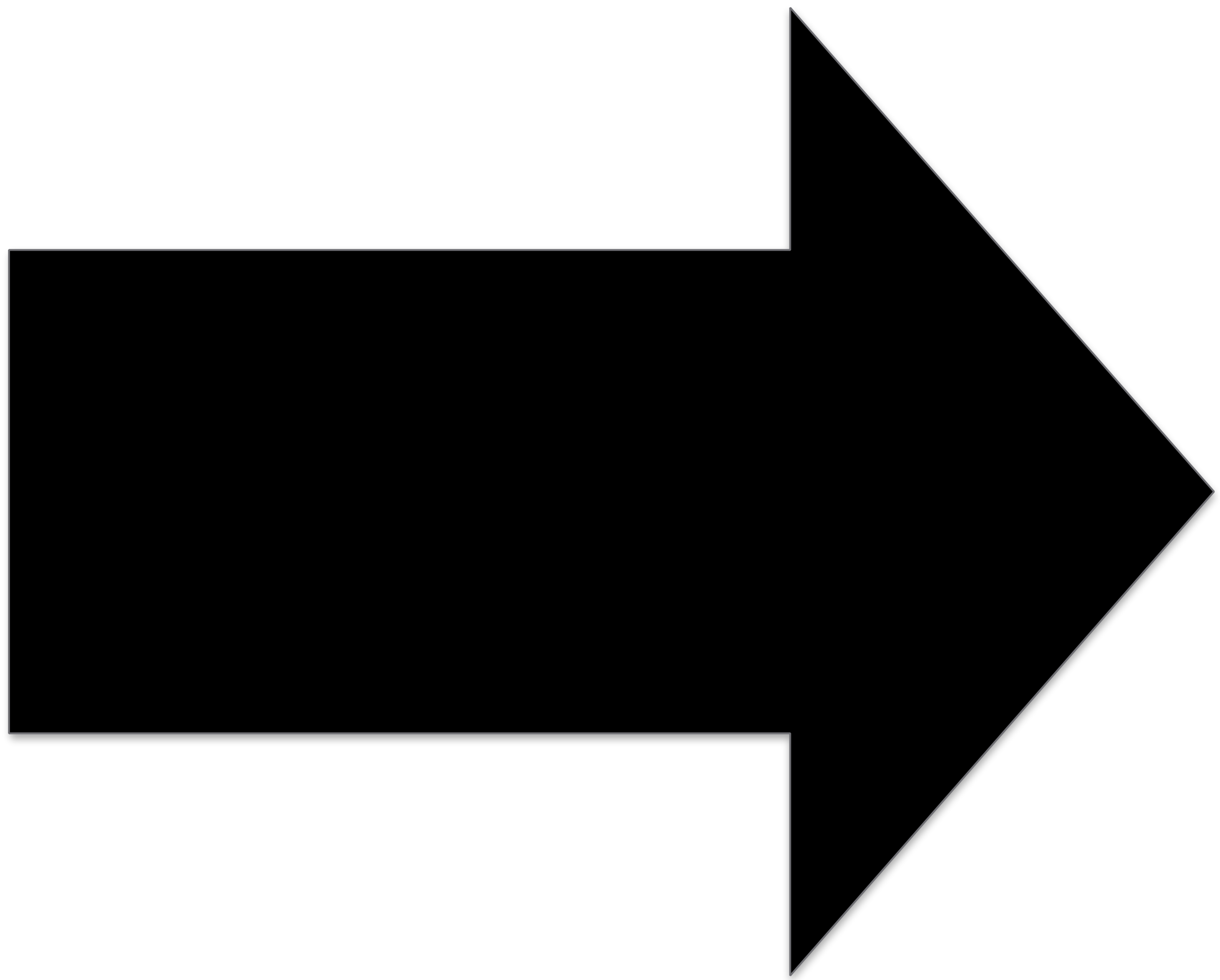
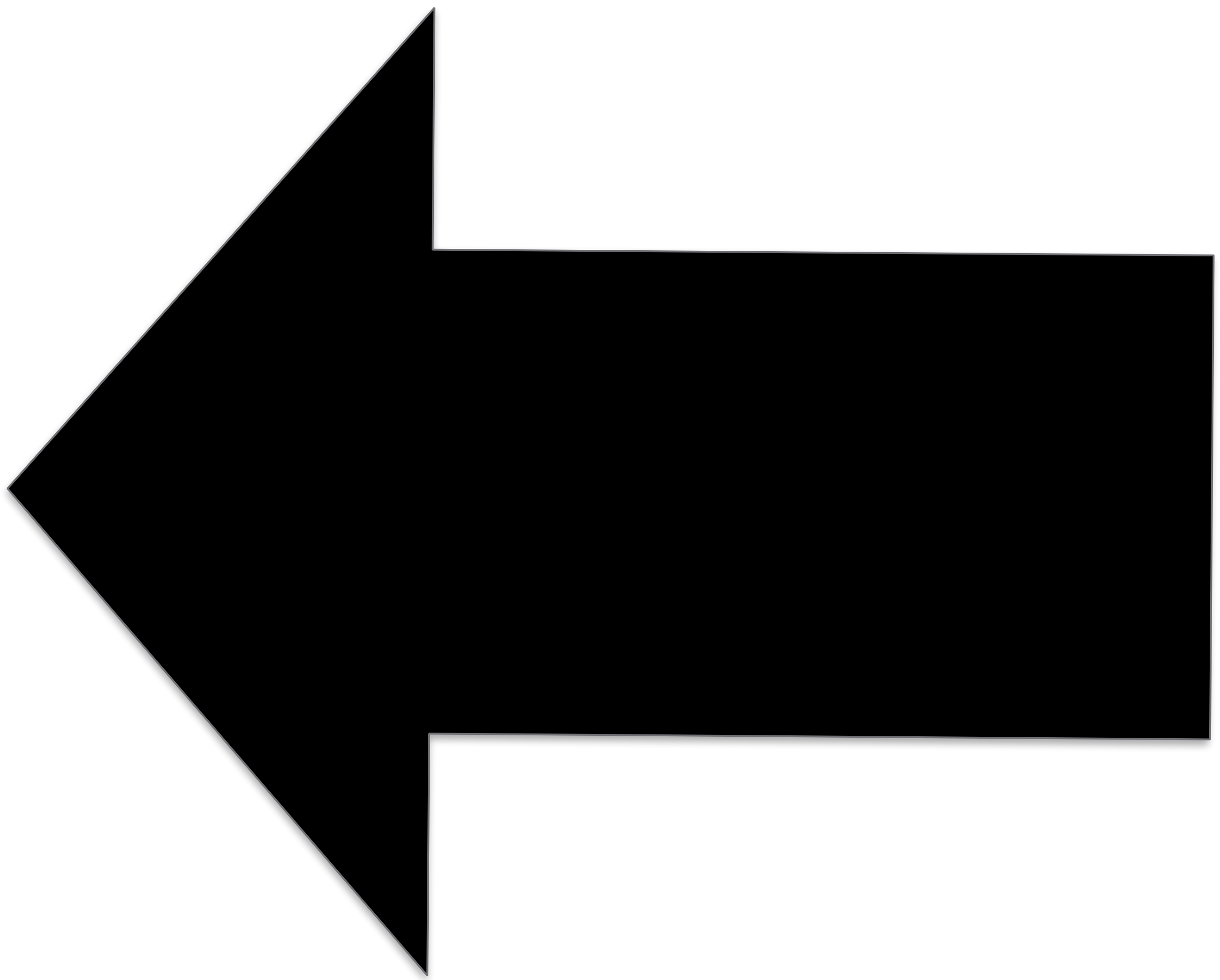
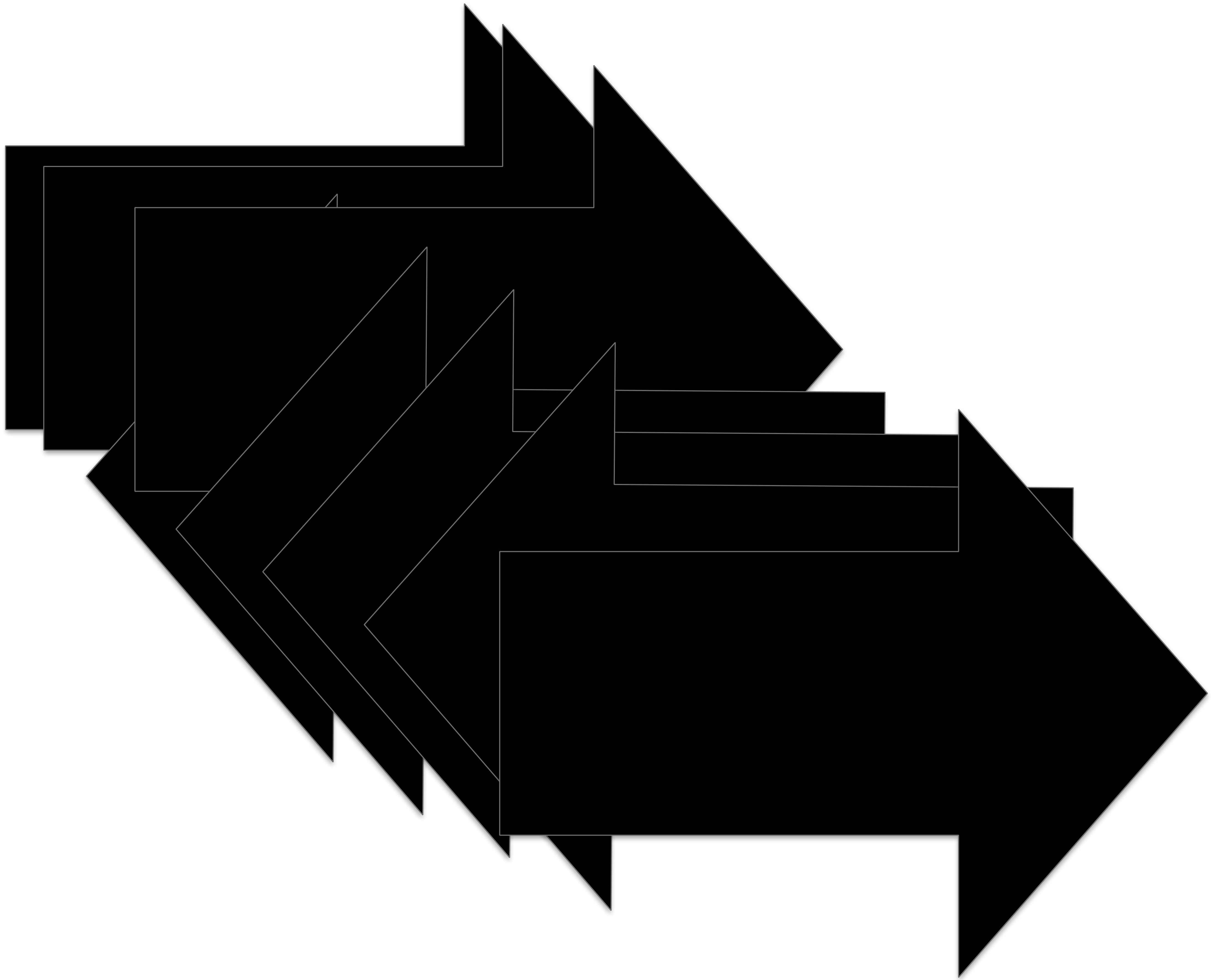
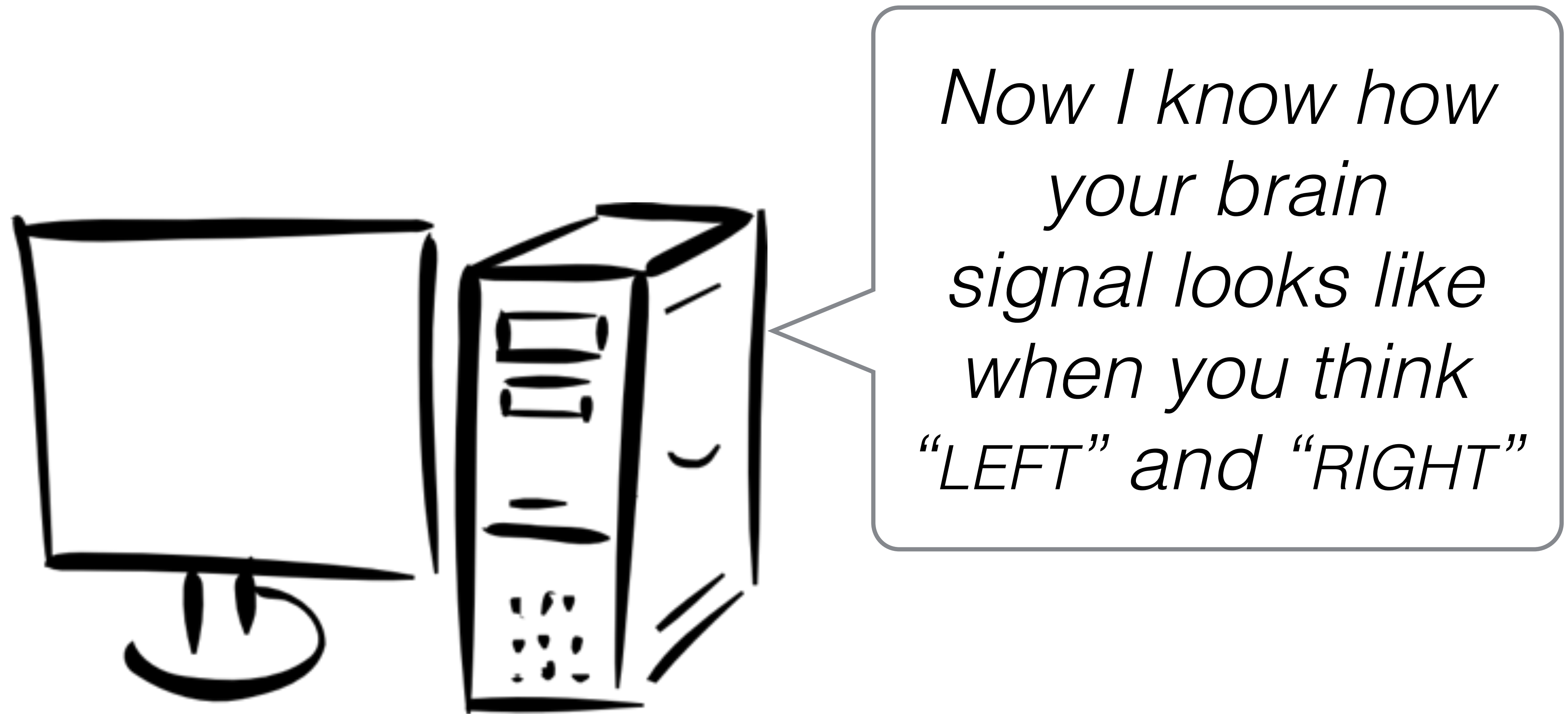
IT Akadeemia
toetab Skype™

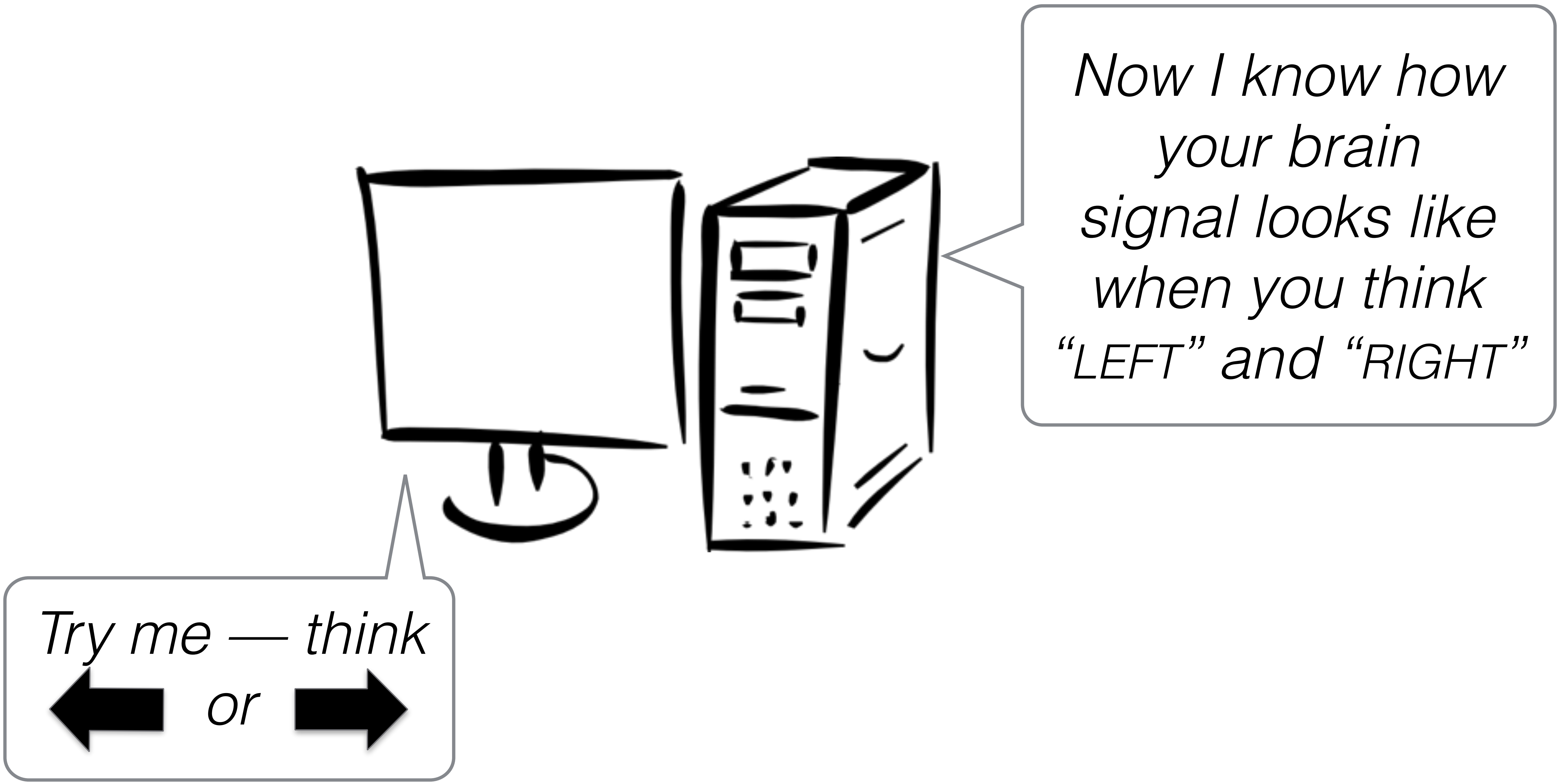
7 June 2014

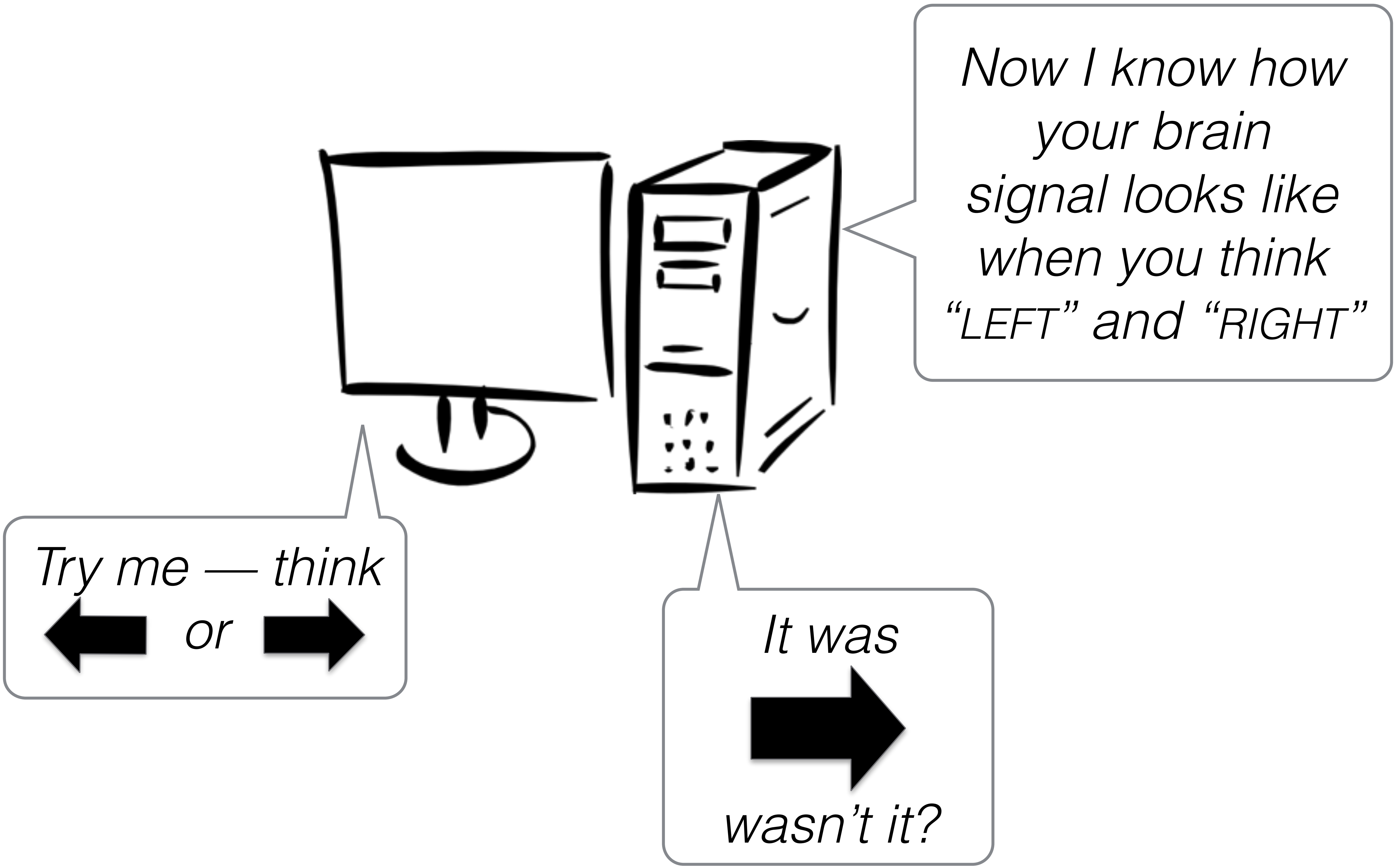




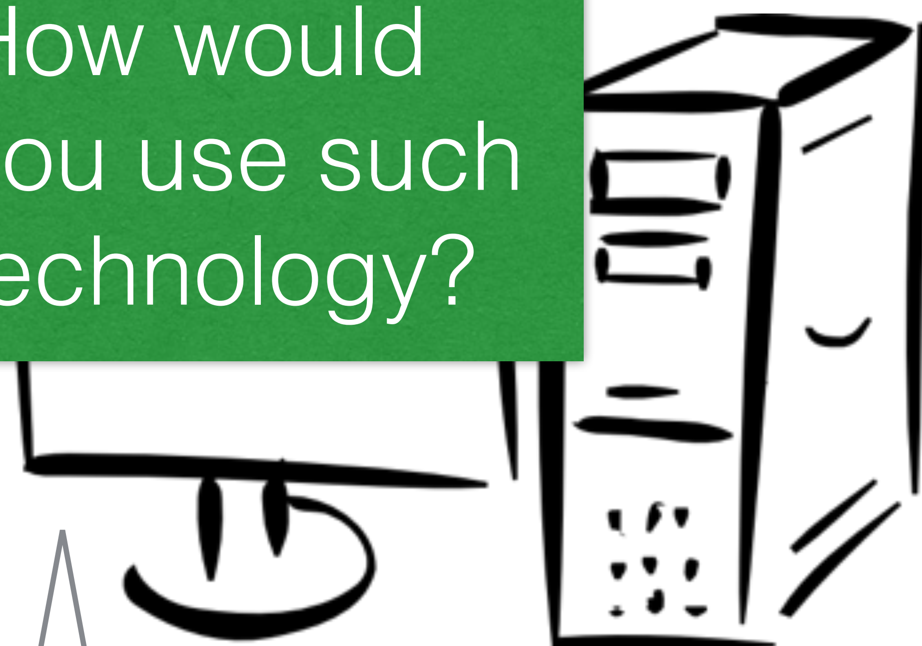



Now I know how
your brain
signal looks like
when you think
"LEFT" and "RIGHT"


Now I know how your brain signal looks like when you think "LEFT" and "RIGHT"
Try me — think ⬅ or ➡

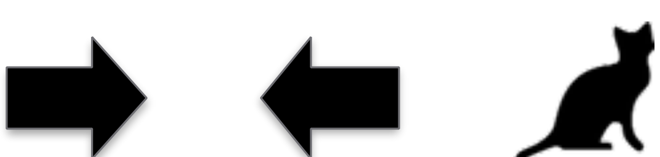

Now I know how your brain signal looks like when you think "LEFT" and "RIGHT"
Try me — think ← or →
It was → wasn't it?

How would you use such technology?



BRAIN-COMPUTER INTERFACE

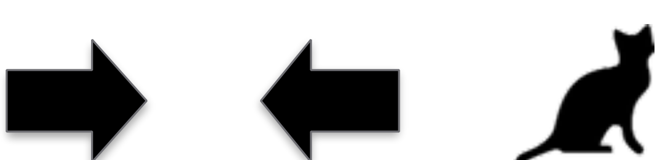
Mental intention



BRAIN-COMPUTER INTERFACE

Neuroimaging

Mental intention

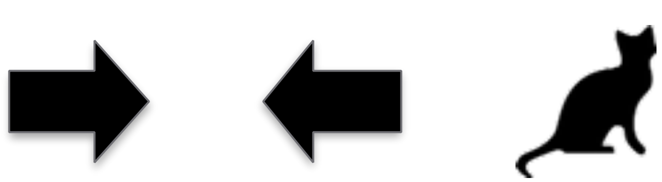


BRAIN-COMPUTER INTERFACE

Name some neuroimaging techniques

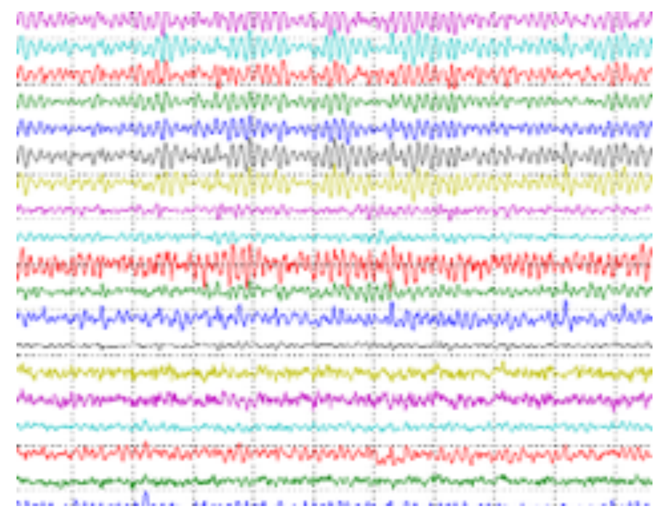
Neuroim

Mental intention



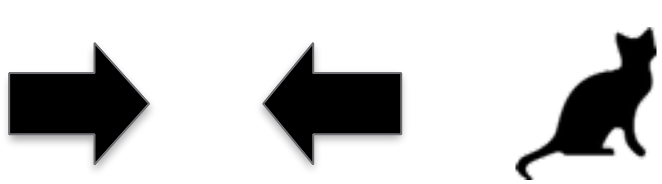
Brain-computer interface

Neuroimaging



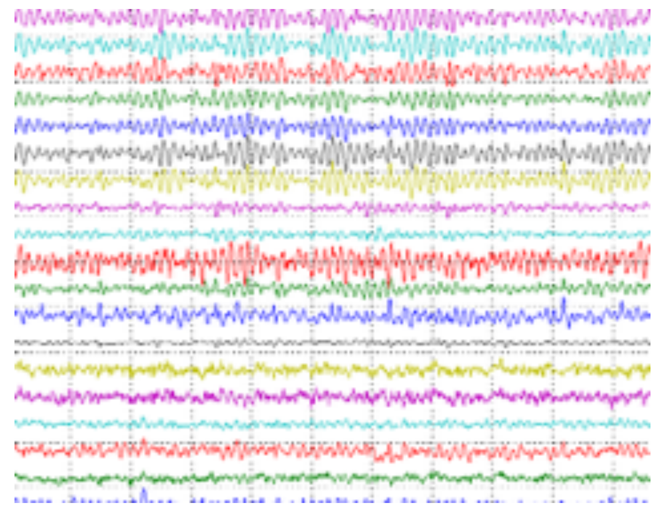
Signal

Mental intention



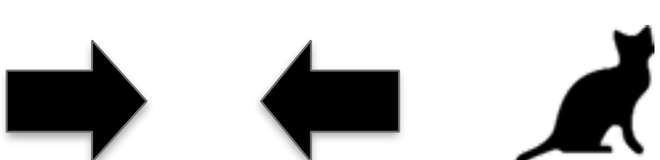
BRAIN-COMPUTER INTERFACE

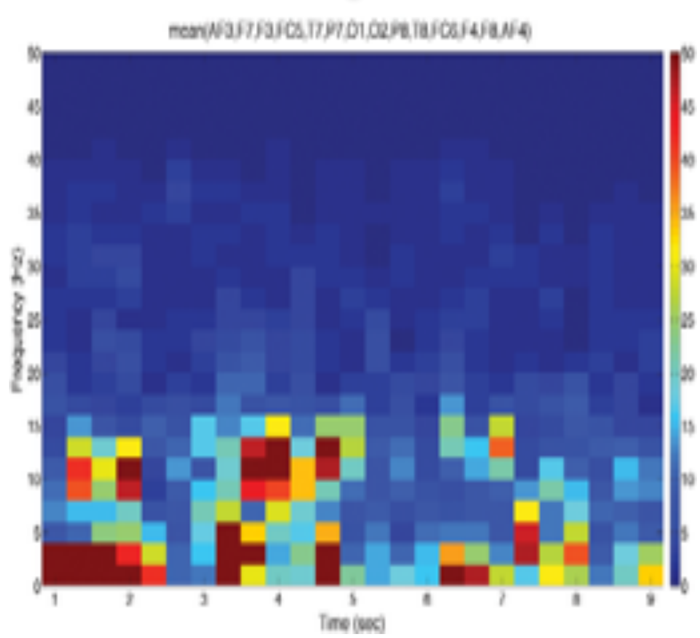
Neuroimaging



Signal

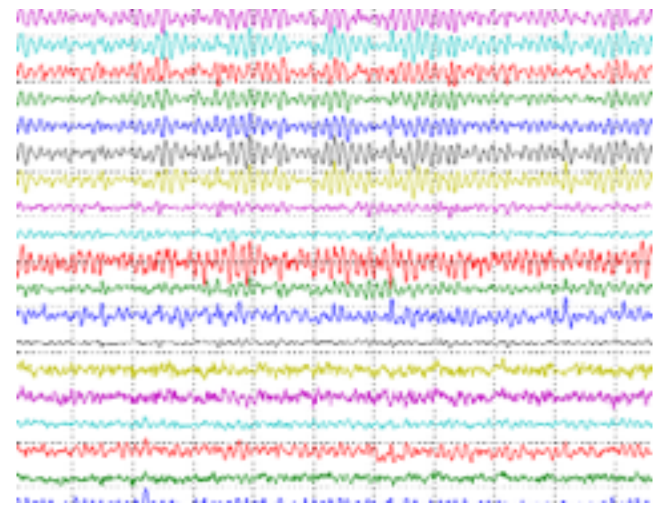
Mental intention





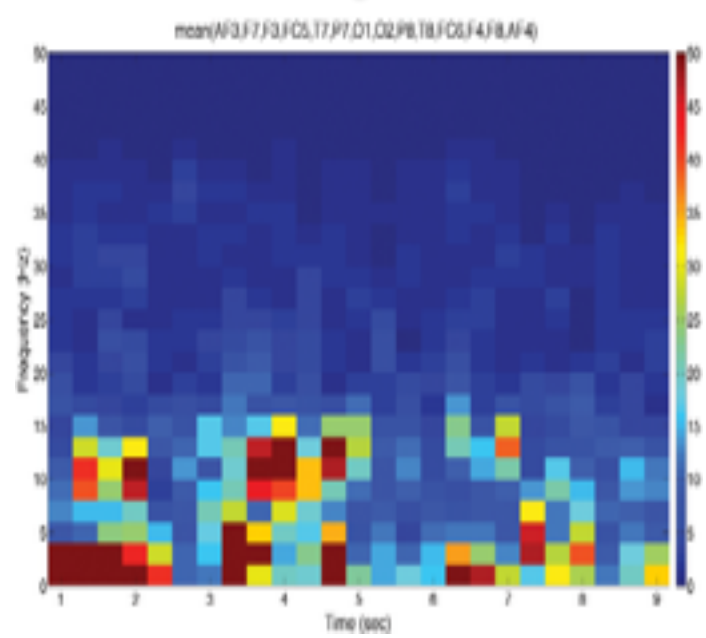
Data

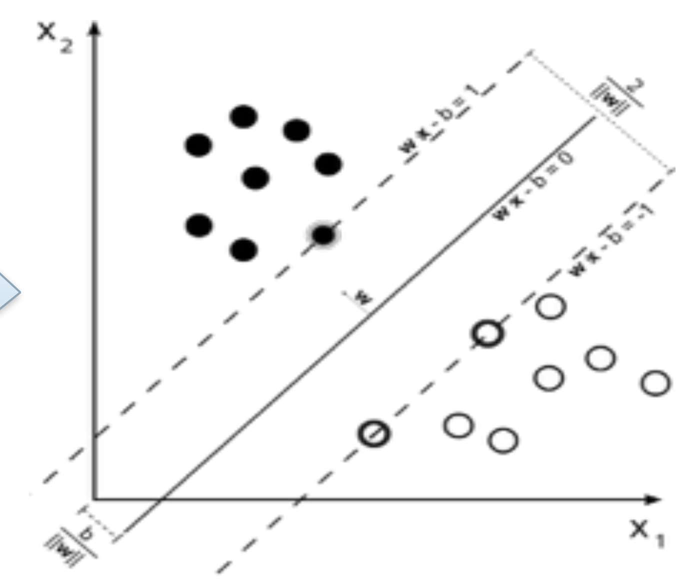
BRAIN-COMPUTER INTERFACE



Neuroimaging

Signal

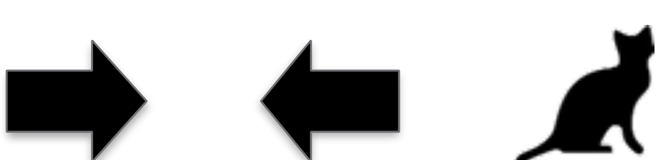




Mental intention

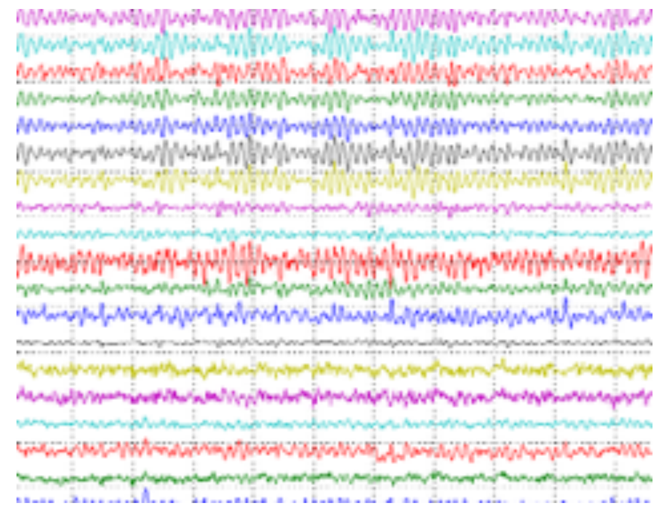
Data

Algorithm



BRAIN-COMPUTER INTERFACE

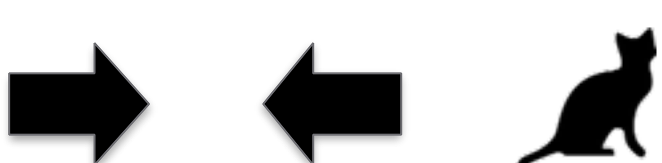
Neuroimaging

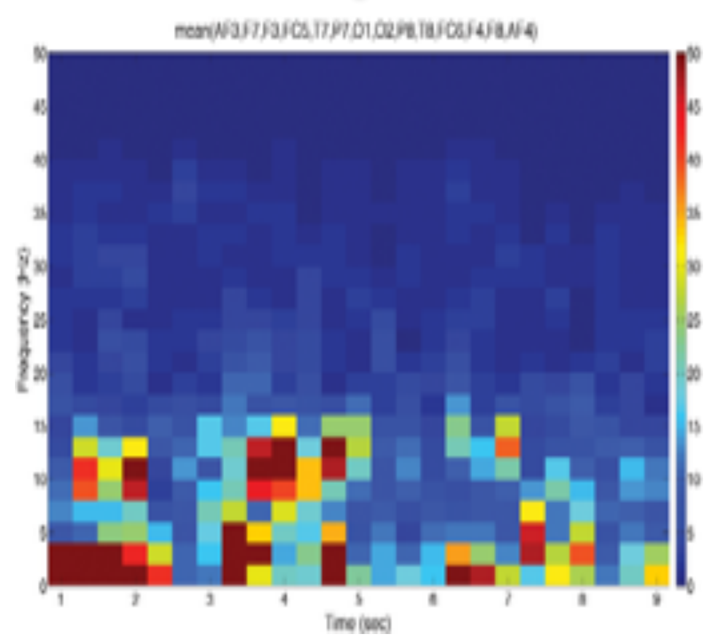


Signal

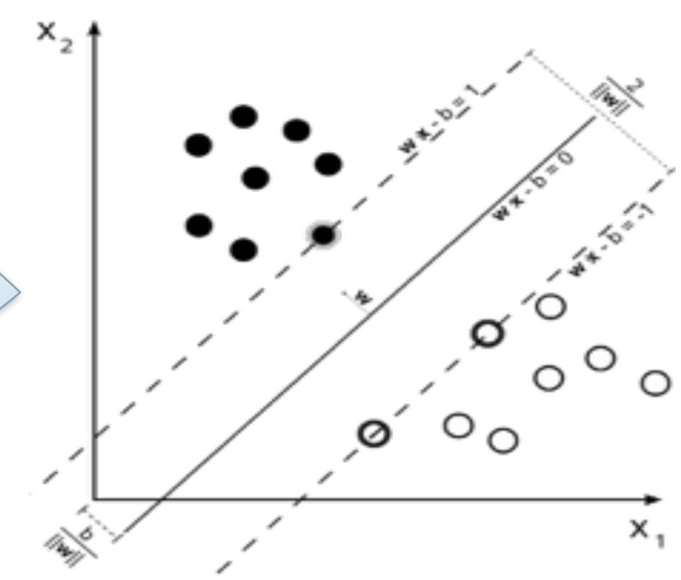
With 87% certainty I can say that you are thinking "LEFT" right now

Mental intention



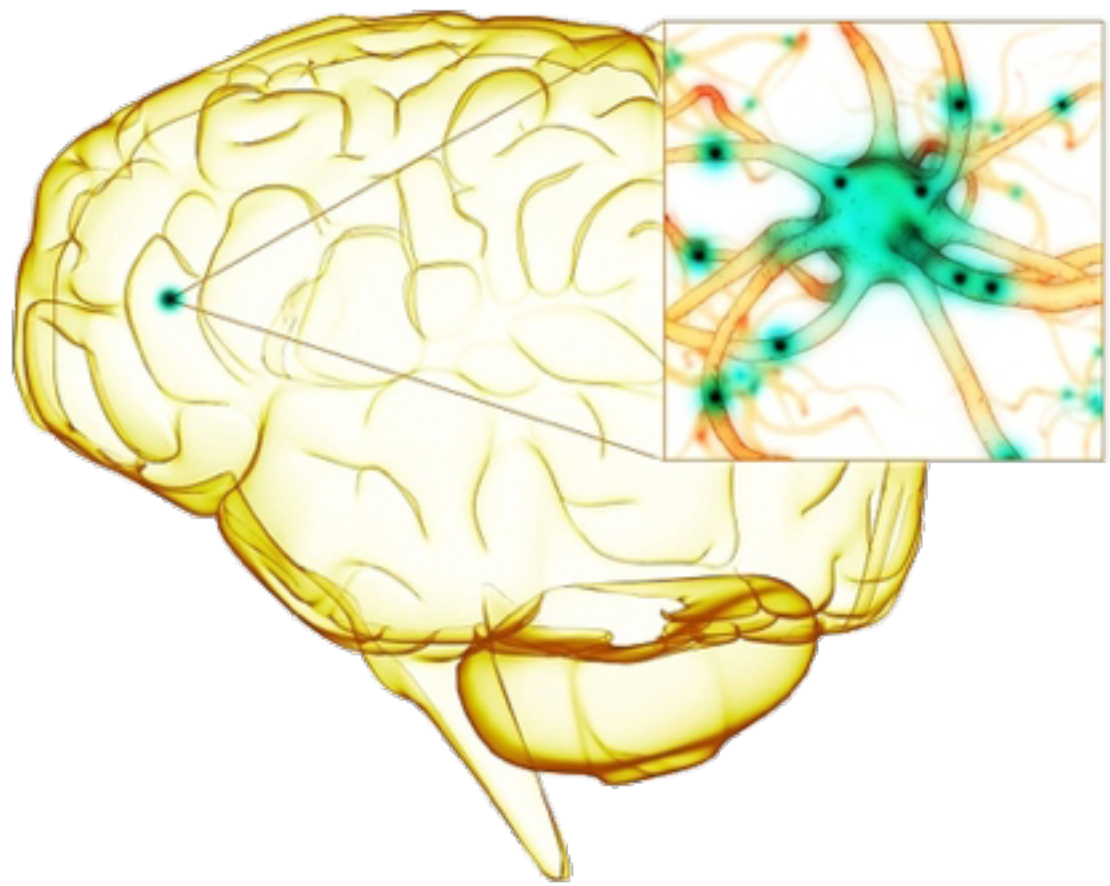


Data



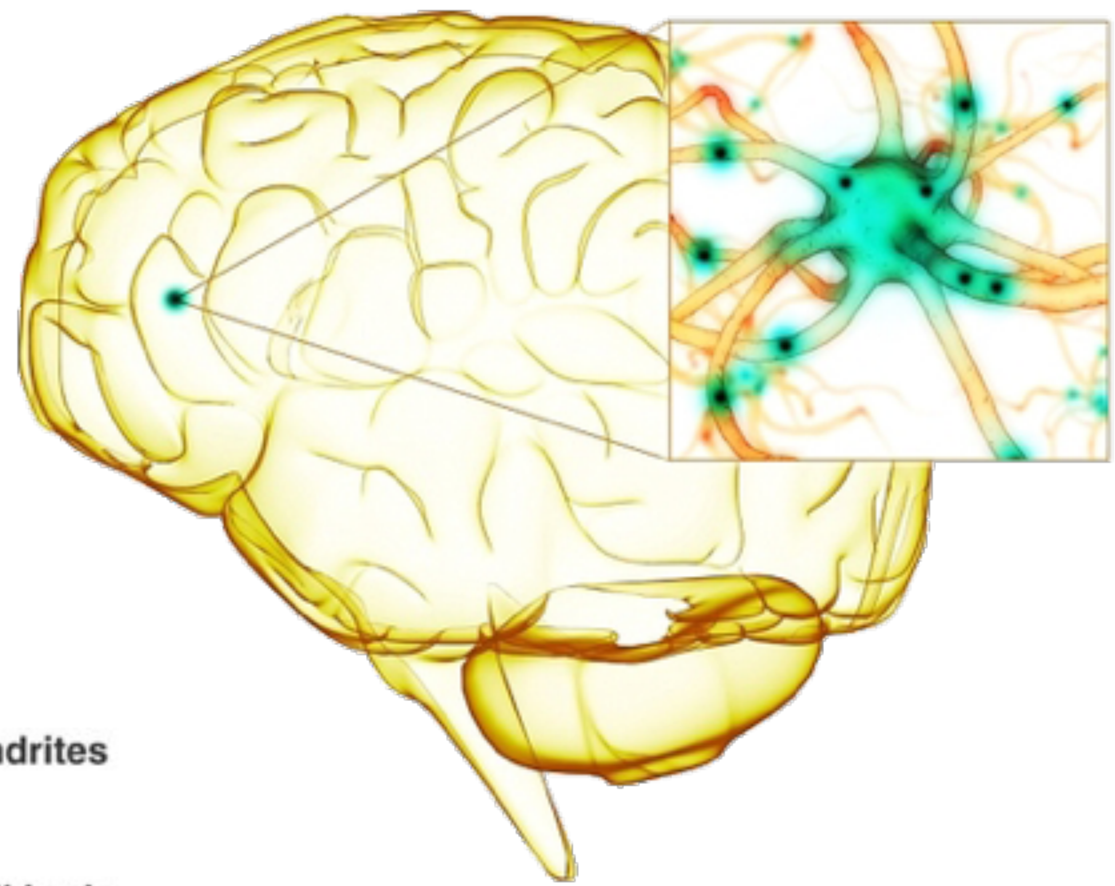
Algorithm

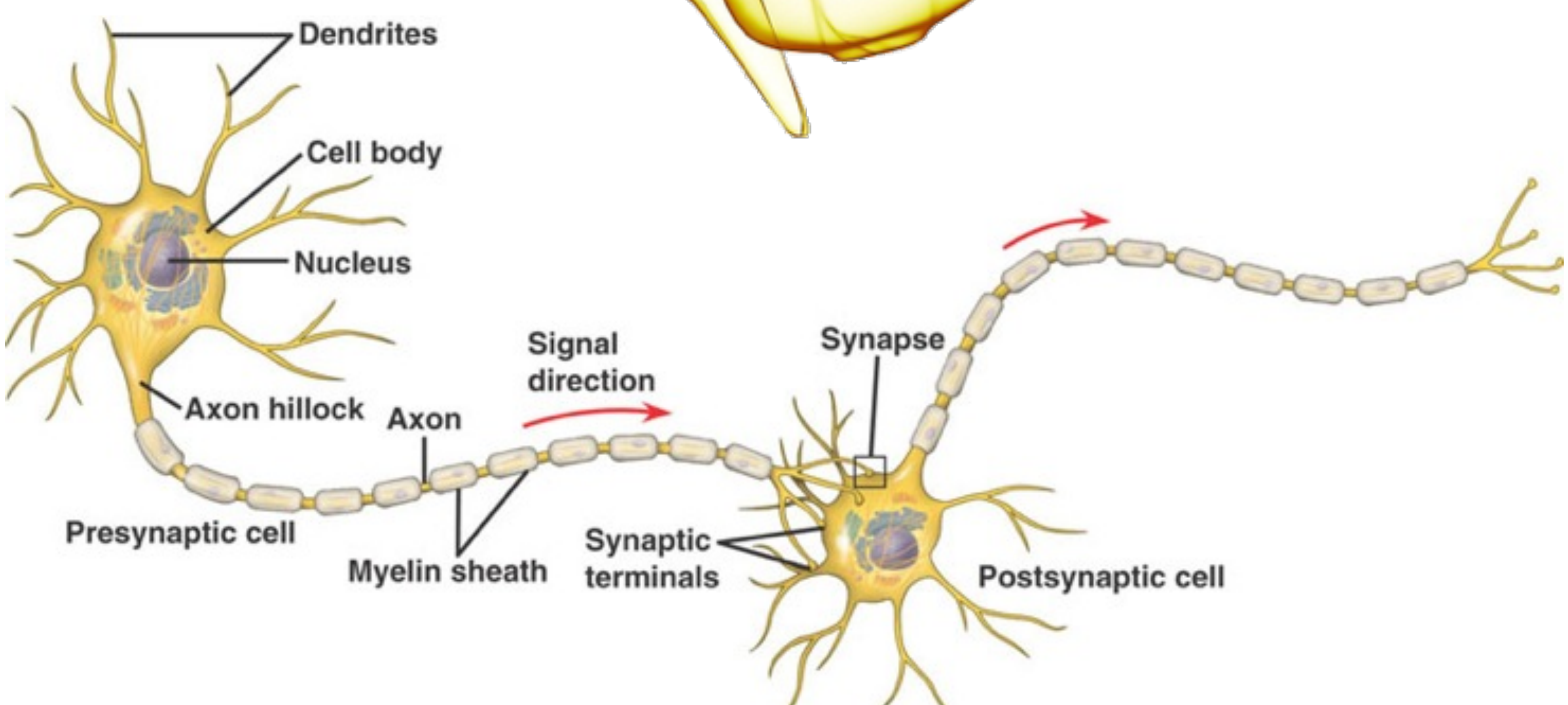
NEURONS



http://biomedicalengineering.yolasite.com

NEURONS





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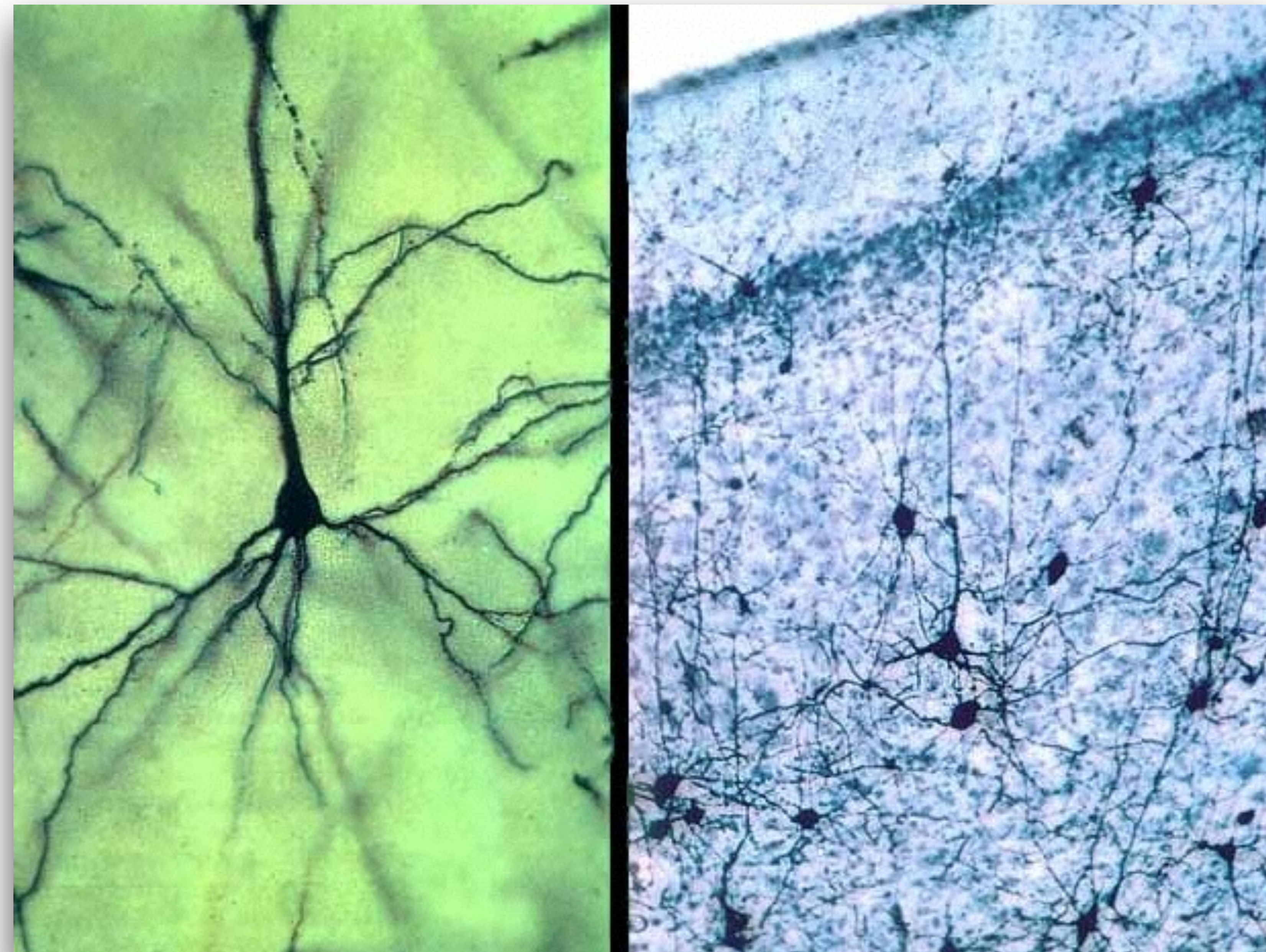
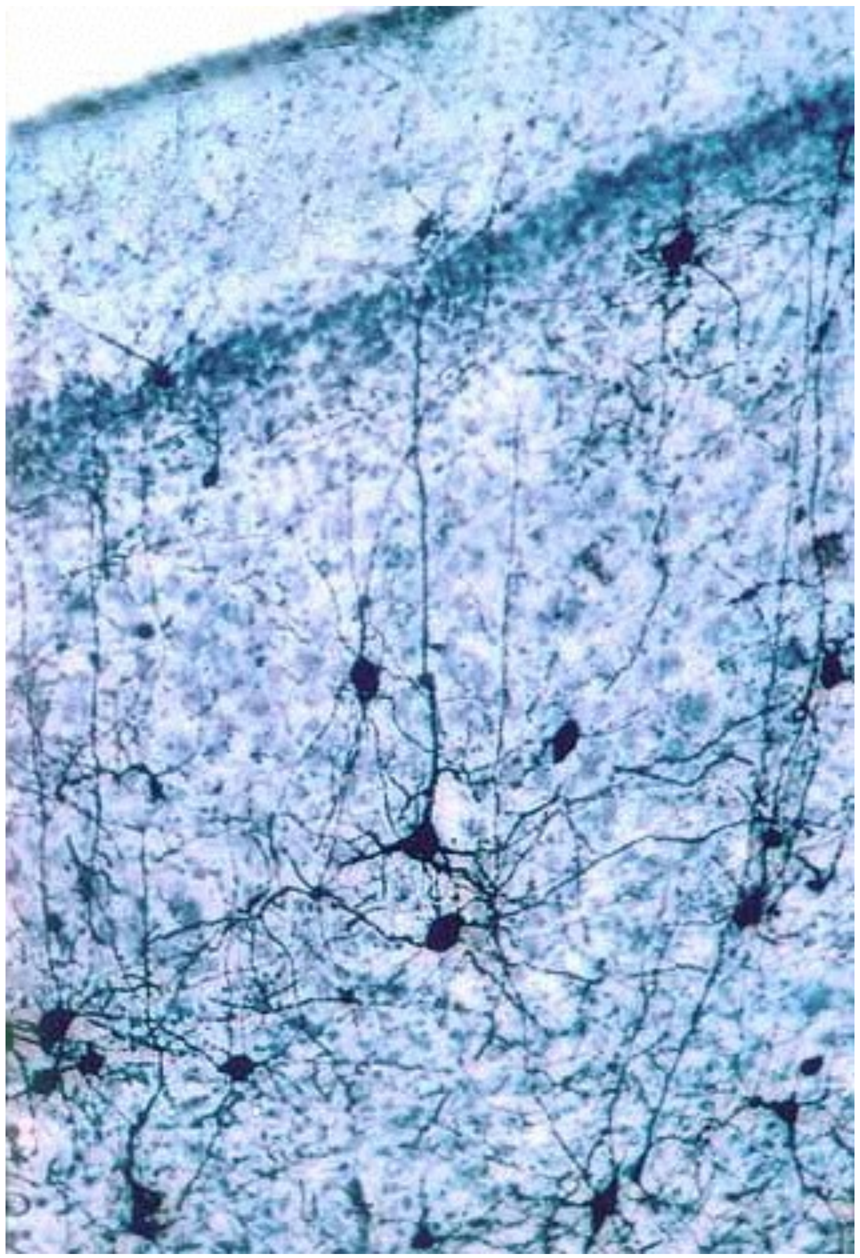
NEURONS



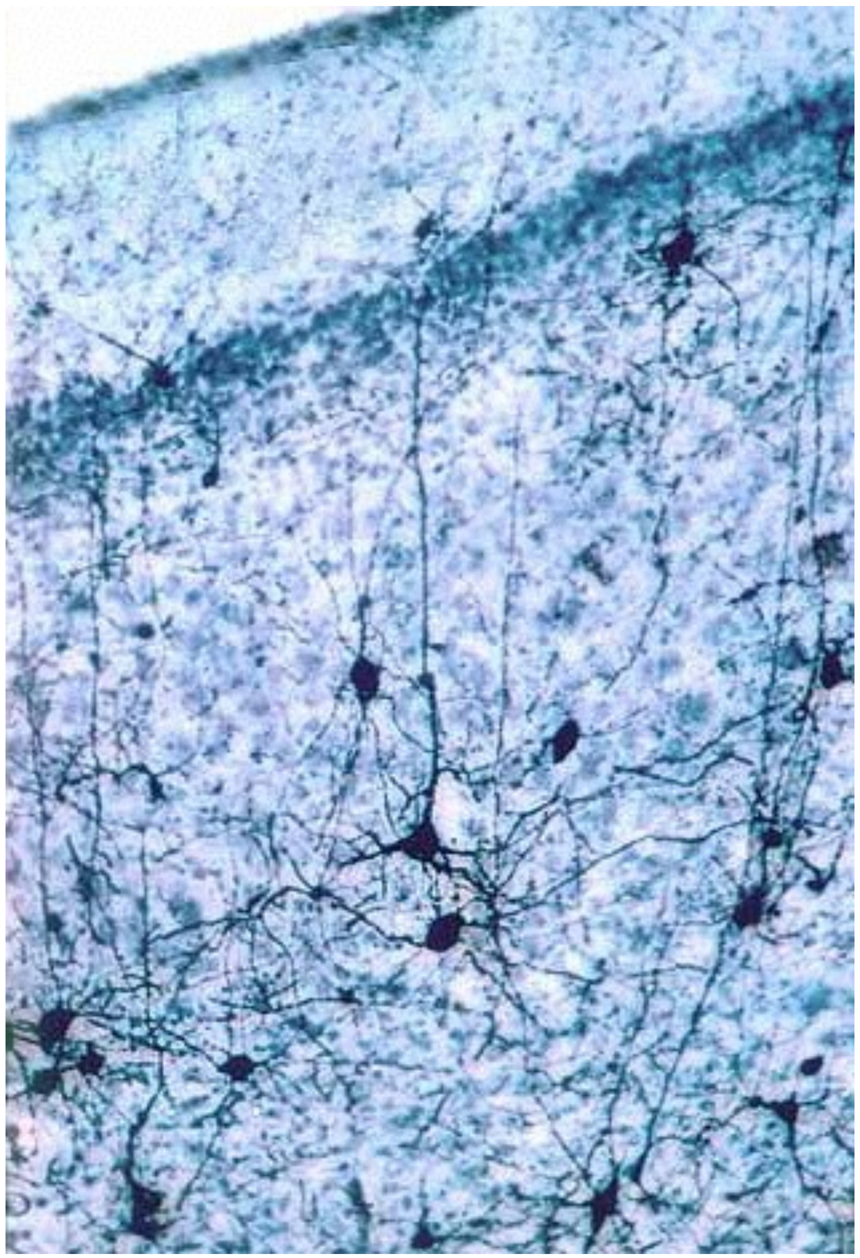
http://www.conncad.com/gallery/single_cells.html

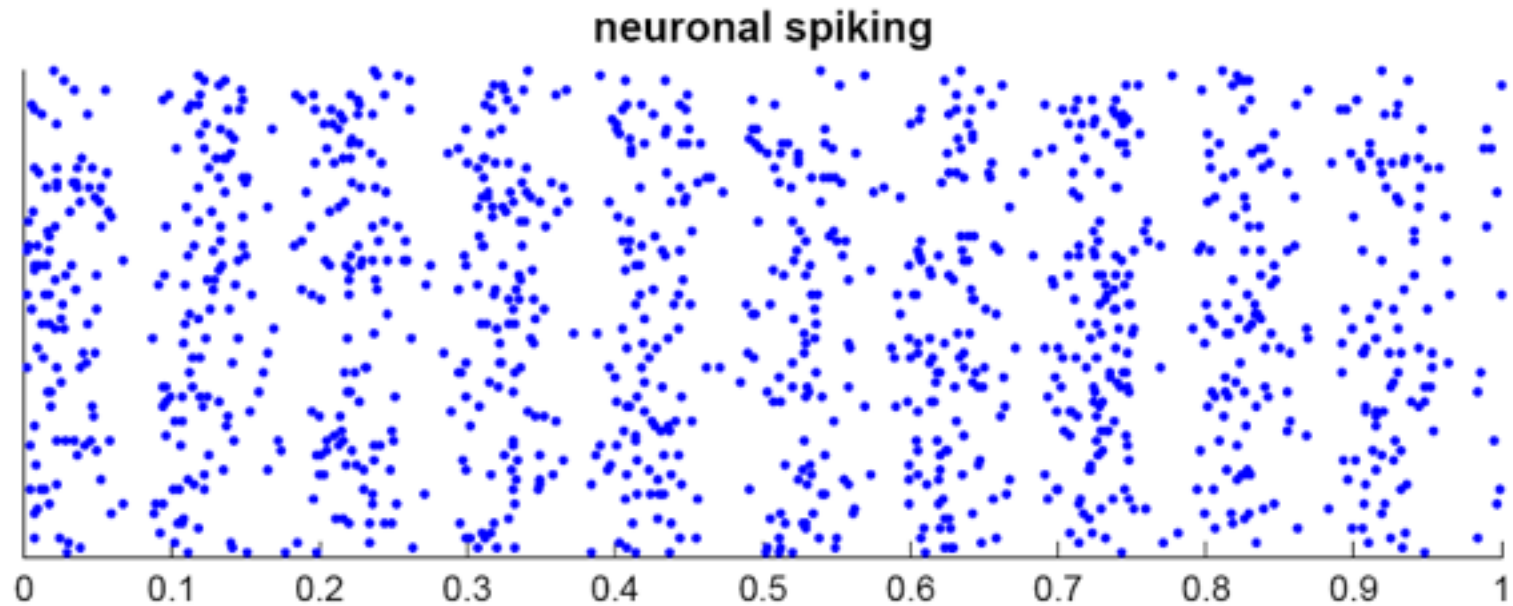
NEURONS



http://en.wikipedia.org/wiki/Neural_oscillation

NEURONS





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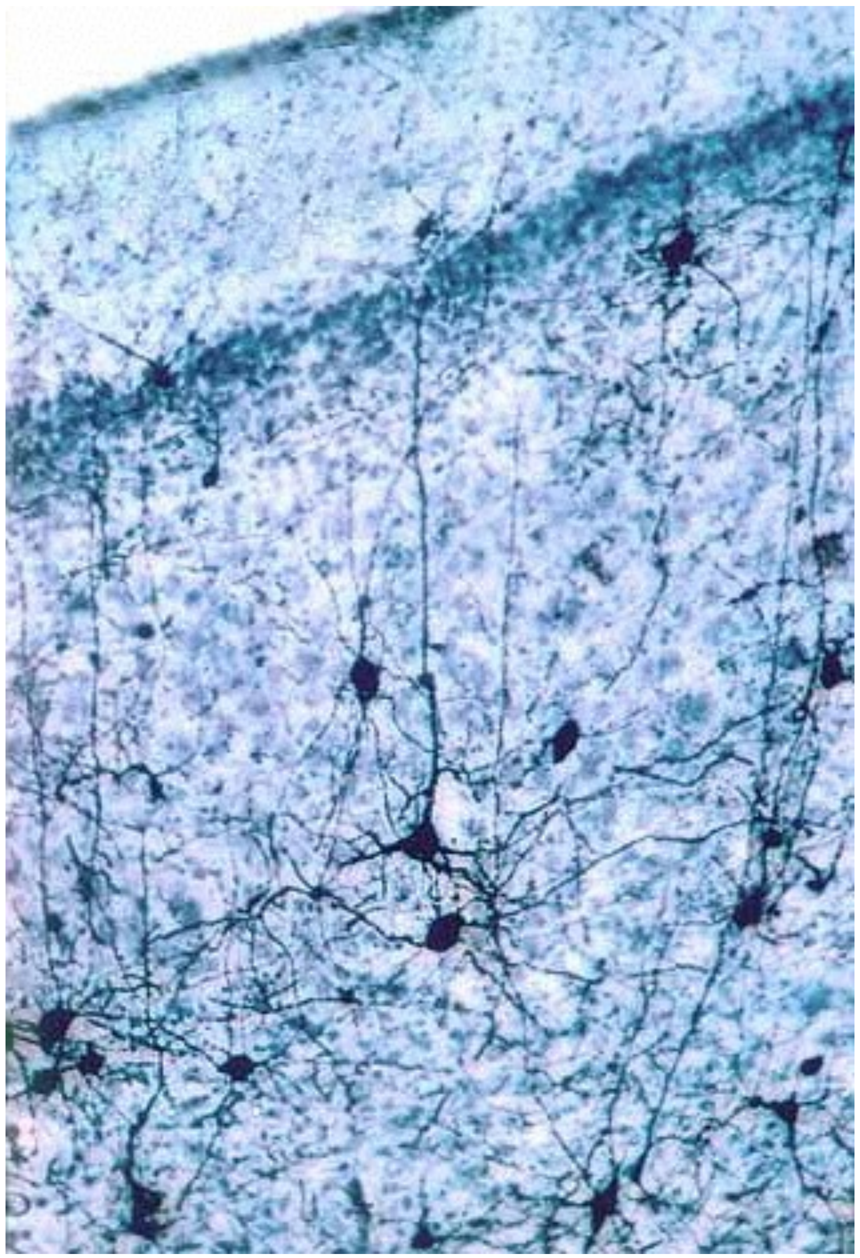
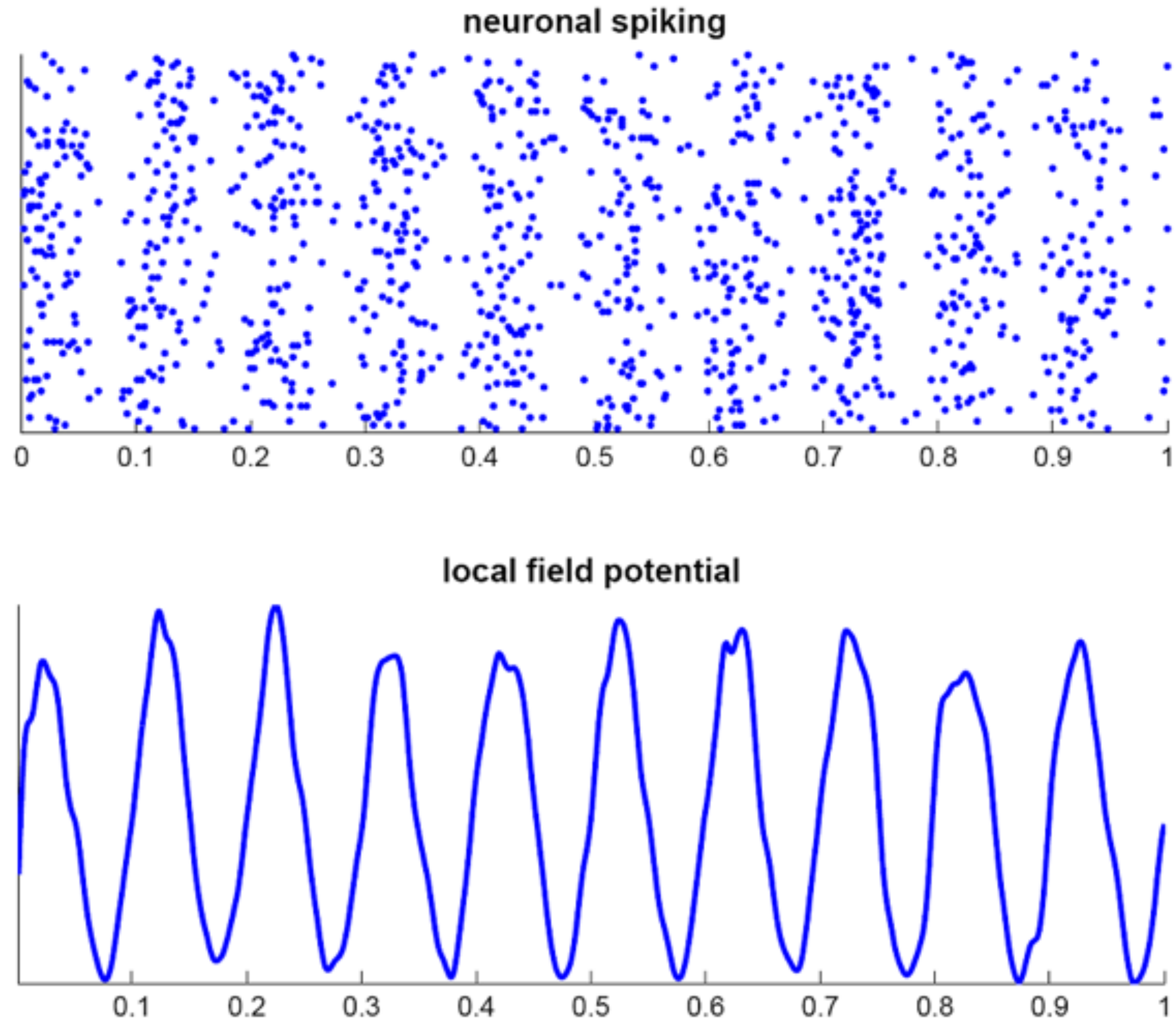
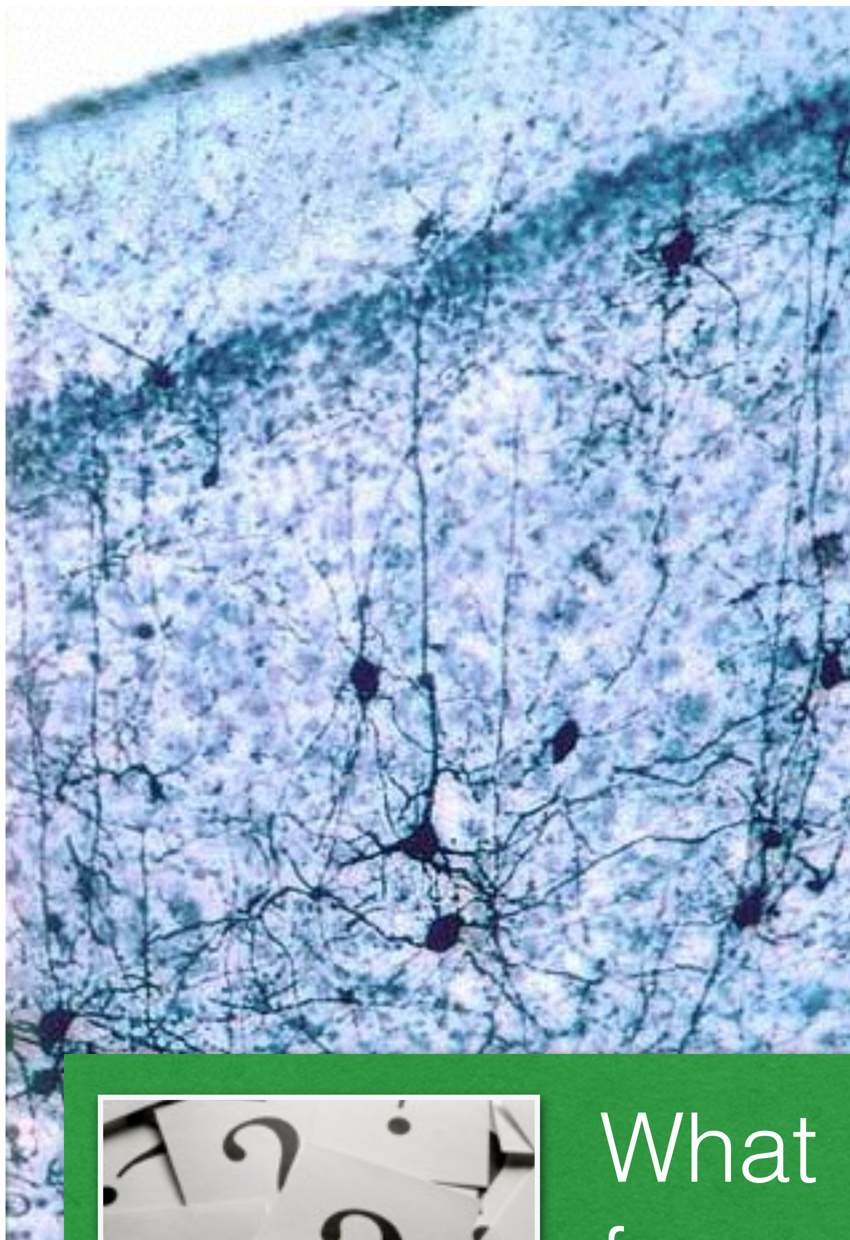
NEURONS

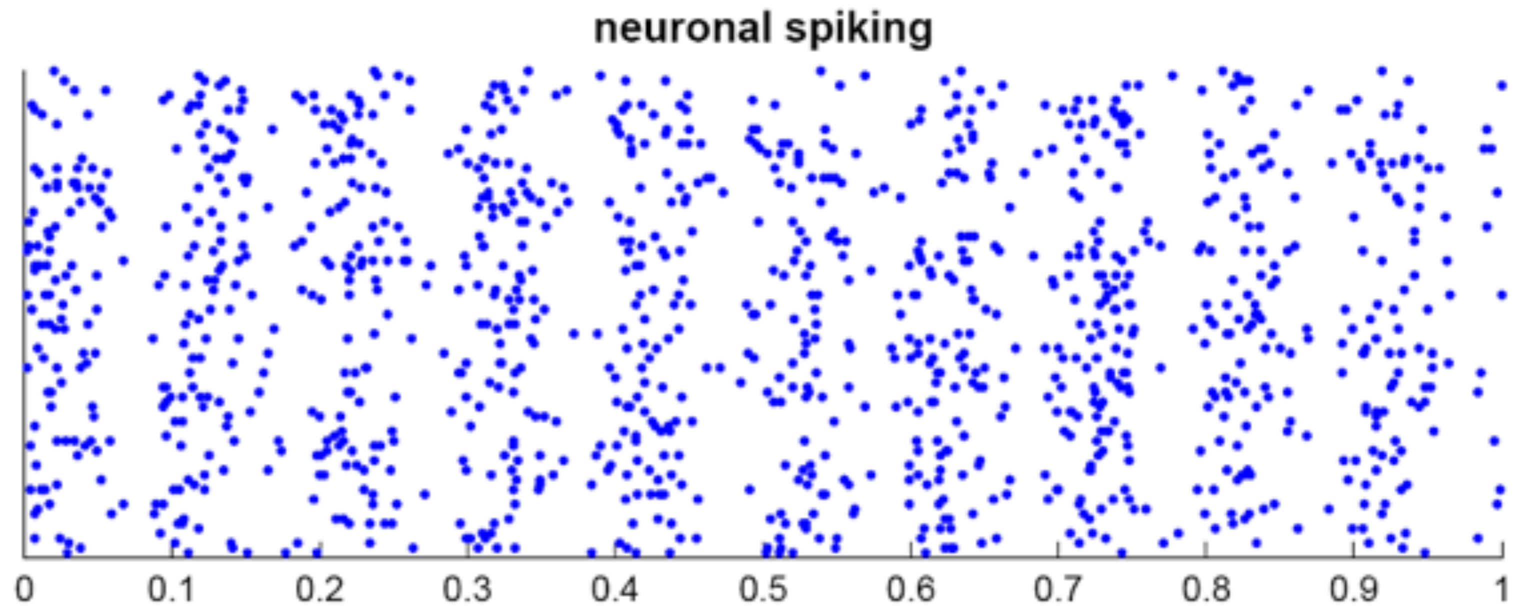


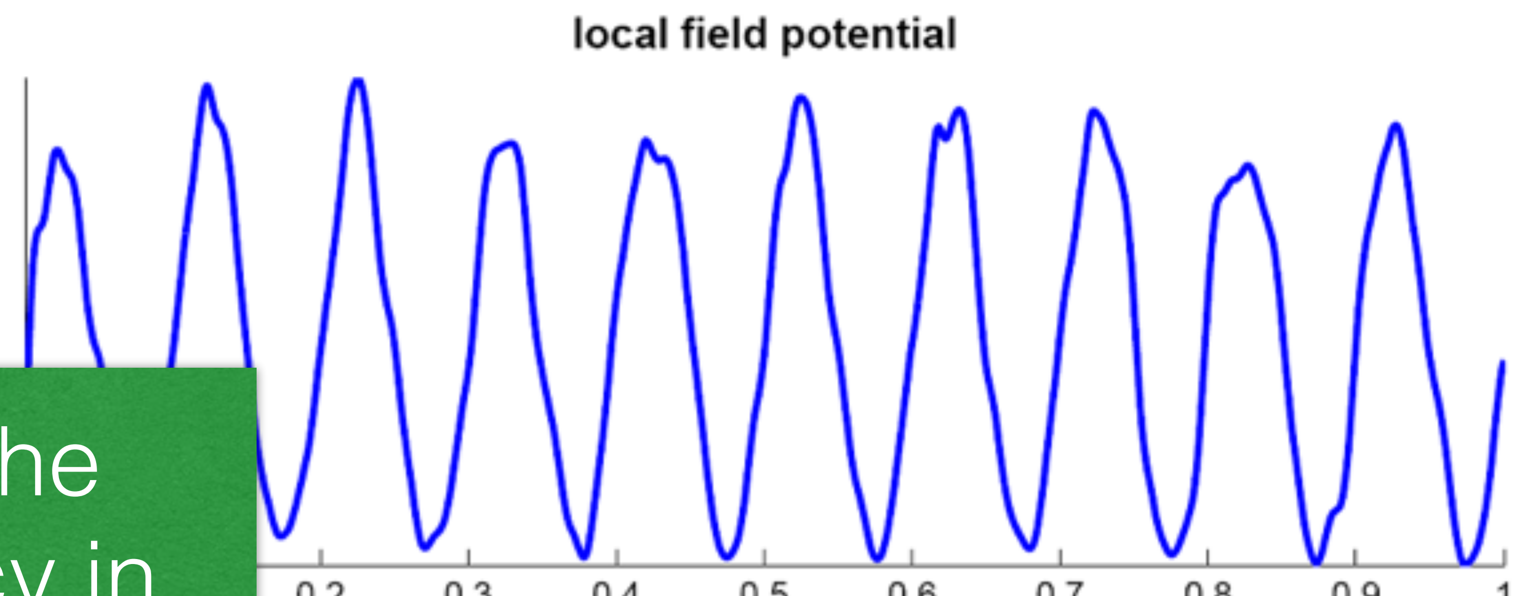


http://en.wikipedia.org/wiki/Neural_oscillation

NEURONS



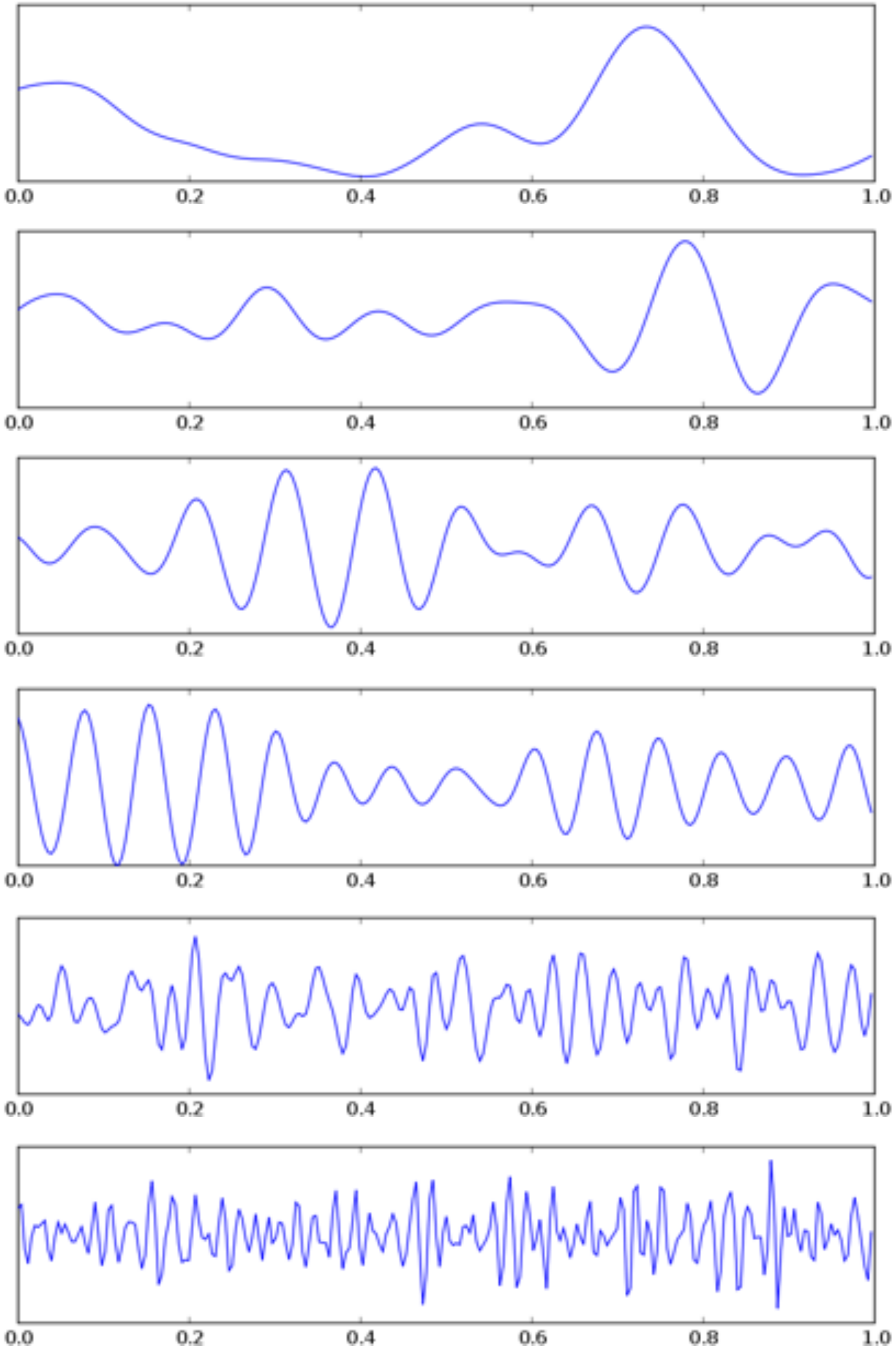




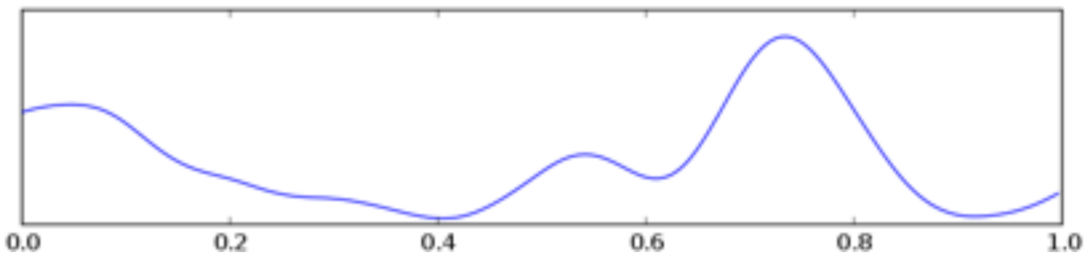
What is the frequency in this example?

http://en.wikipedia.org/wiki/Neural_oscillation

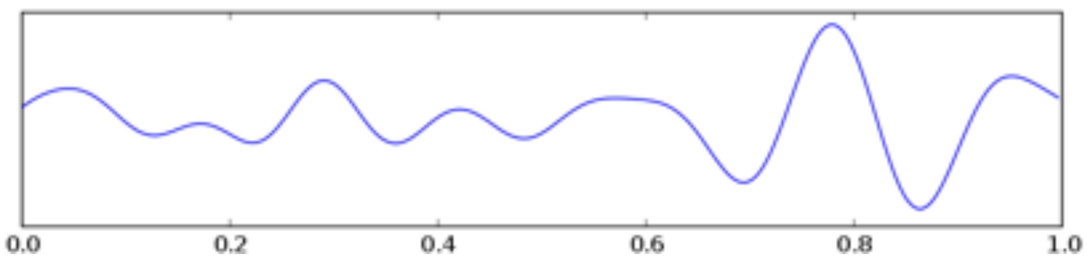
Brainwaves



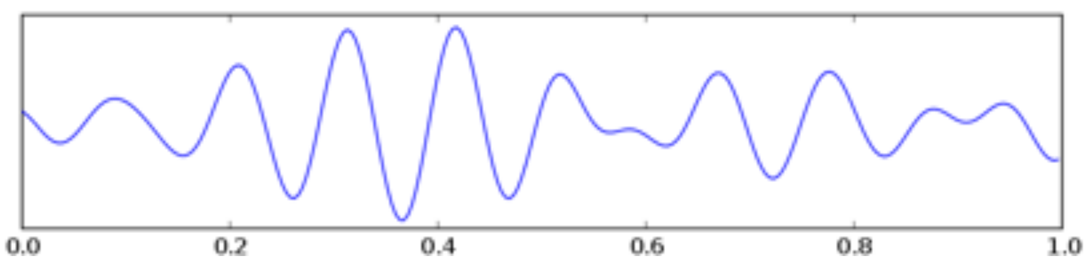
BRAINWAVES



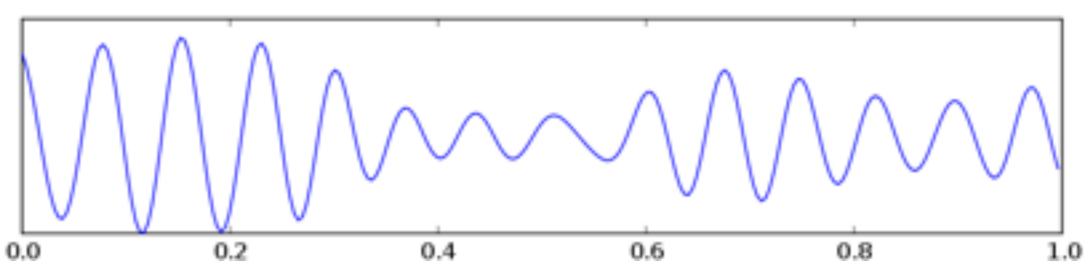
Delta
0-4 Hz



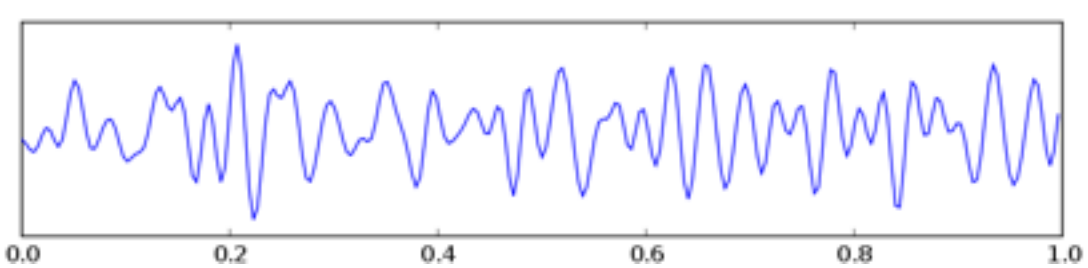
Theta
4-7 Hz



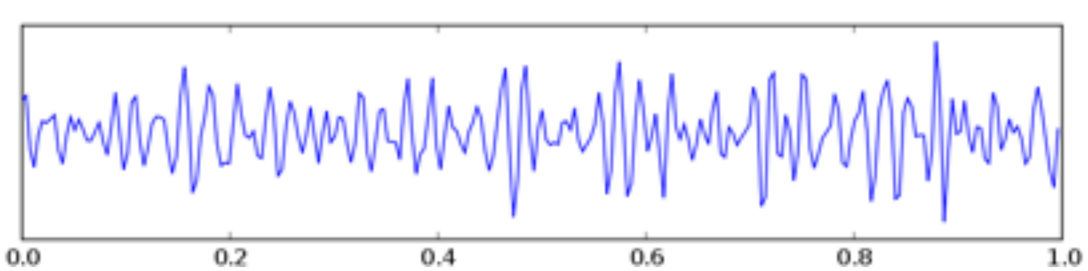
Alpha
7-14 Hz



Mu
8-13 Hz

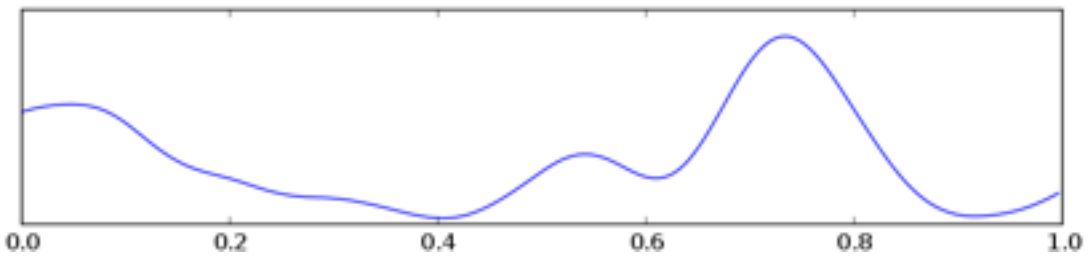


Beta
15-30 Hz



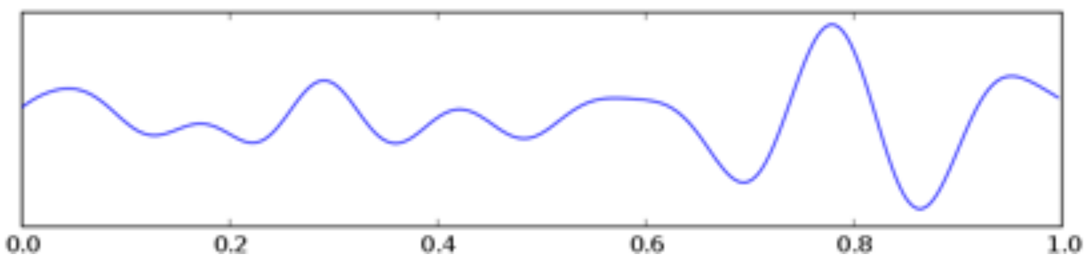
Gamma
30-100 Hz

Brainwaves



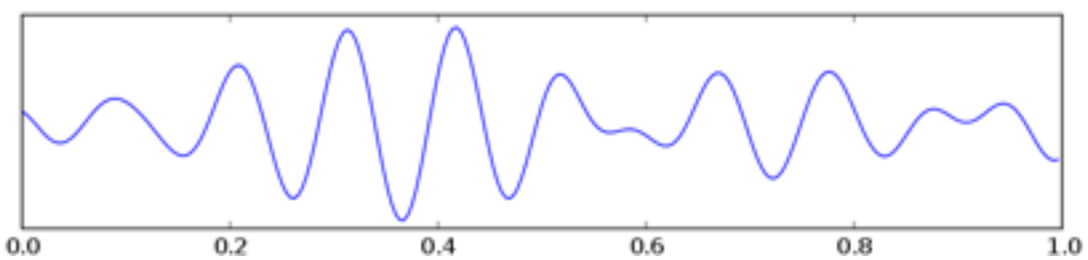
Delta
0-4 Hz

slow wave sleep, babies, lesions



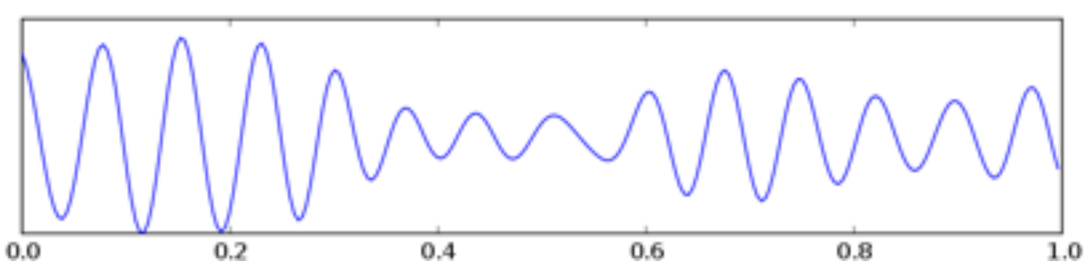
Theta
4-7 Hz

children, drowsiness, meditation, relaxed



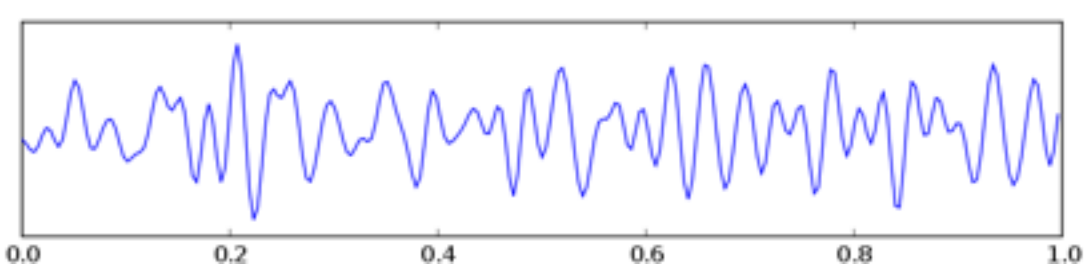
Alpha
7-14 Hz

closed eyes, relaxed



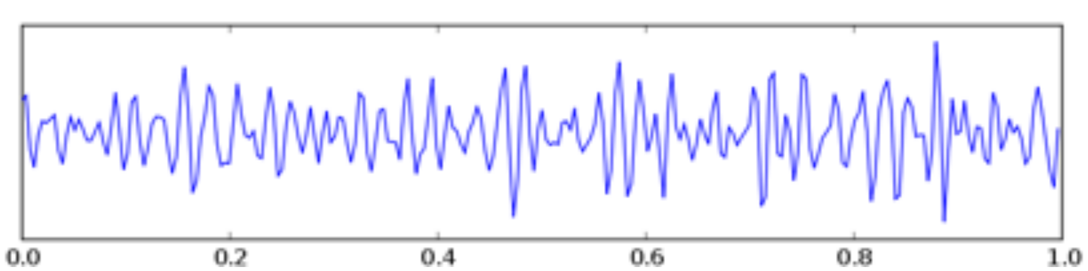
Mu
8-13 Hz

motor neuron in rest, mirror neurons



Beta
15-30 Hz

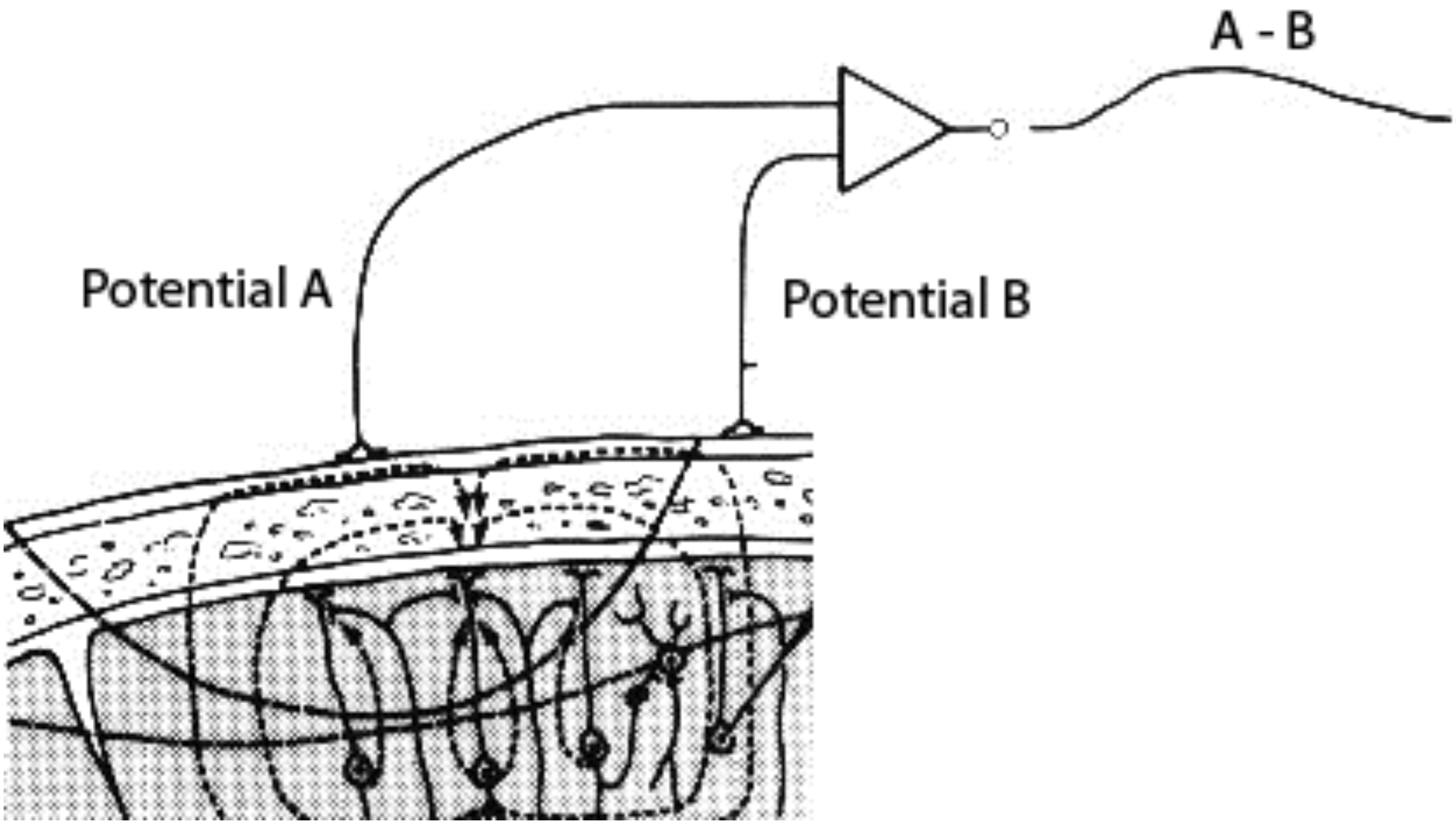
motor activity, anxious thinking, concentration



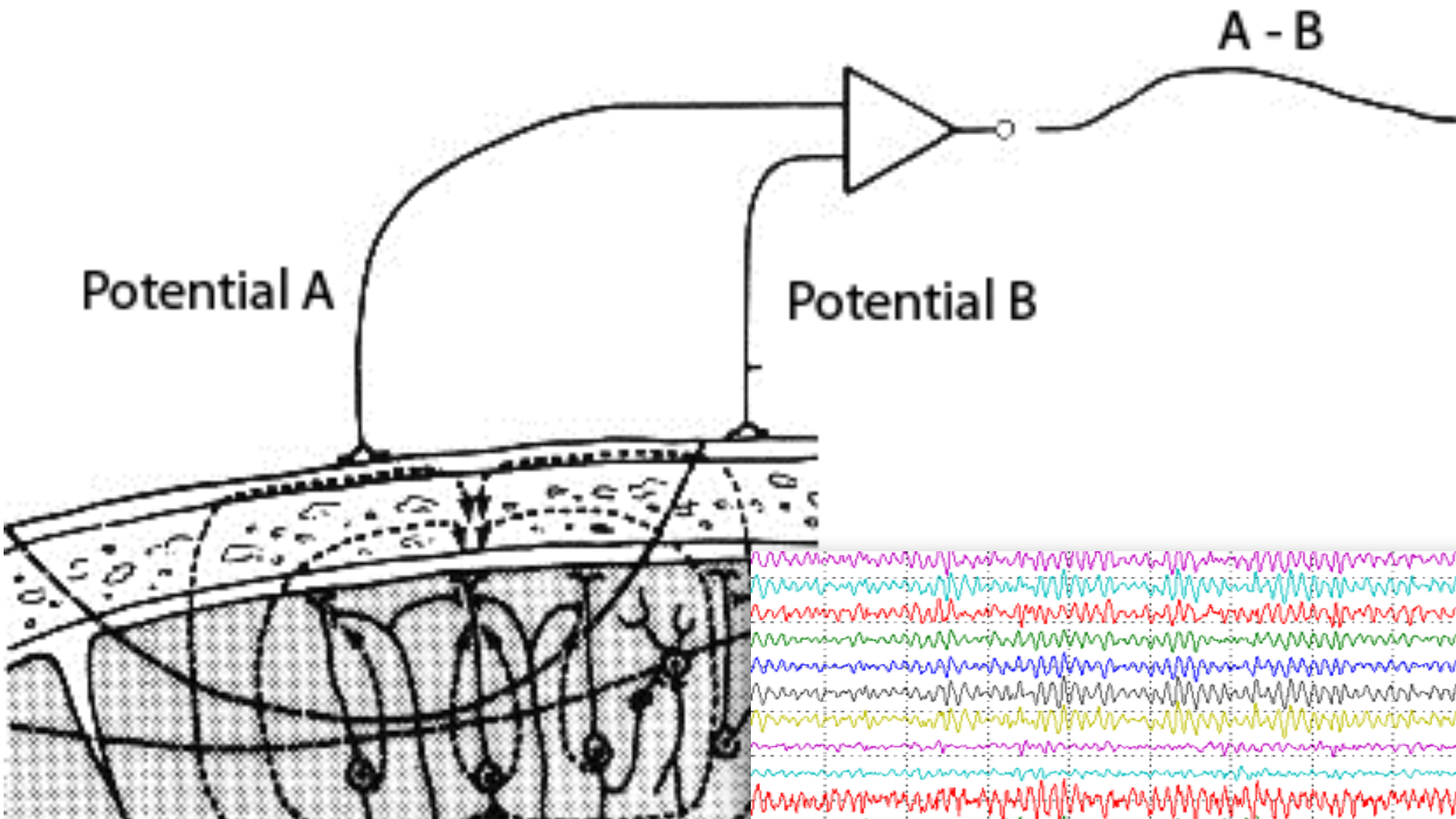
Gamma
30-100 Hz

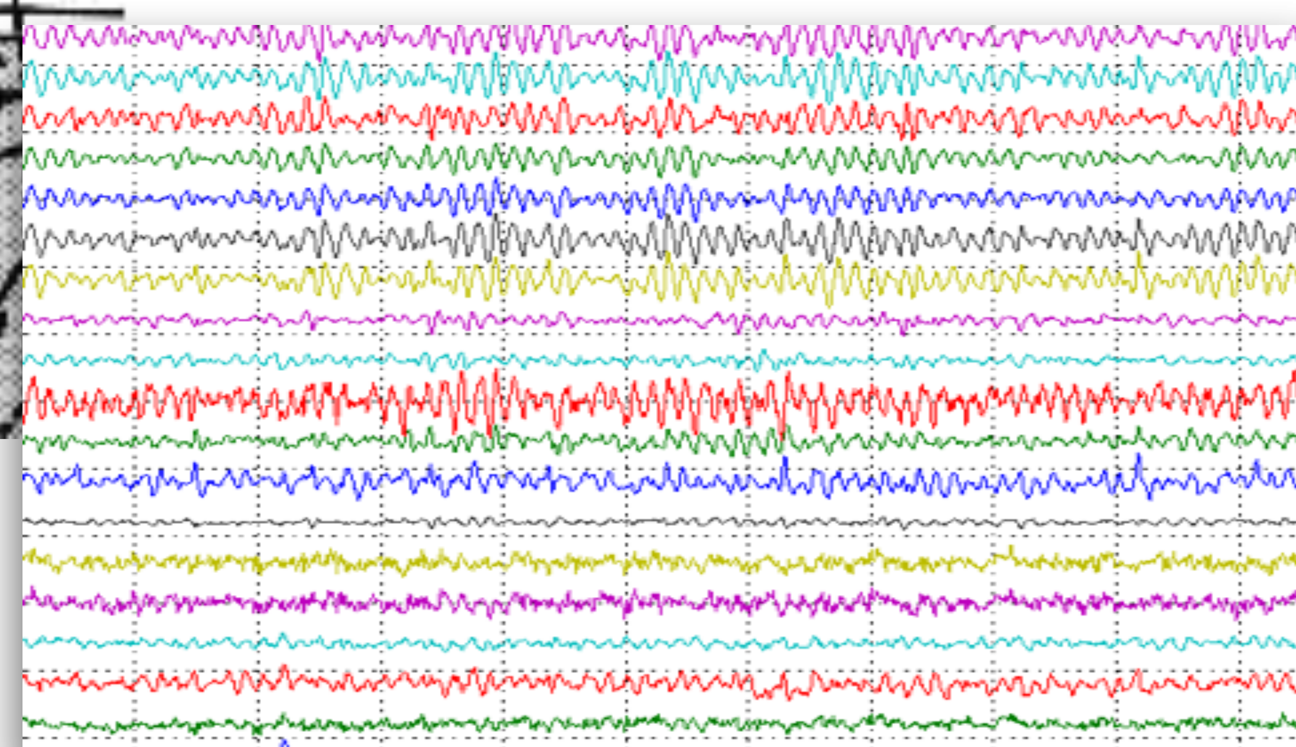
networking between populations of neurons

EEG



EEG





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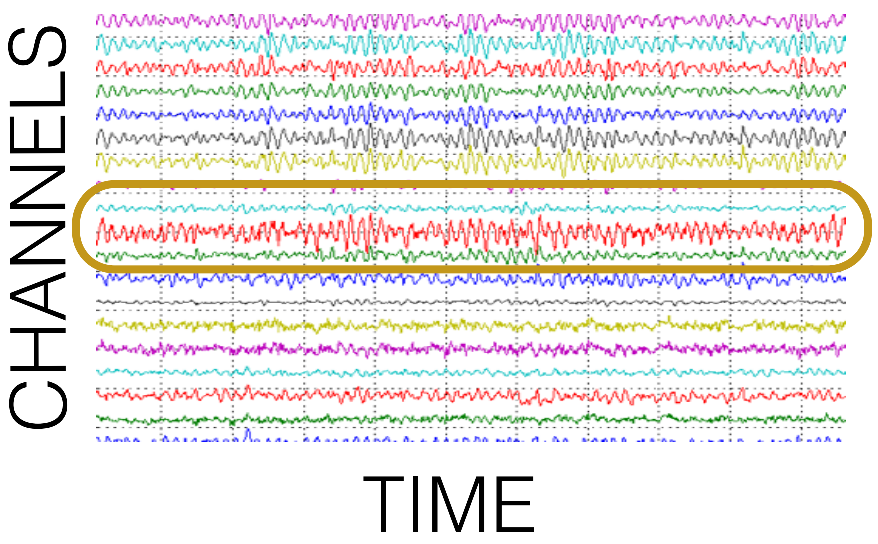
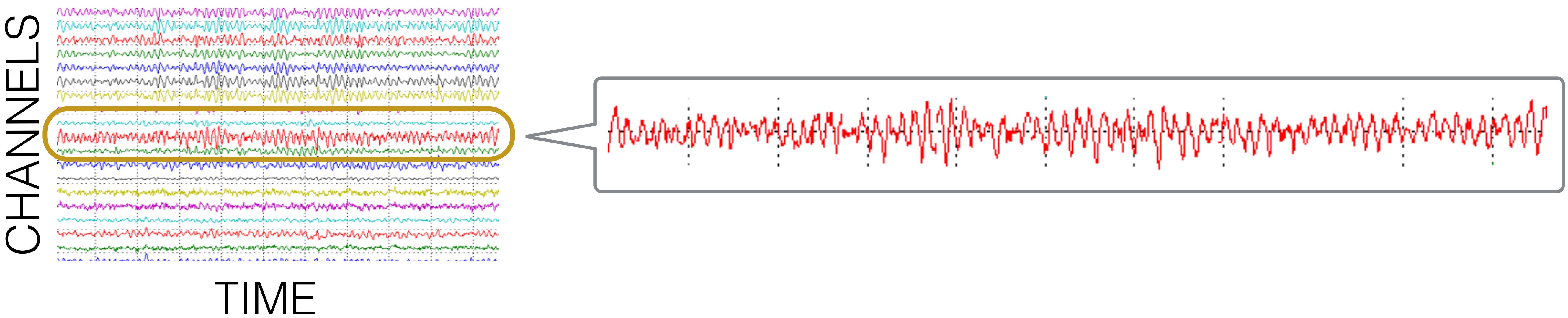
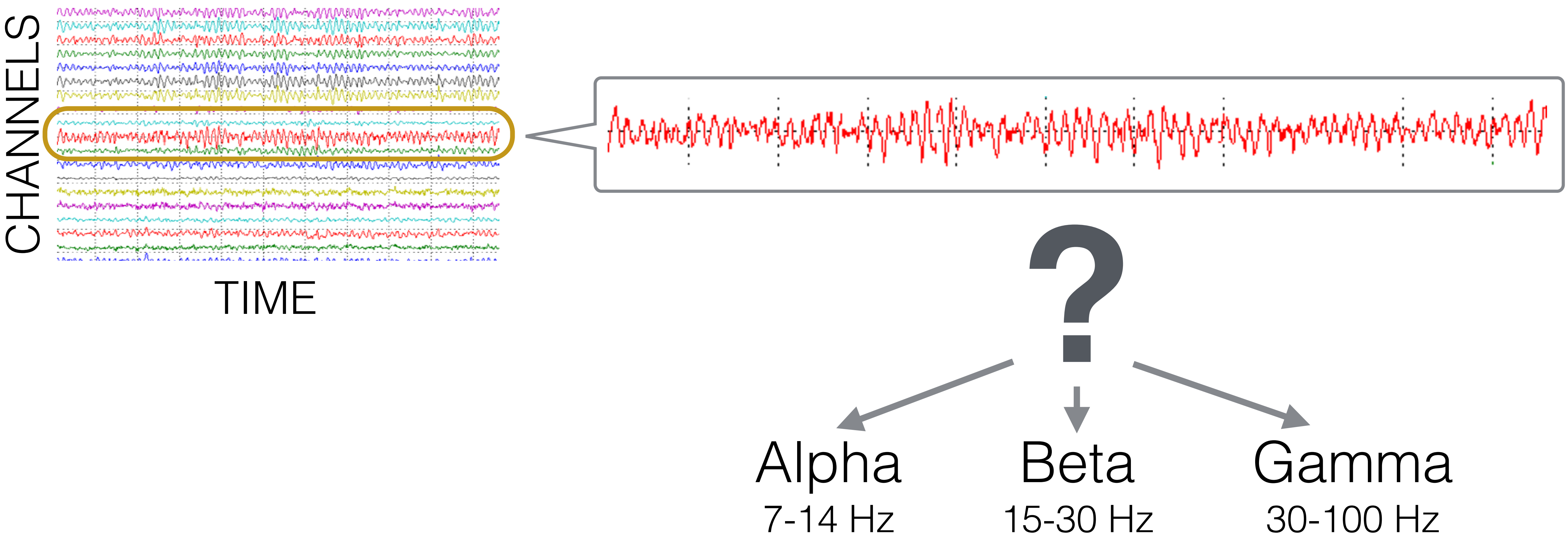
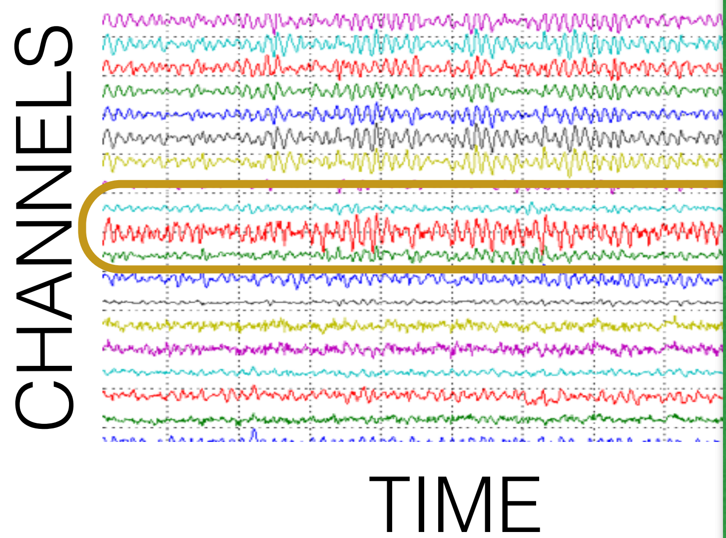


EEG

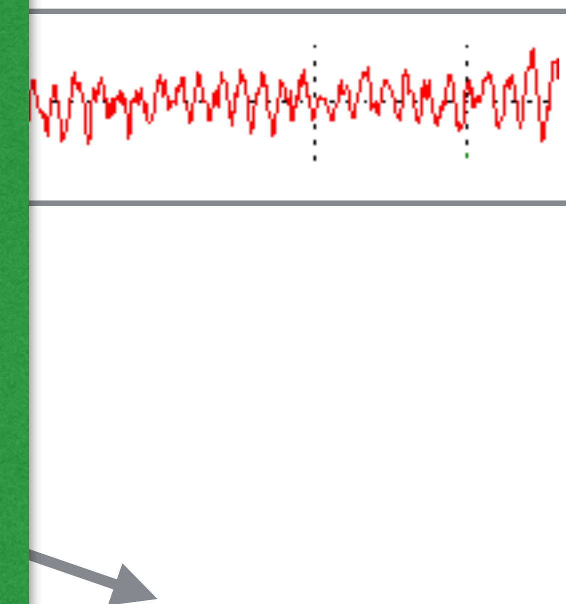


EEG





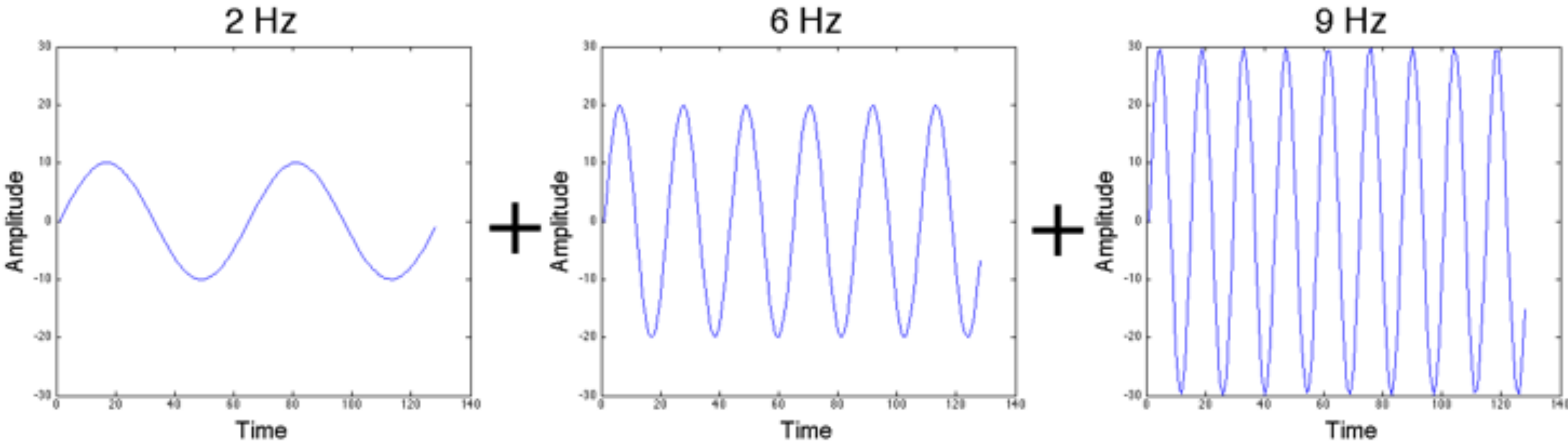
Jean Baptiste Joseph Fourier
1768 — 1830



Gamma
30-100 Hz

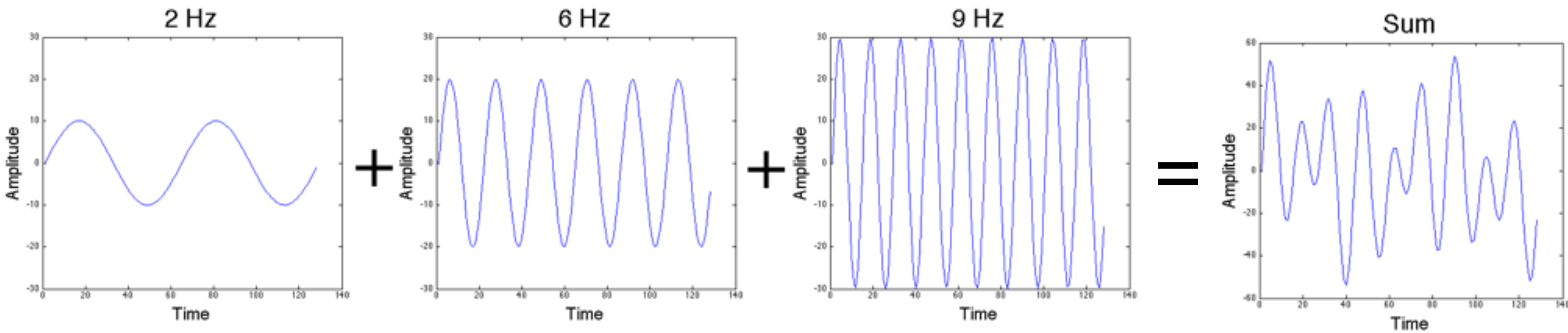
Fourier transform

FOURIER TRANSFORM*



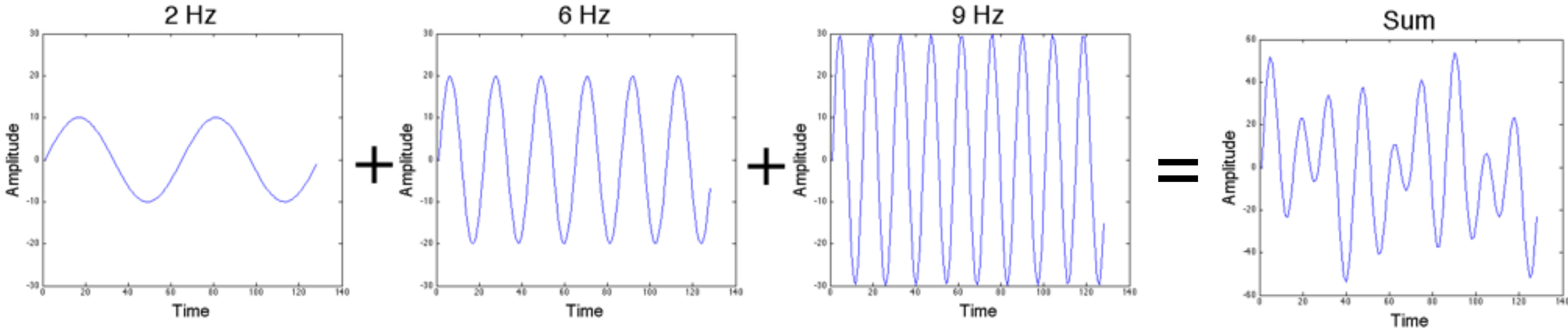
*discrete

Fourier transform*



*discrete

FOURIER TRANSFORM*



$$X_k = \sum_{t=0}^{N-1} x_t e^{-i2\pi k \frac{t}{N}}$$

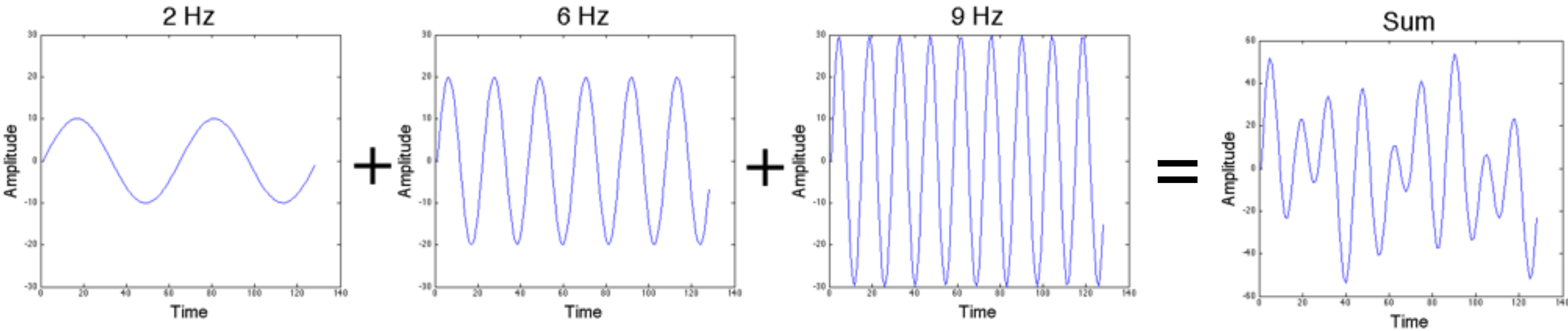
x_t signal at time t

k frequency

X_k complex number

*discrete

FOURIER TRANSFORM*



$$X_k = \sum_{t=0}^{N-1} x_t e^{-i2\pi k \frac{t}{N}}$$

x_t signal at time t

k frequency

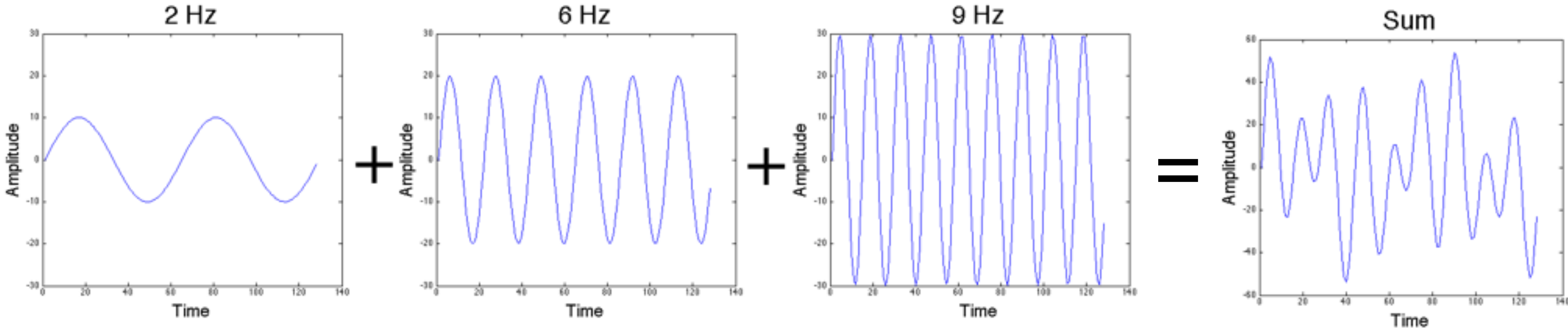
X_k complex number

$$\sqrt{Re(X_k)^2 + Im(X_k)^2}$$

Amplitude of the component with frequency *k*

*discrete

FOURIER TRANSFORM*



$$X_k = \sum_{t=0}^{N-1} x_t e^{-i2\pi k \frac{t}{N}}$$

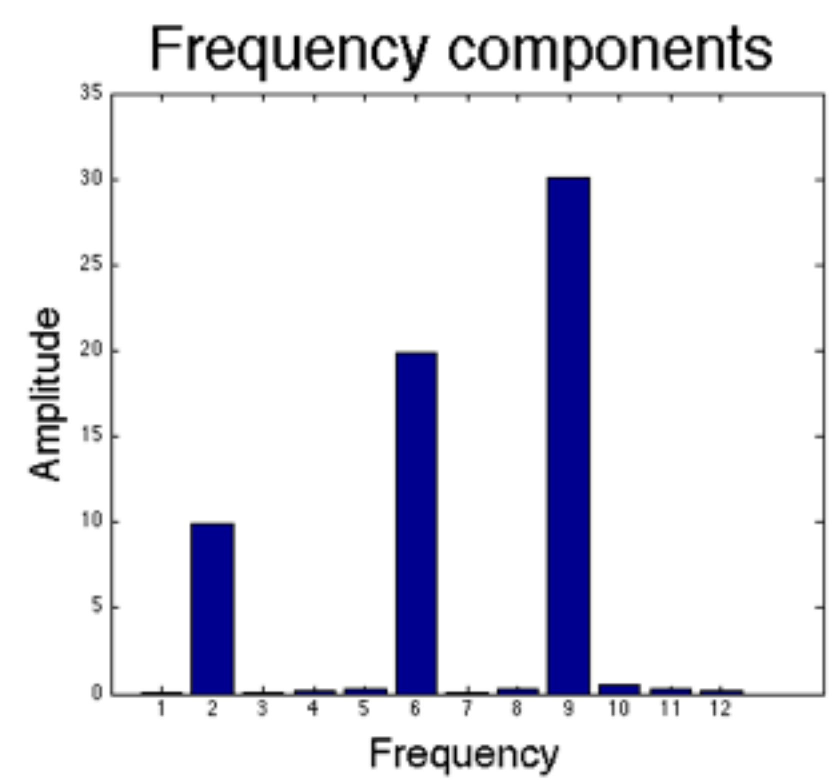
x_t signal at time t

$\boldsymbol{k}$ frequency

X_k complex number

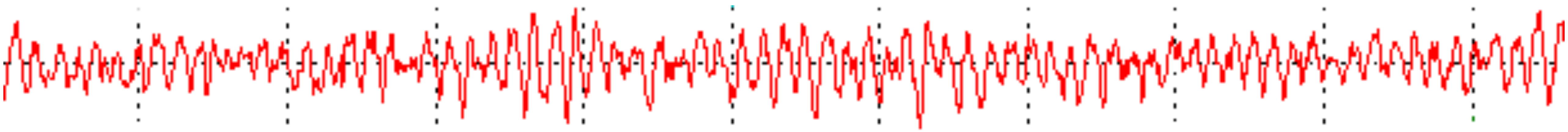
$$\sqrt{Re(X_k)^2 + Im(X_k)^2}$$

Amplitude of the component with frequency *k*



*discrete

DATA



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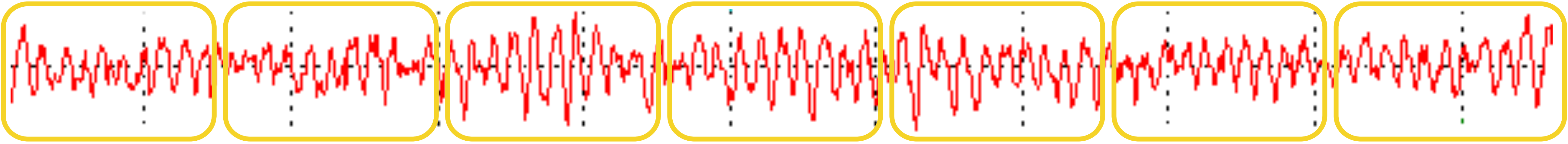
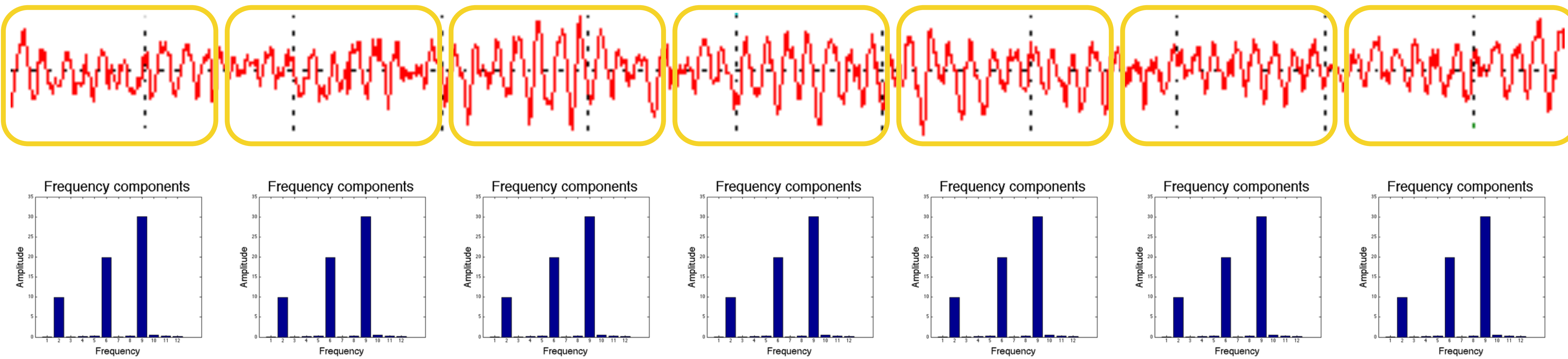


DATA



Frequency components
Amplitude
Frequency
Frequency components
Amplitude
Frequency
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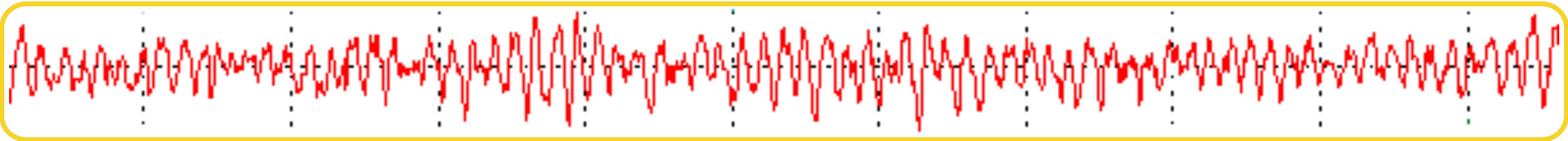
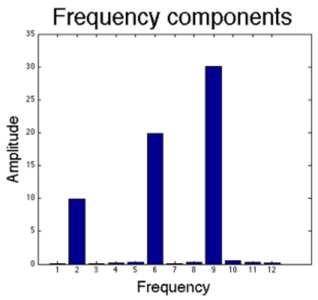
Amplitude
Frequency

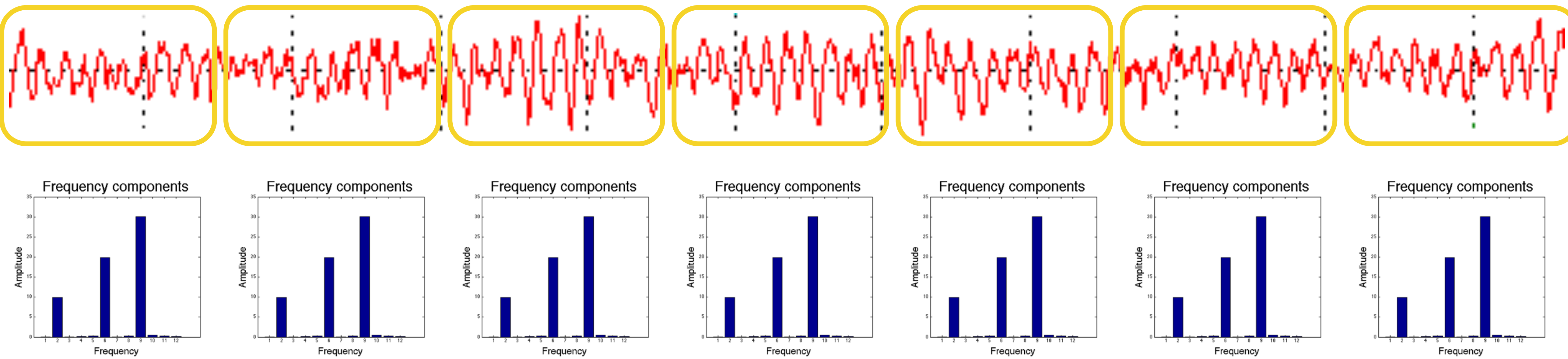
DATA





Why not like this?

Data


Frequency components
Amplitude
Frequency
Frequency components
Amplitude
Frequency
Frequency components
Amplitude
Frequency
Frequency components
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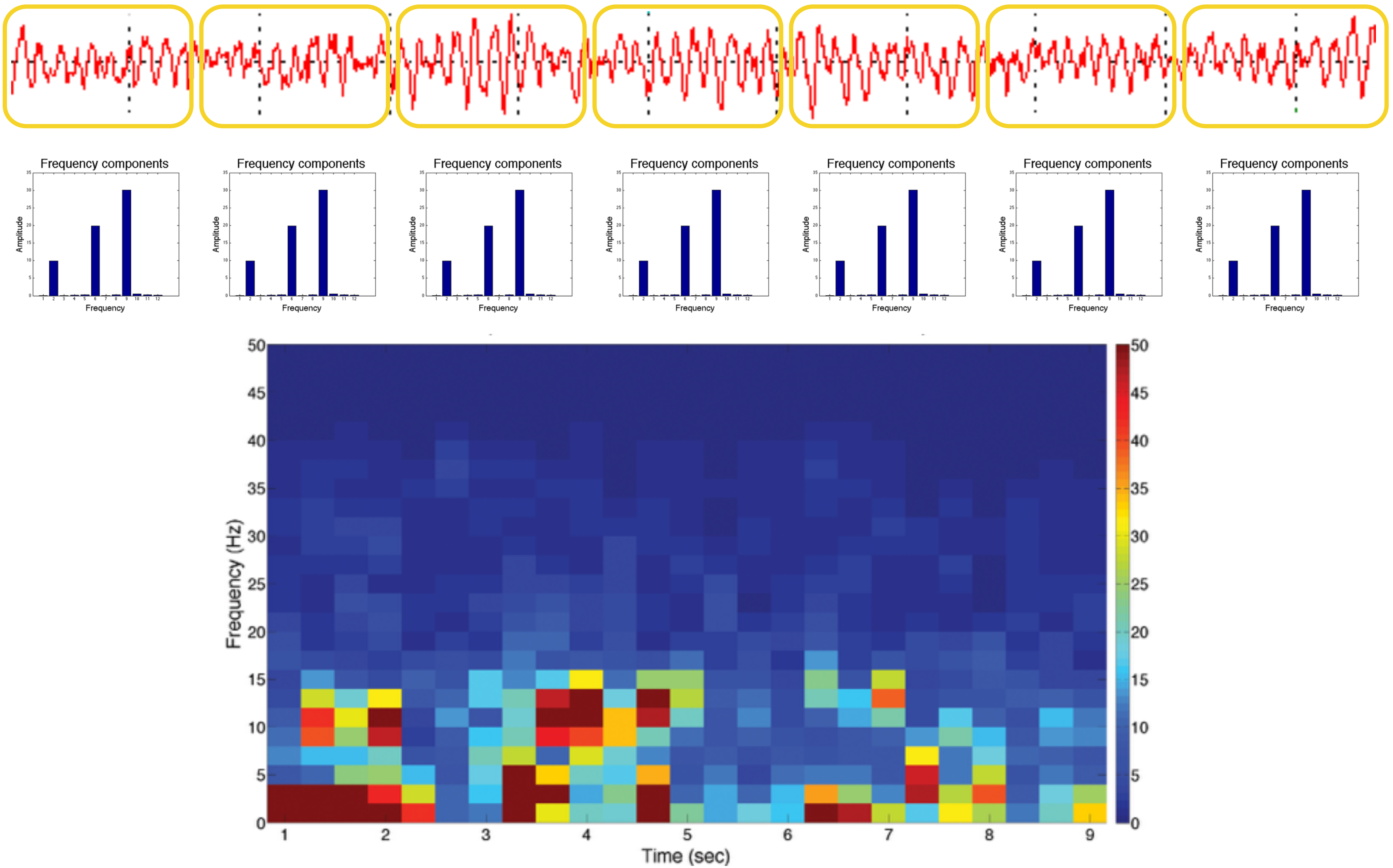
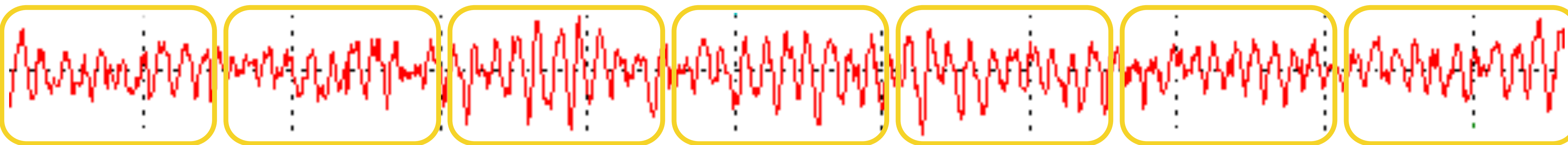
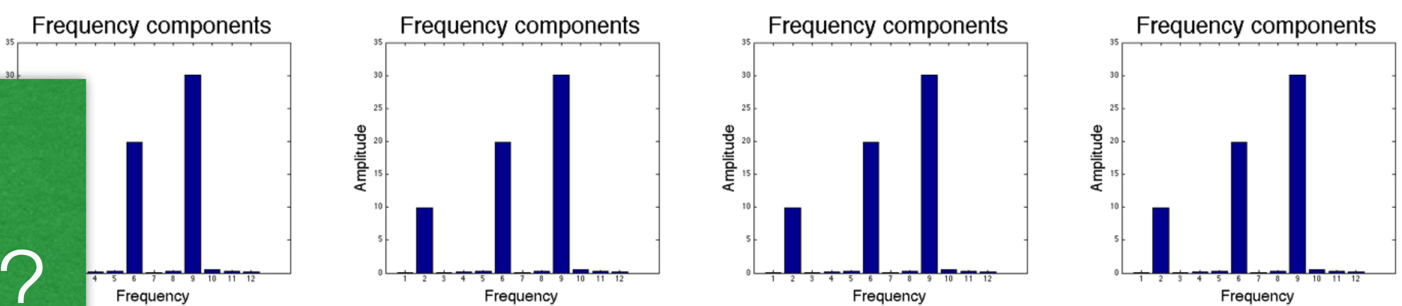
Frequency components
Amplitude
Frequency
Frequency components
Amplitude
Frequency
Frequency components
Amplitude
Frequency

TIME-FREQUENCY DOMAIN

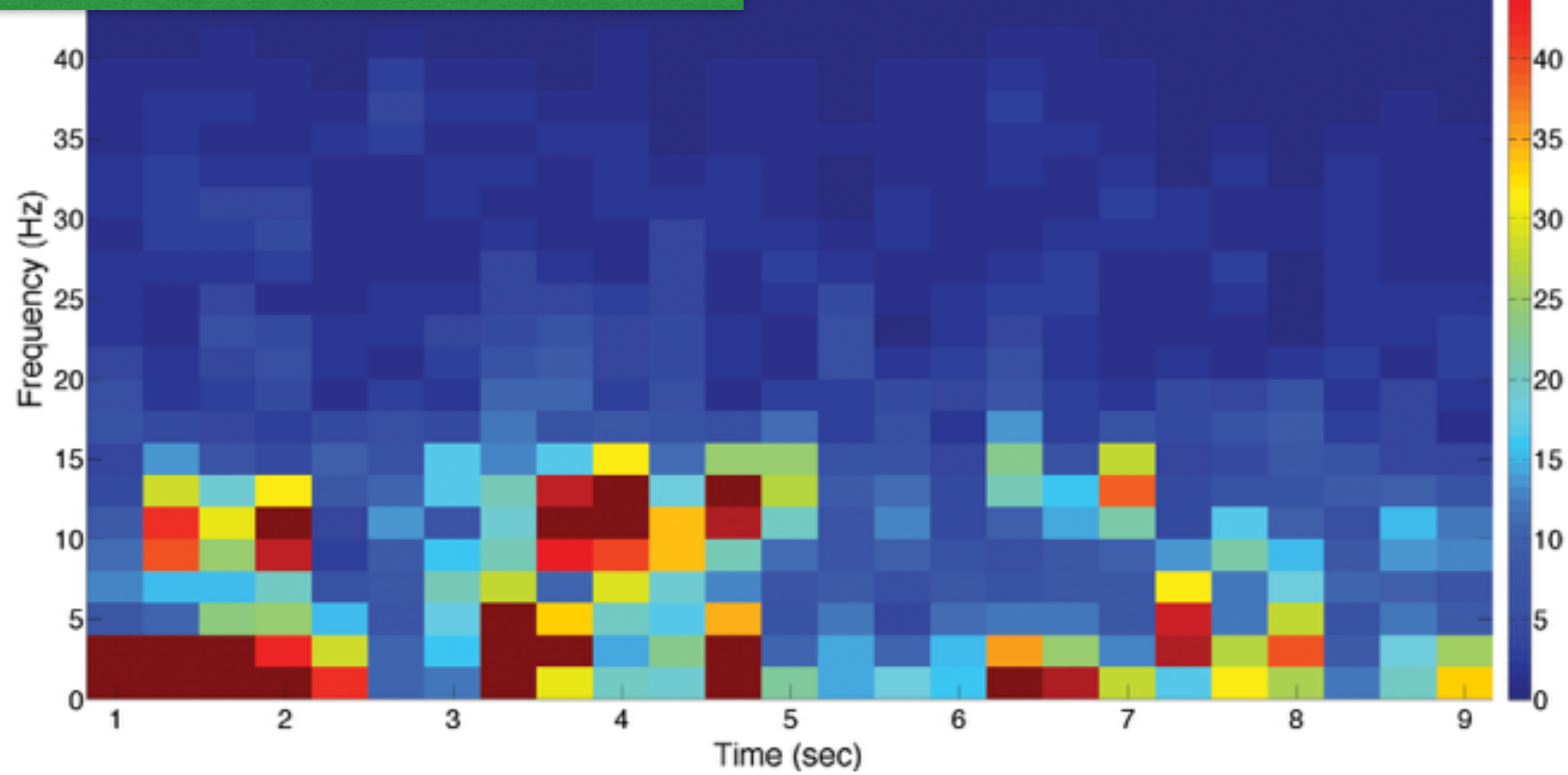


DATA

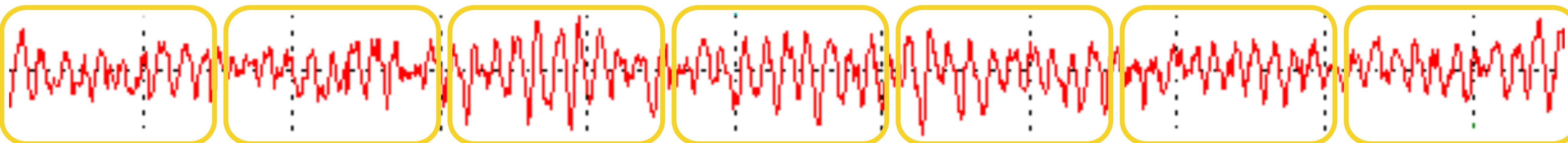


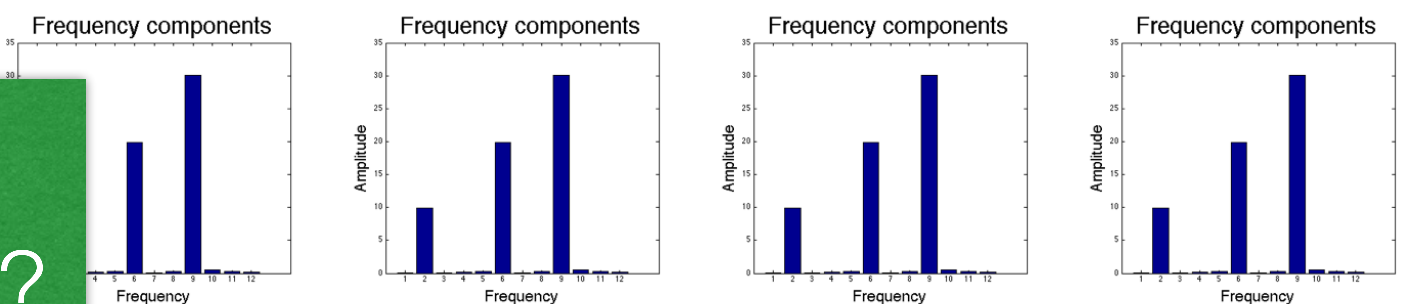


Are we done?



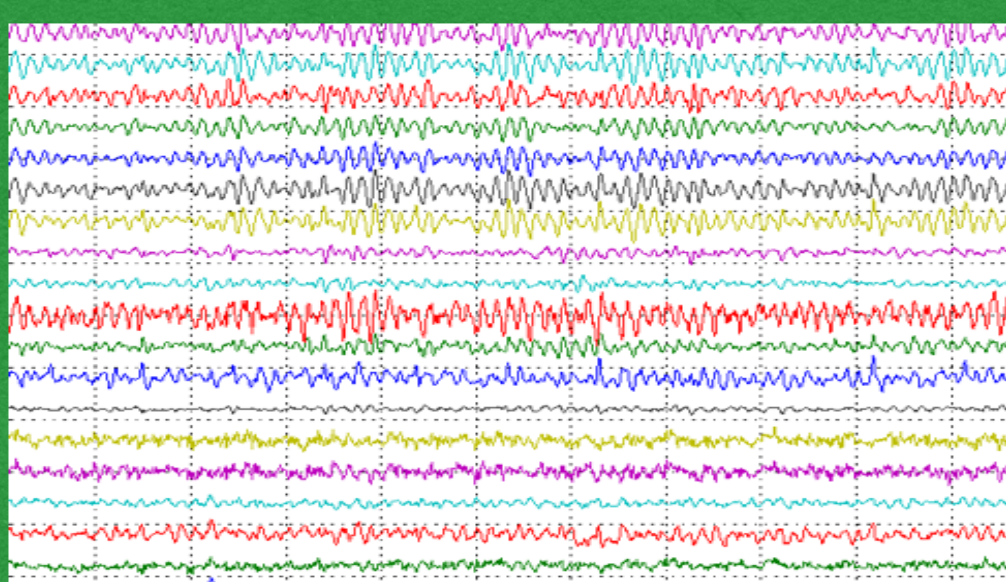
DATA

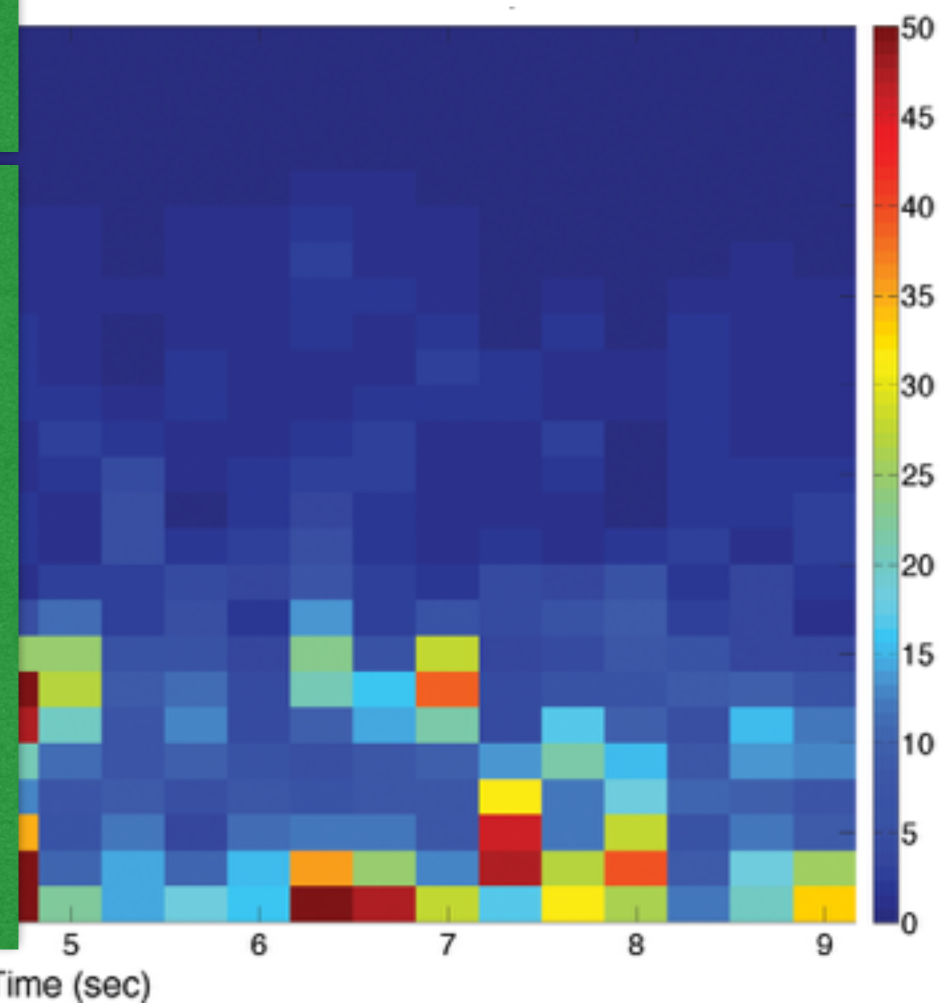




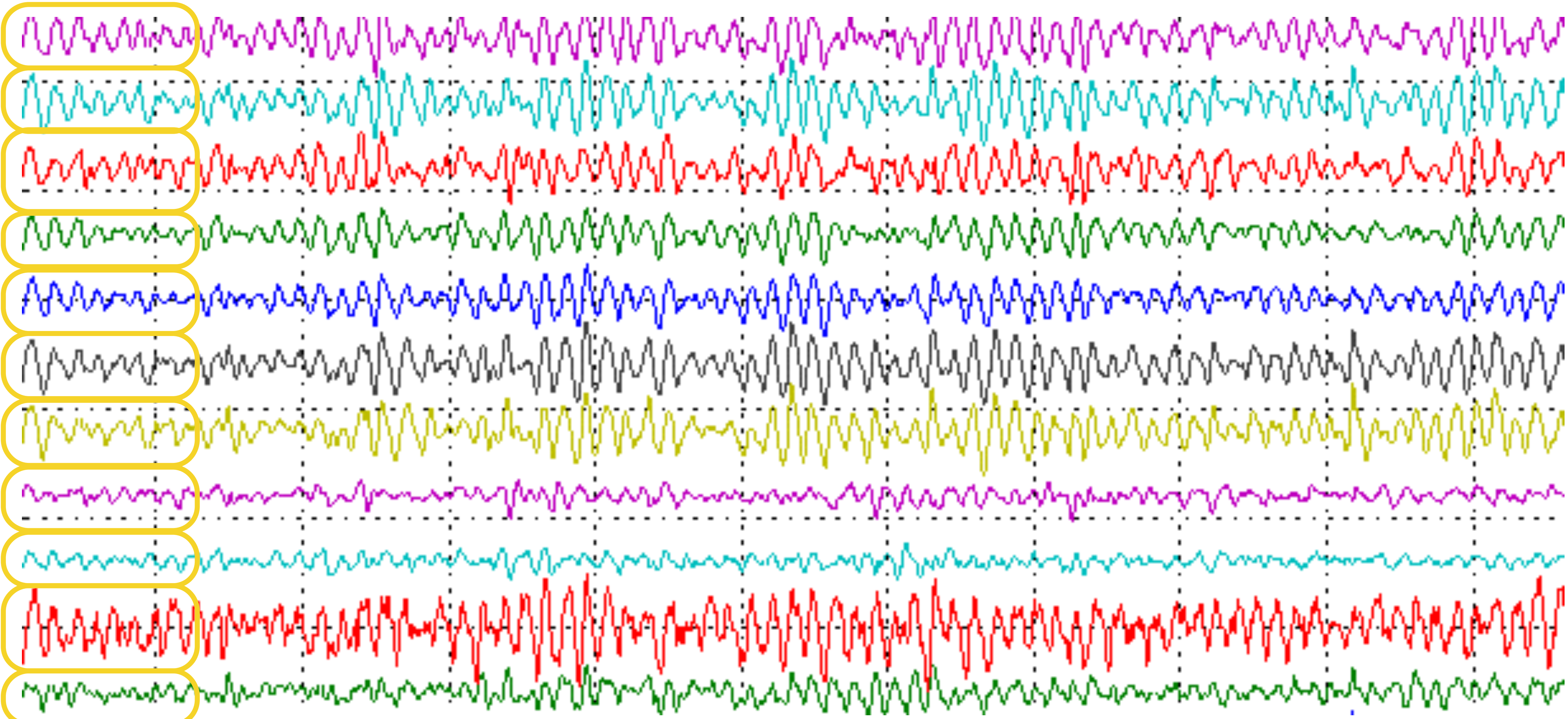
Are we done?

Hint:



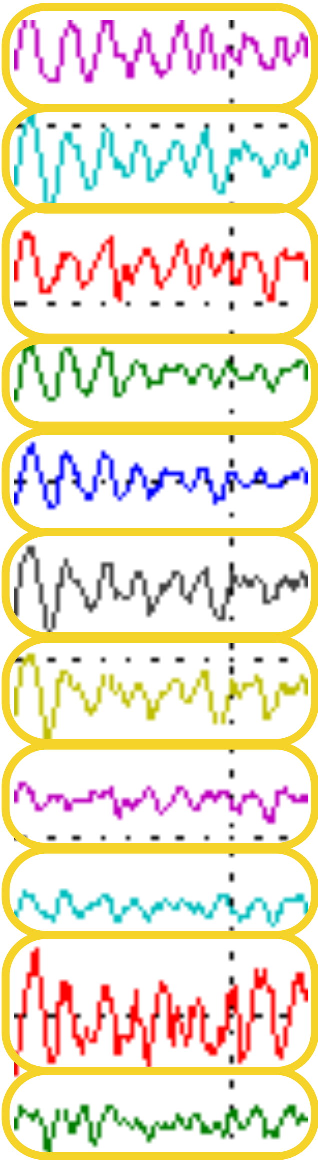


Data



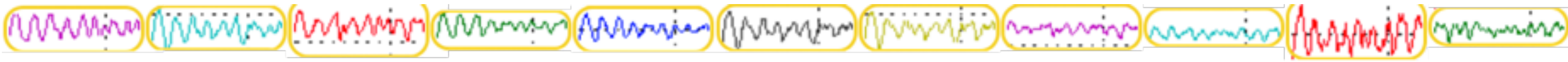
300 ms

DATA



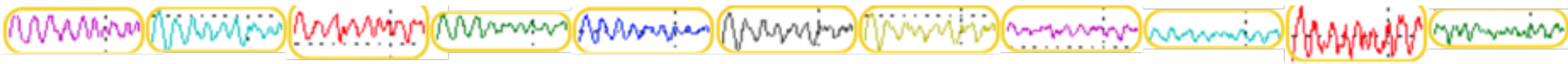
300 MS

DATA

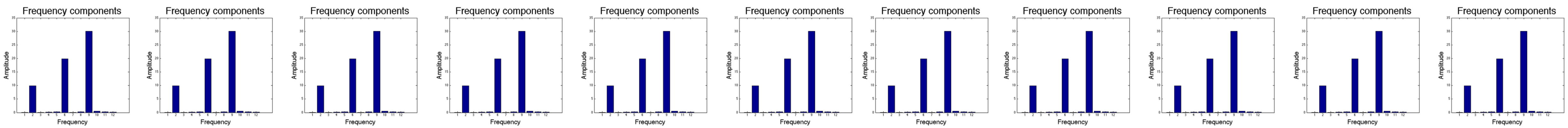


300 MS

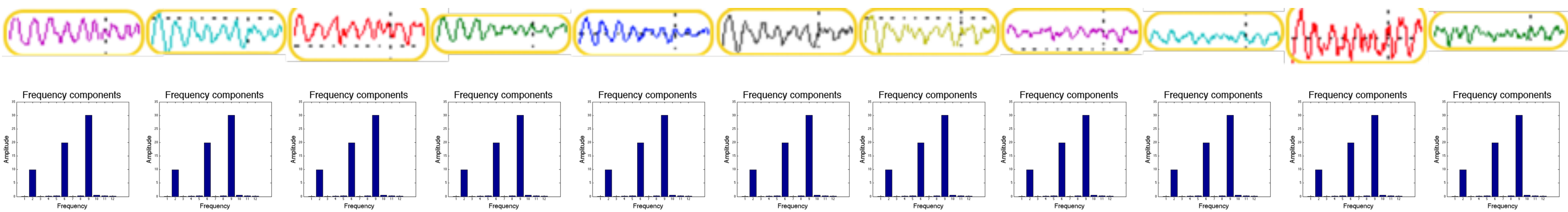
DATA



300 MS



DATA

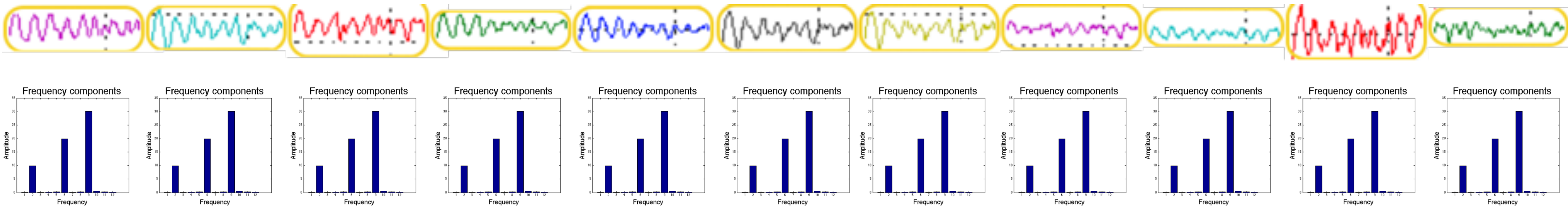


300 MS

11 channels
50 frequencies on each
3 seconds of data
300 ms window

- How many numbers to describe 1 reading of 300 ms?

DATA

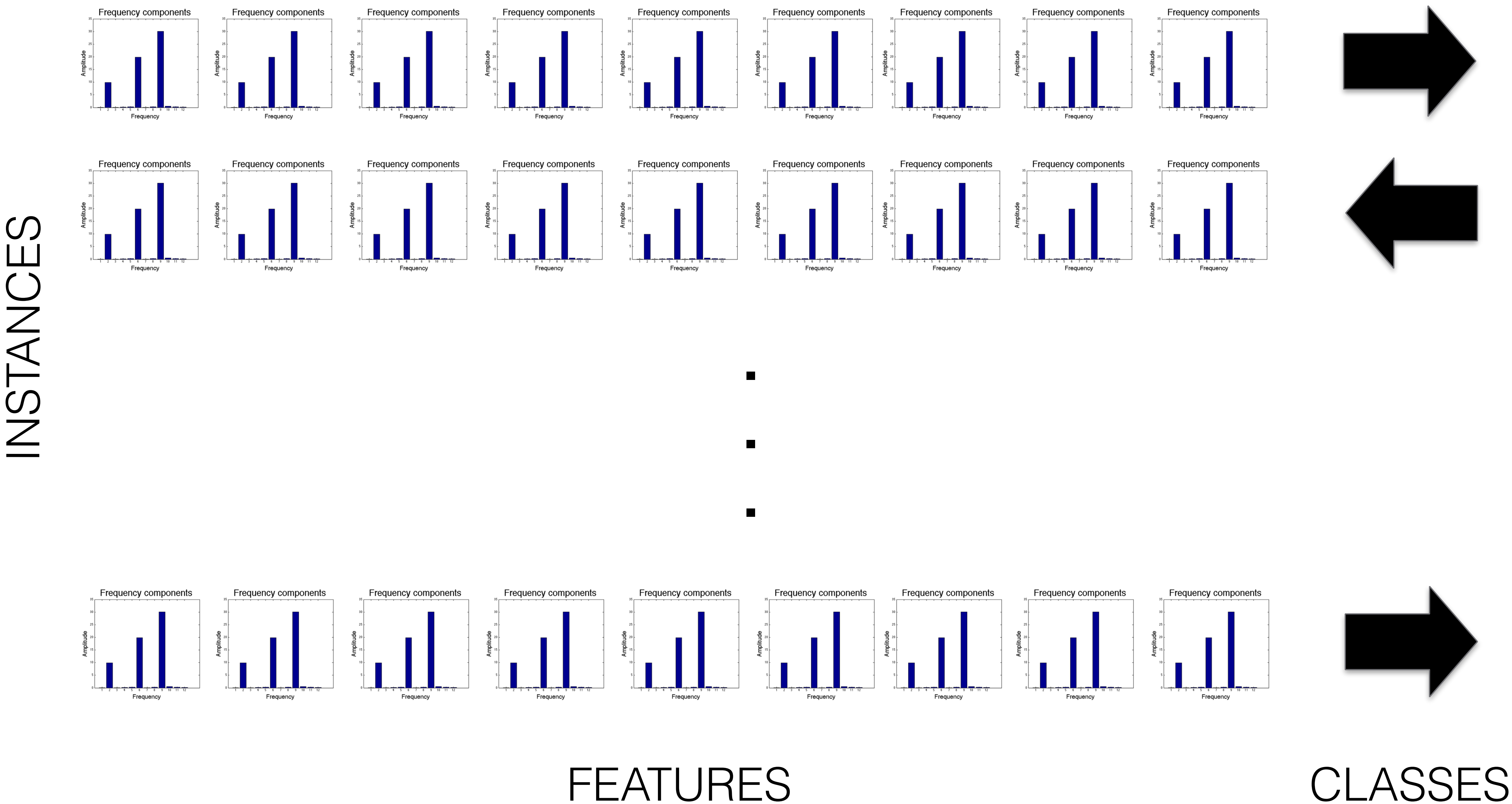


300 MS

11 channels
50 frequencies on each
3 seconds of data
300 ms window

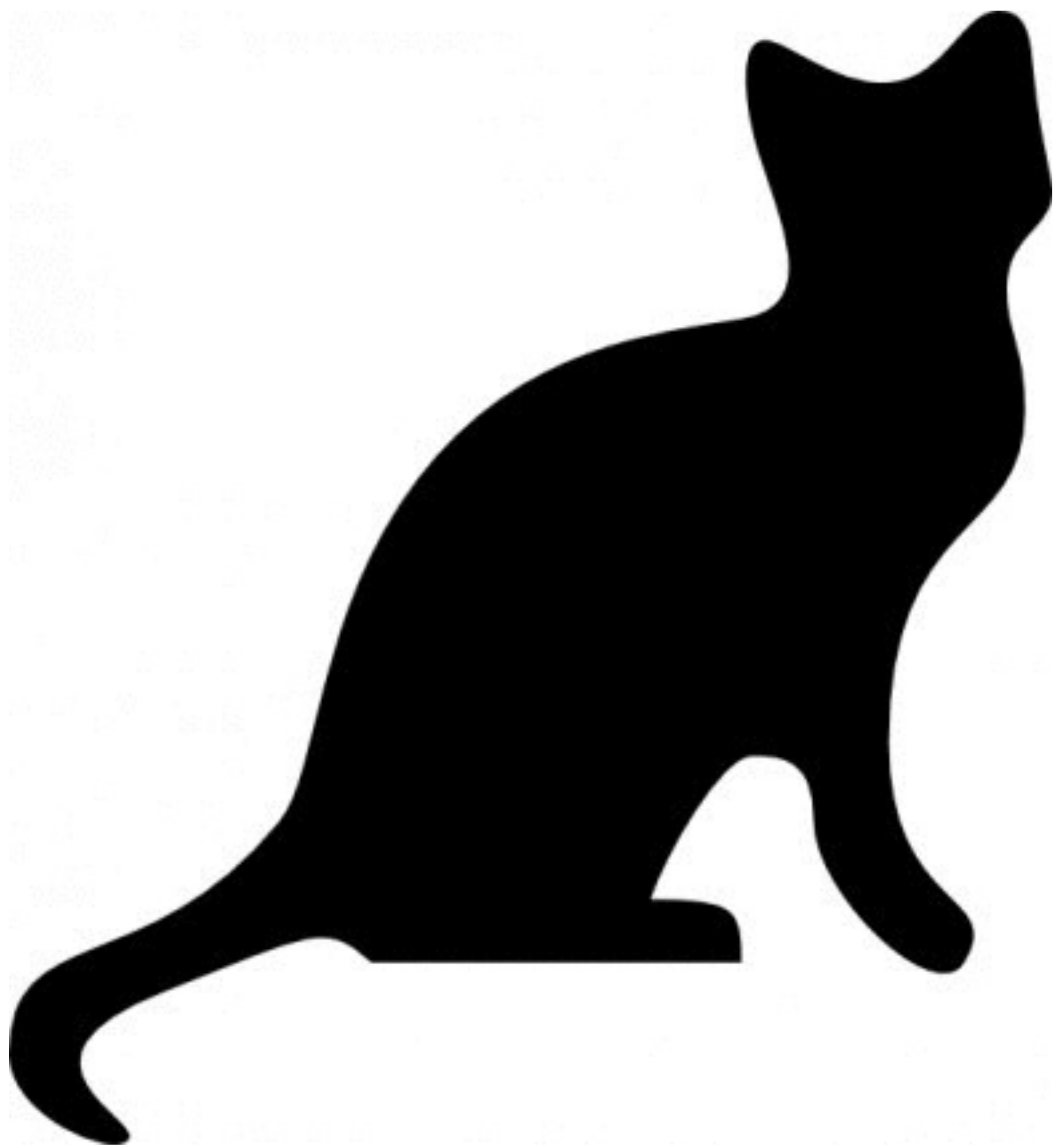
- How many numbers to describe 1 reading of 300 ms?
- How many numbers to describe all 3 seconds of data?

DATASET

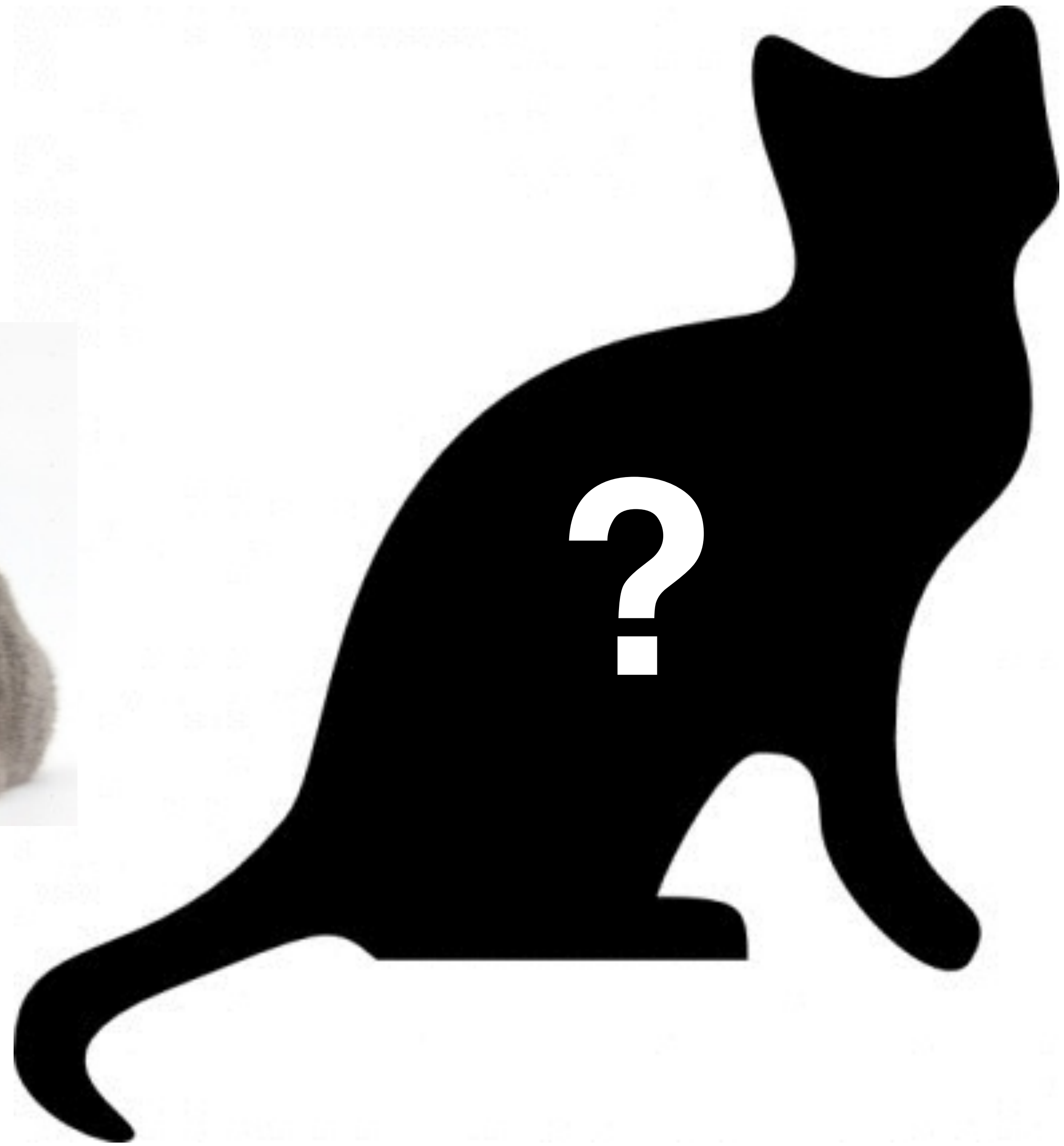


Frequency components
Amplitude
Frequency
INSTANCES
FEATURES
CLASSES

Machine learning



MACHINE LEARNING



MACHINE LEARNING

Machine Learning algorithm learns from examples,

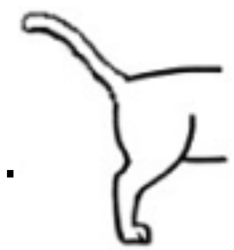
set of sample objects (**samples**) is called **training set**

MACHINE LEARNING

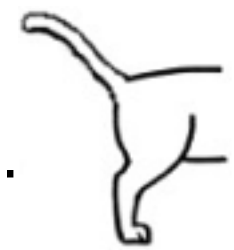
Each object

can be described with a set of parameters
called **features**

MACHINE LEARNING

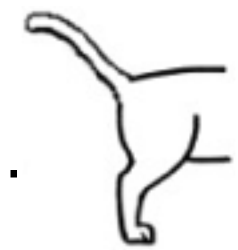
Tail length f_1 :  . 

MACHINE LEARNING

Tail length f_1 :  . 

Furriness f_2 :  . 

MACHINE LEARNING

Tail length f_1 :  . 

Furriness f_2 :  . 

Form a **feature vector** $\mathbf{f} = (f_1, f_2)$

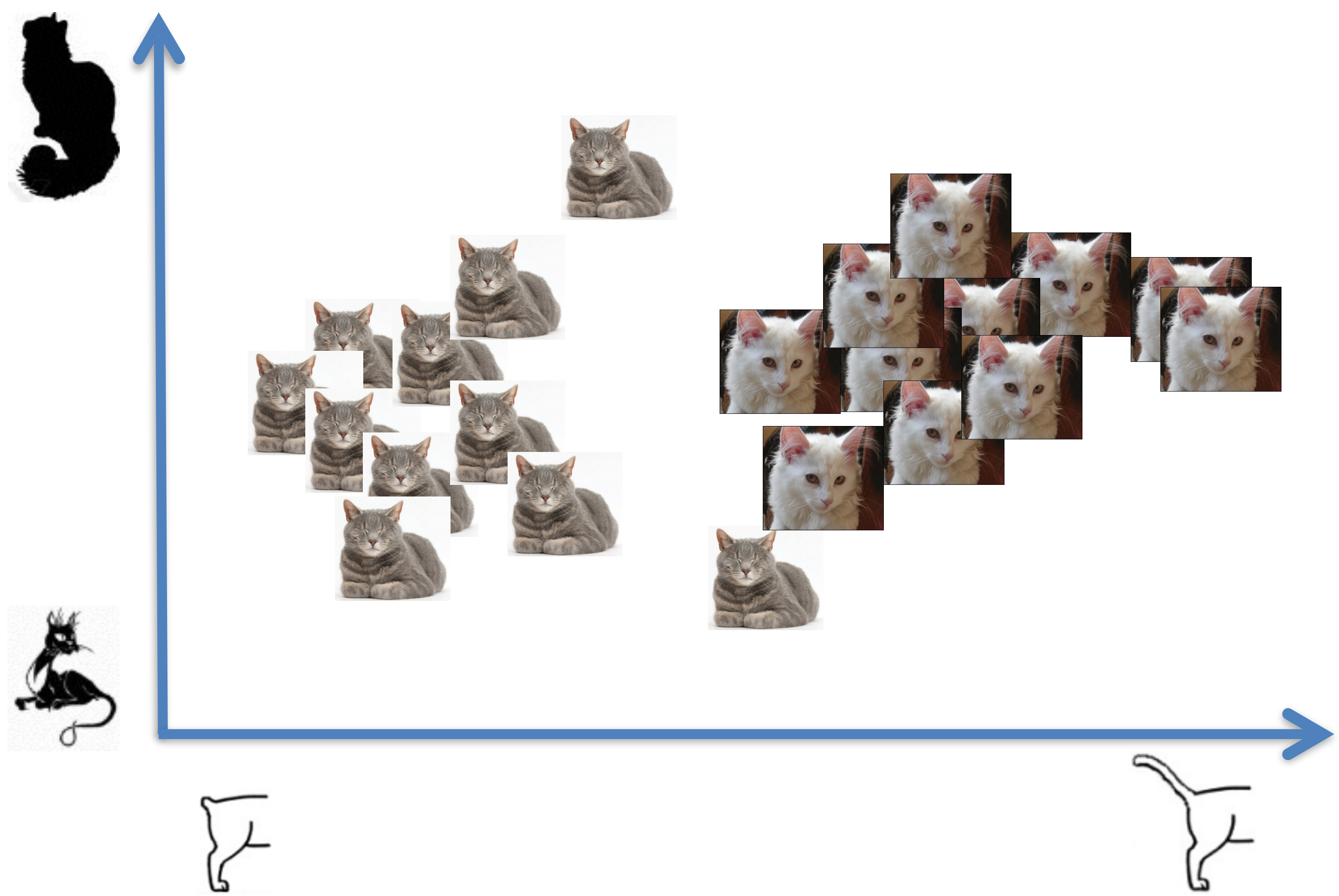
MACHINE LEARNING

Together feature vectors and corresponding classes form a **dataset**

Instance	Feature 1	Feature 2	Class
Cat 1	8 cm	546 h/cm	M
Cat 2	7.5 cm	363 h/cm	M
...	...		...
Cat N	11 cm	614 h/cm	F

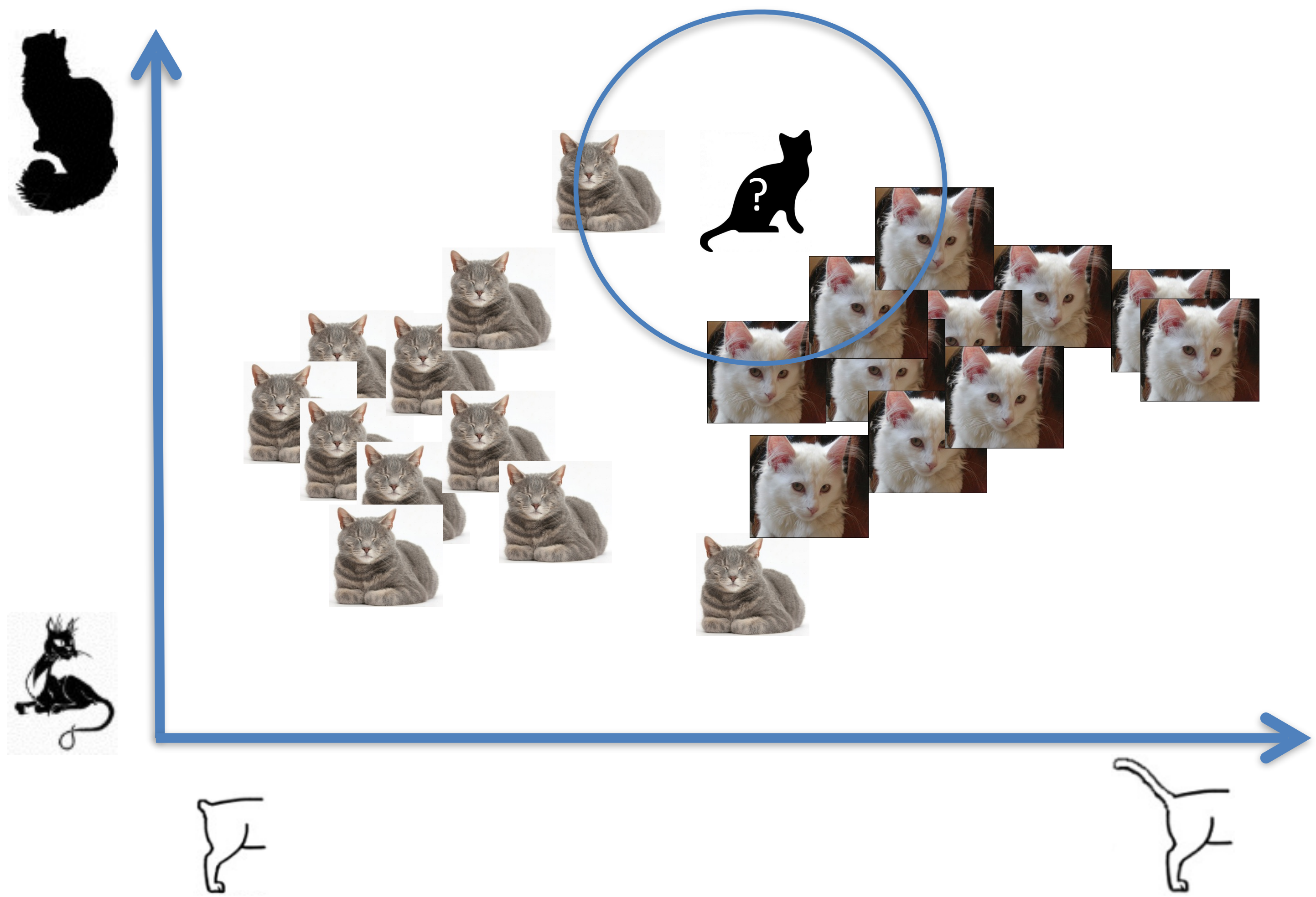
MACHINE LEARNING

Feature vectors live in a **feature space**



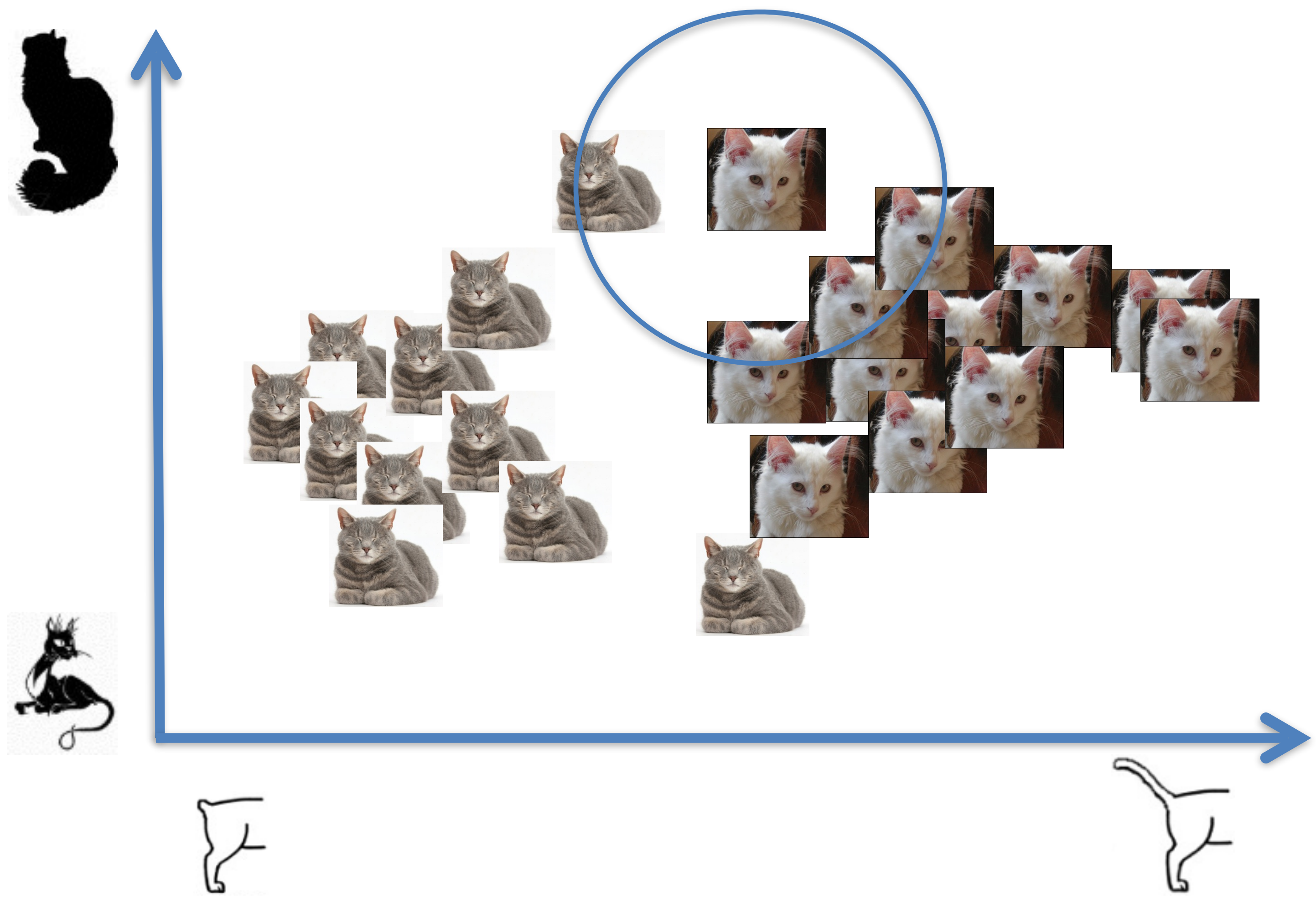
Machine learning

Feature vectors live in a **feature space**



MACHINE LEARNING

Feature vectors live in a **feature space**



Machine learning

Feature vectors live in a **feature space**

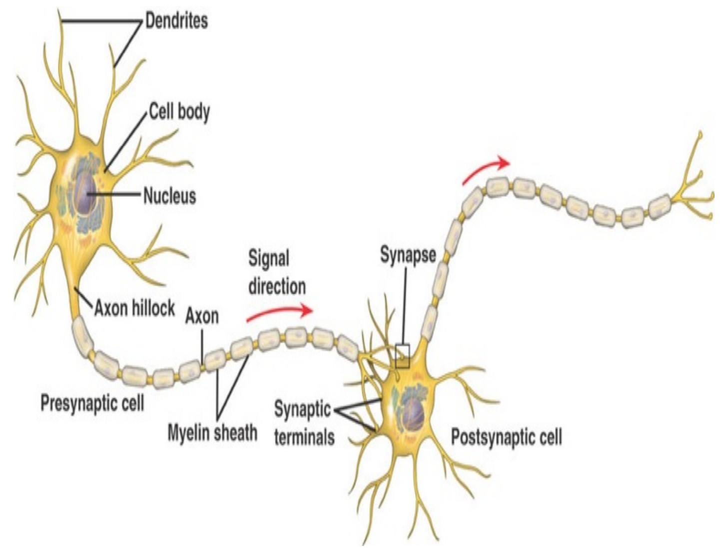
K-Nearest Neighbors

MACHINE LEARNING

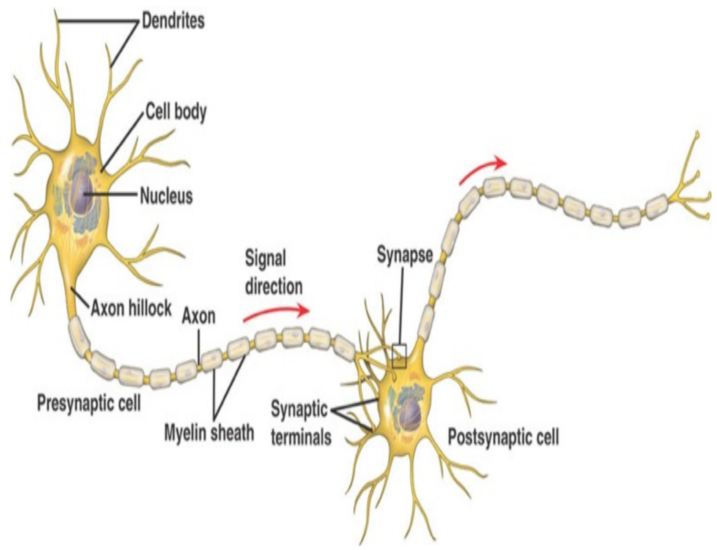
- Decision trees
- C4.5
- Random forests
- Bayesian networks
- Hidden Markov models
- Artificial neural network
- Data clustering
- Expectation-maximization algorithm
- Self-organizing map
- Radial basis function network
- Vector Quantization
- Generative topographic map
- Information bottleneck method
- IBSEAD
- Apriori algorithm
- Eclat algorithm
- FP-growth algorithm
- Single-linkage clustering
- Conceptual clustering
- K-means algorithm
- Fuzzy clustering
- Temporal difference learning
- Q-learning
- Learning Automata
- Monte Carlo Method
- SARSA
- Instance-based learning
- Nearest Neighbor Algorithm
- Analogical modeling
- Probably approximately correct learning (PAC)
- Symbolic machine learning algorithms
- Subsymbolic machine learning algorithms
- Support vector machines
- Random Forests
- Ensembles of classifiers
- Bootstrap aggregating (bagging)
- Boosting (meta-algorithm)
- Ordinal classification
- Regression analysis
- Information fuzzy networks (IFN)
- ANOVA
- Linear classifiers
- Fisher's linear discriminant
- Logistic regression
- Naive Bayes classifier
- Perceptron
- Support vector machines
- Quadratic classifiers
- k-nearest neighbor
- Boosting
- AODE
- Artificial neural network
- Backpropagation
- Naive Bayes classifier
- Bayesian network
- Bayesian knowledge base
- Case-based reasoning
- Decision trees
- Inductive logic programming
- Gaussian process regression
- Gene expression programming
- Group method of data handling (GMDH)
- Learning Automata
- Learning Vector Quantization
- Logistic Model Tree
- Decision trees
- Decision graphs
- Lazy learning

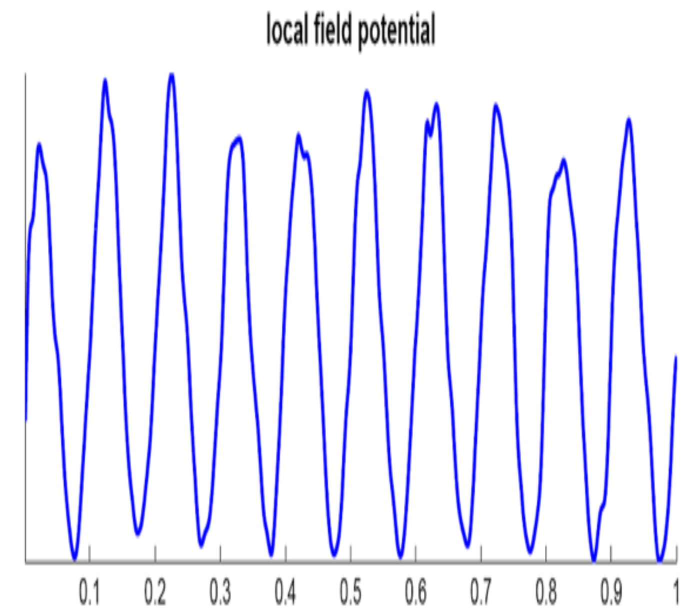
Brain-computer interface

BRAIN-COMPUTER INTERFACE

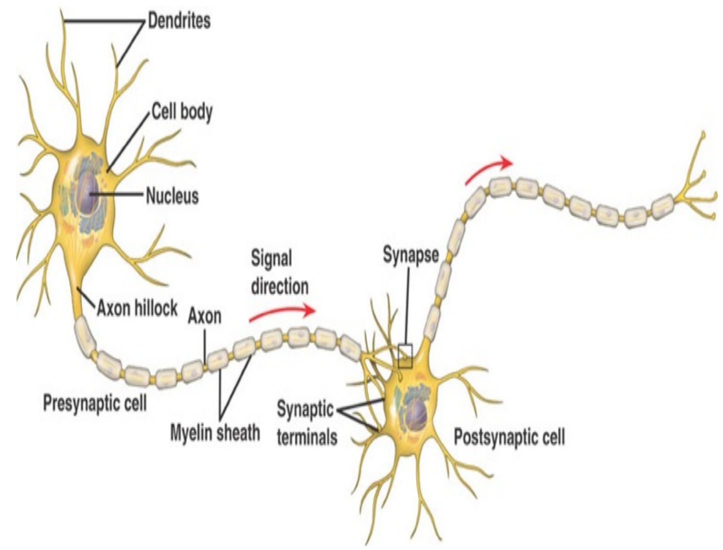


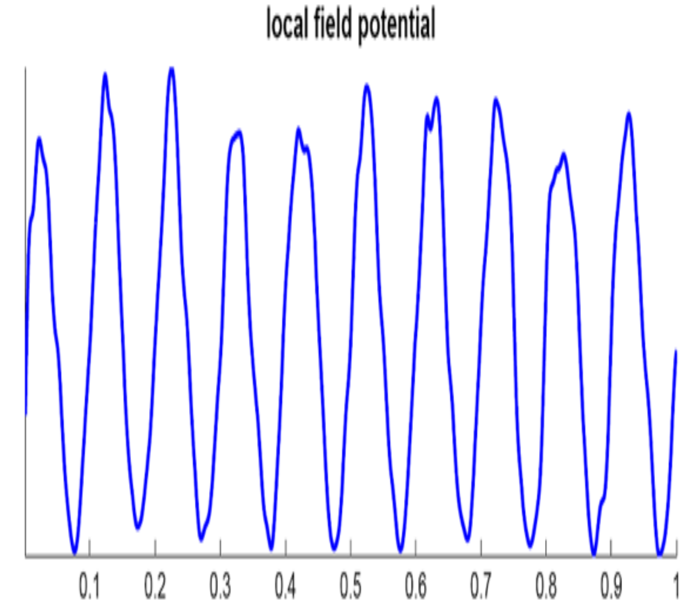
BRAIN-COMPUTER INTERFACE



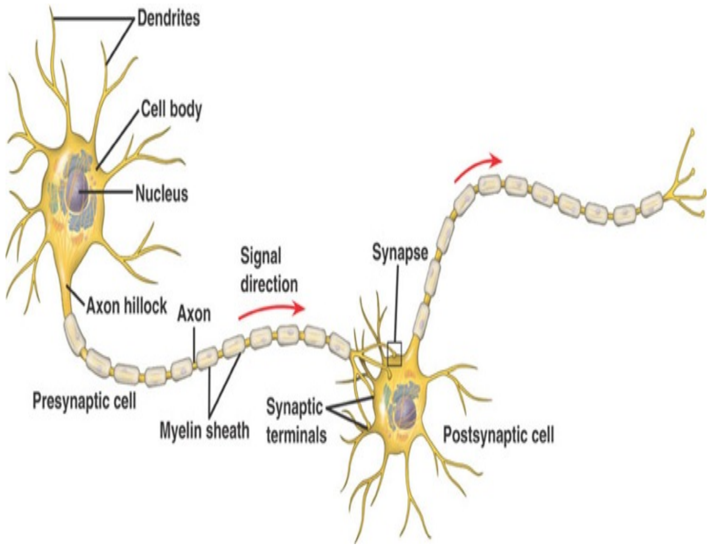


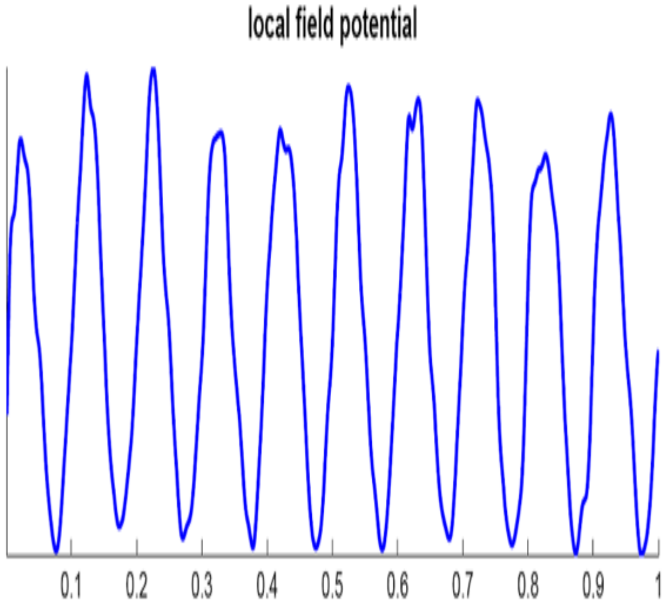
Brain-computer interface

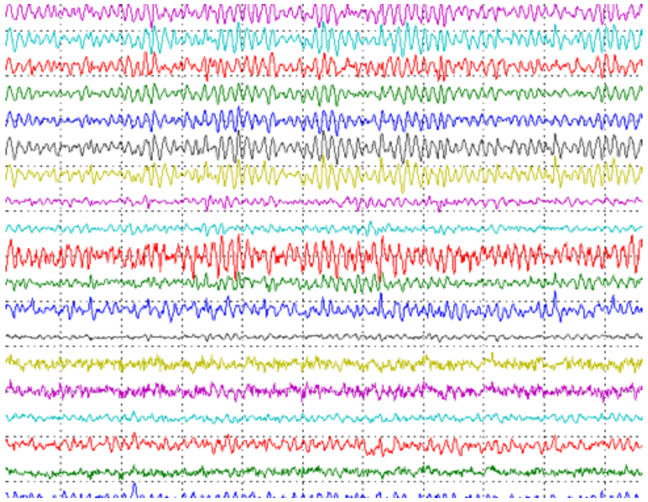




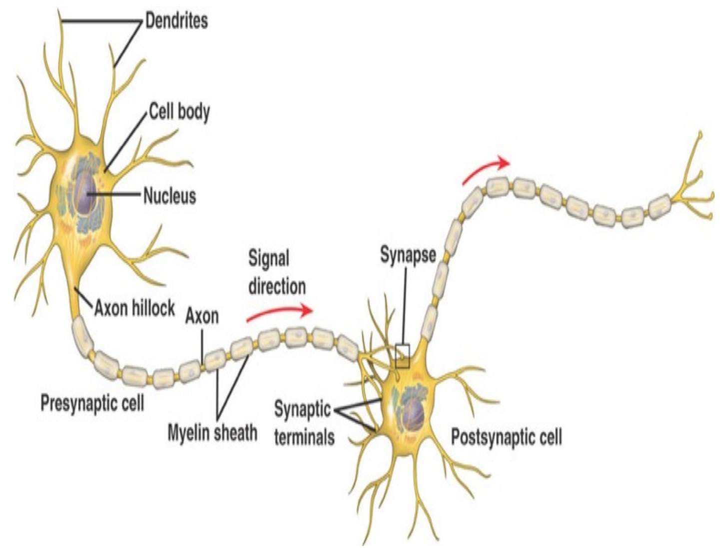
Brain-computer interface

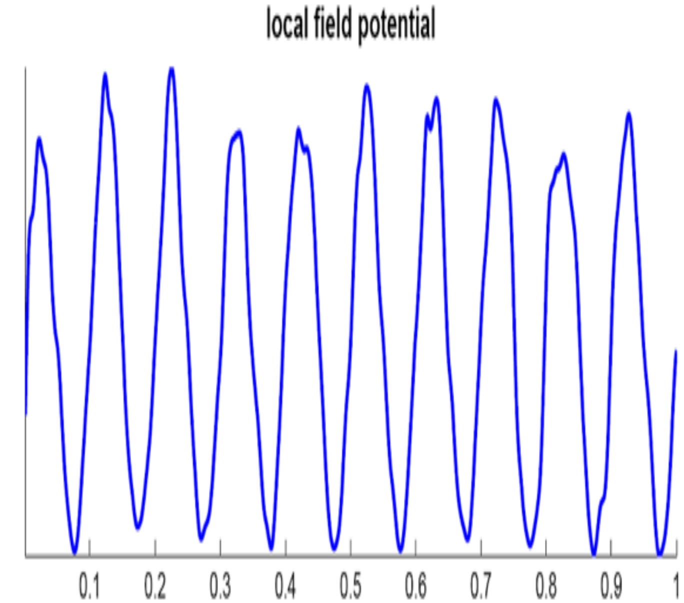


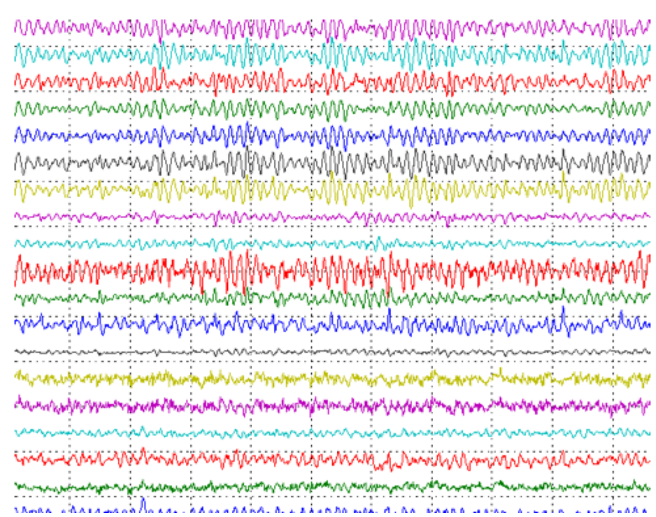




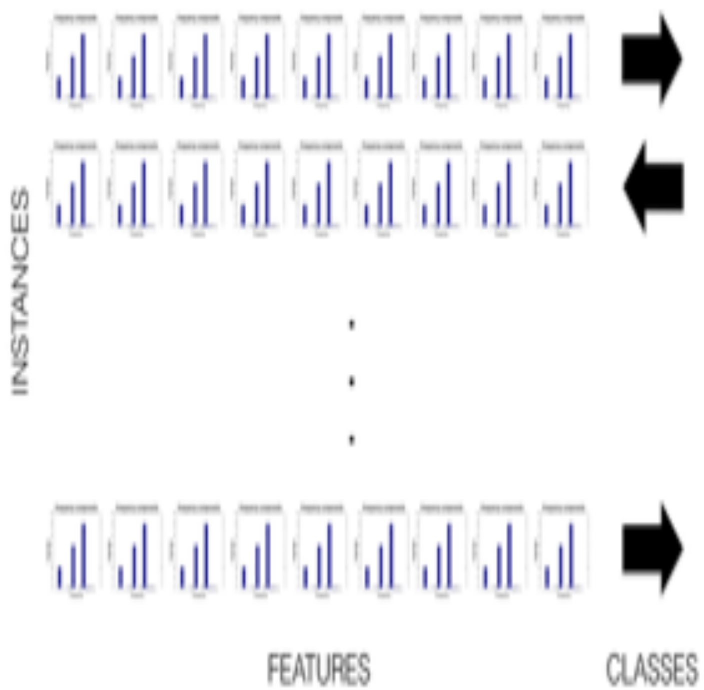
Brain-computer interface



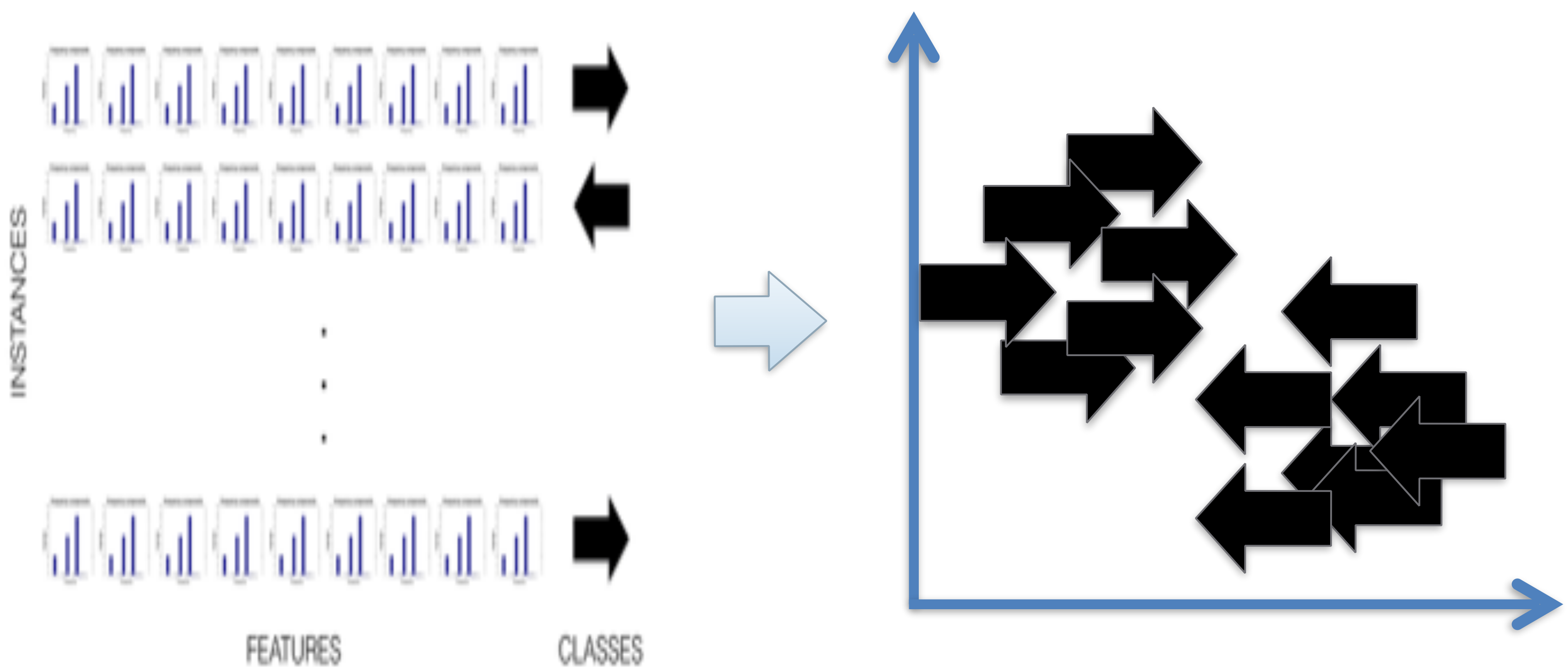




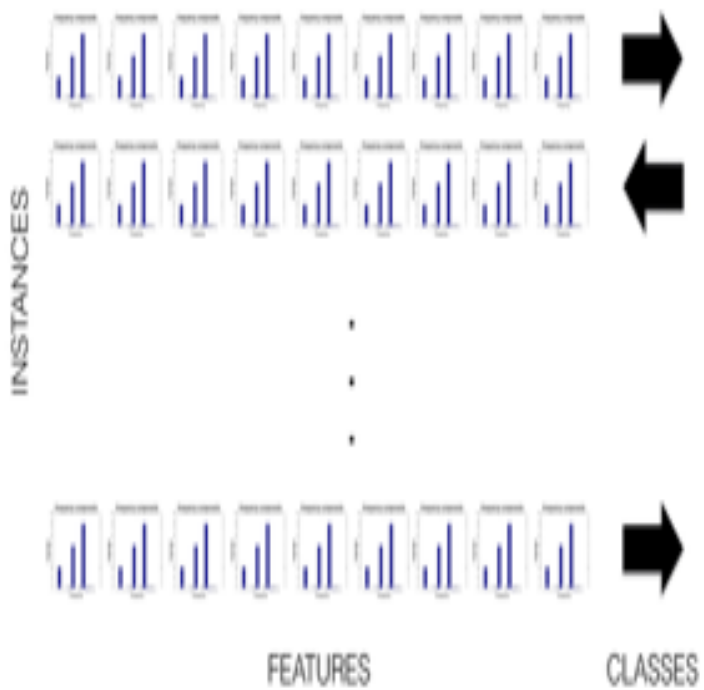
Brain-computer interface

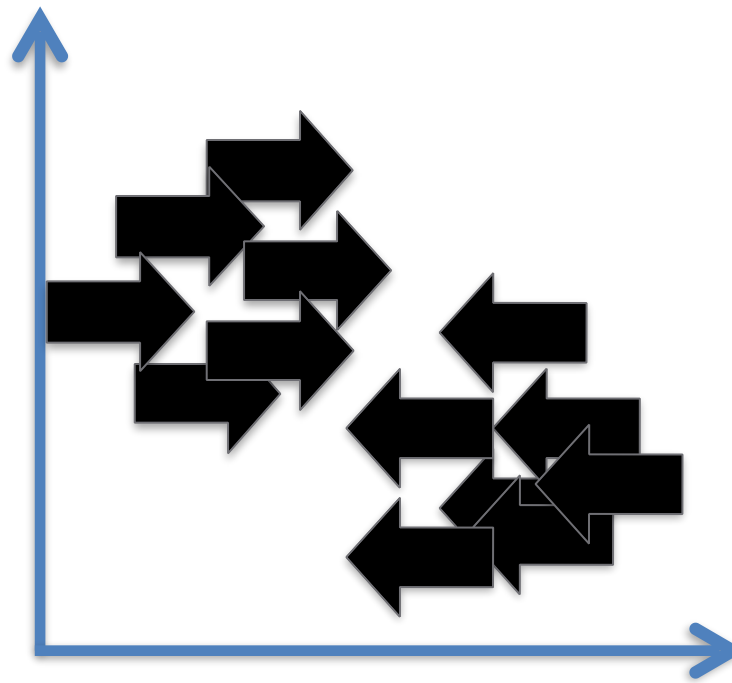


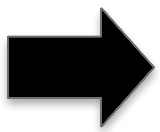
Brain-computer interface



BRAIN-COMPUTER INTERFACE







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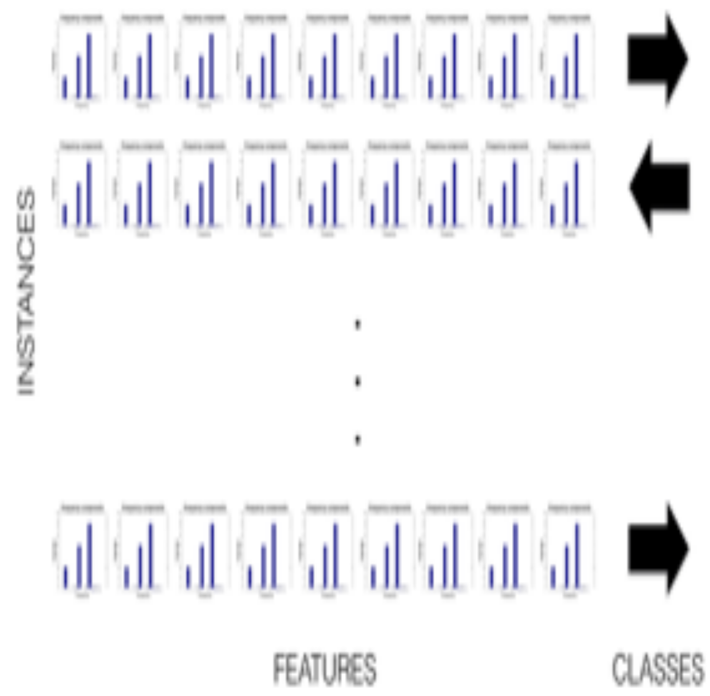
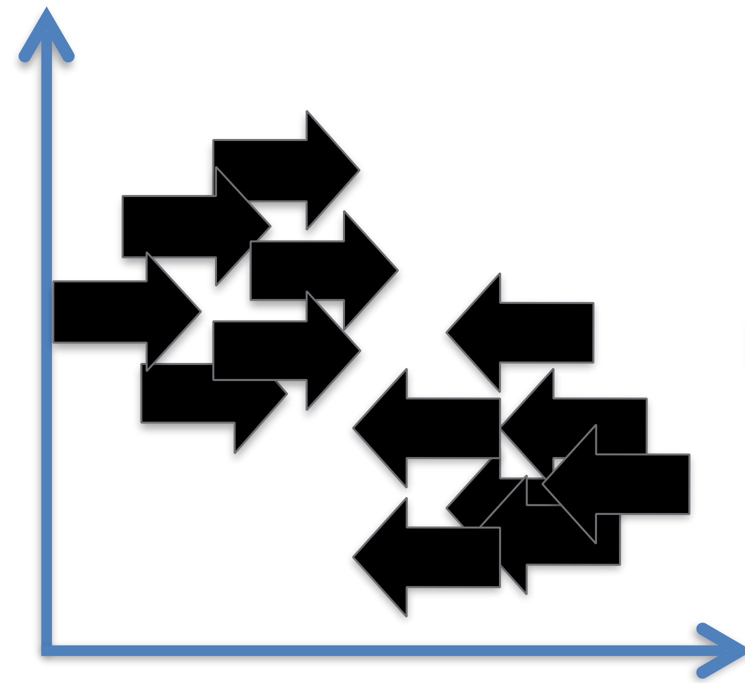
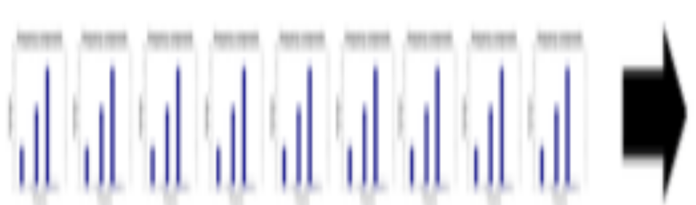
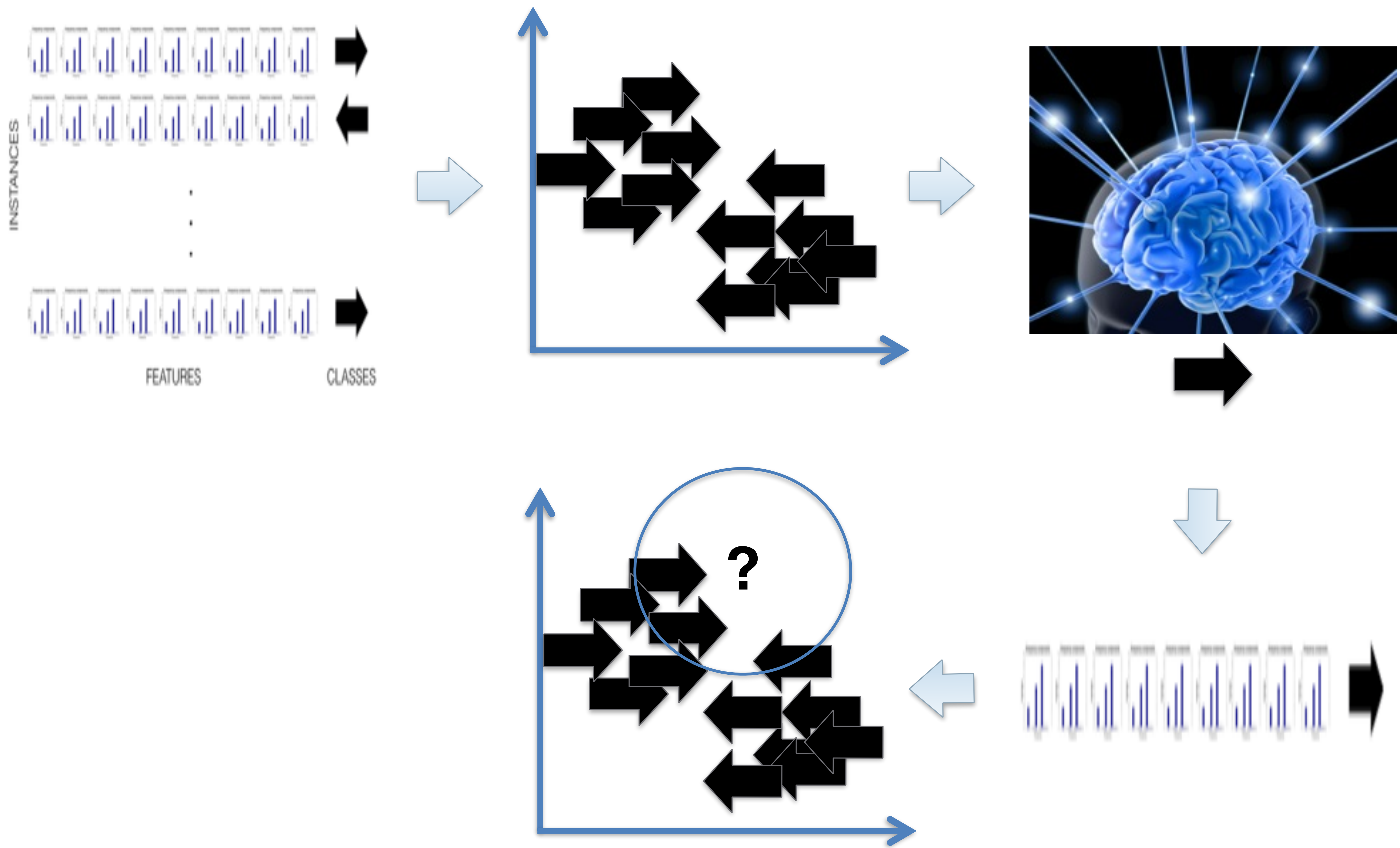


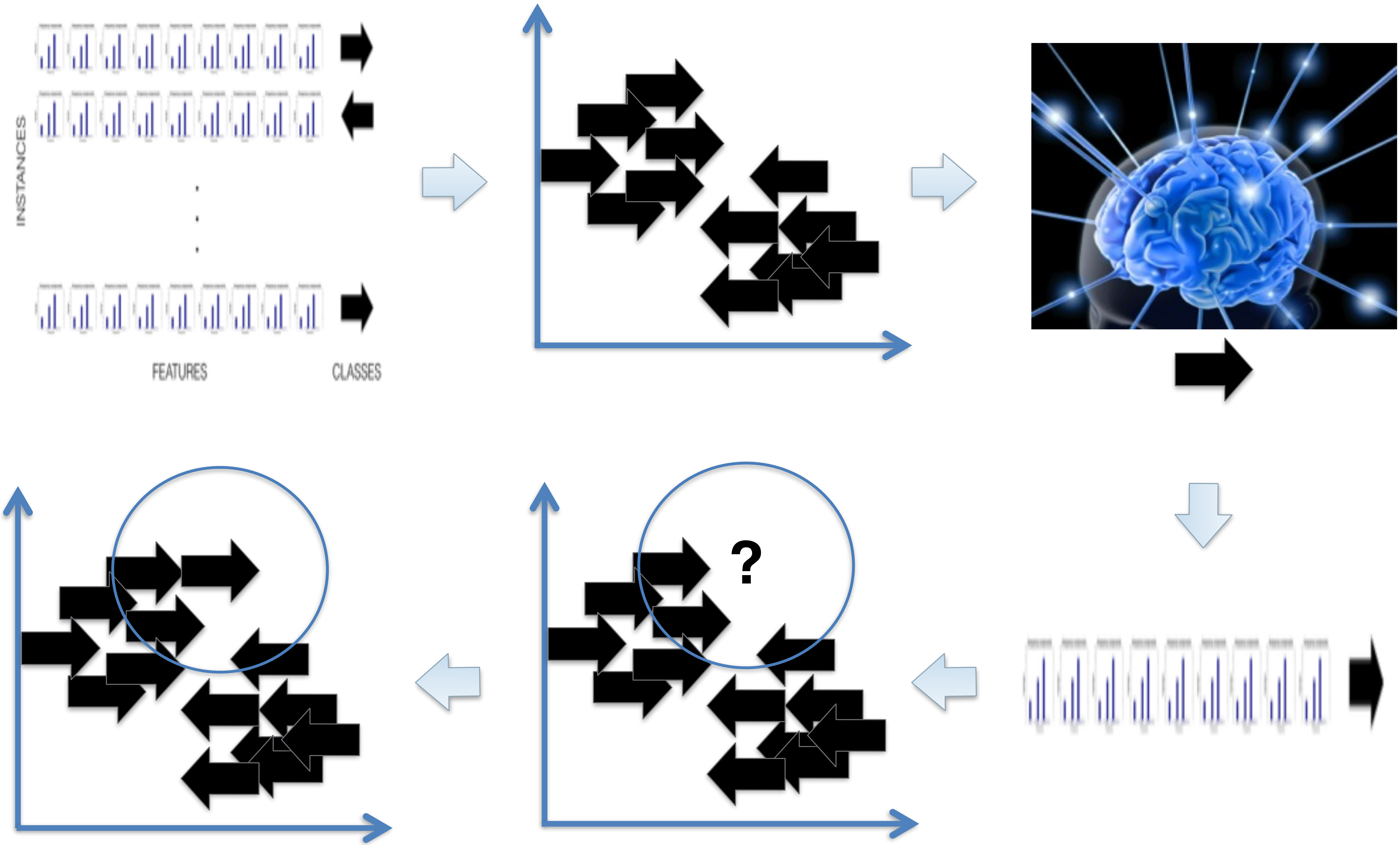




Brain-computer interface



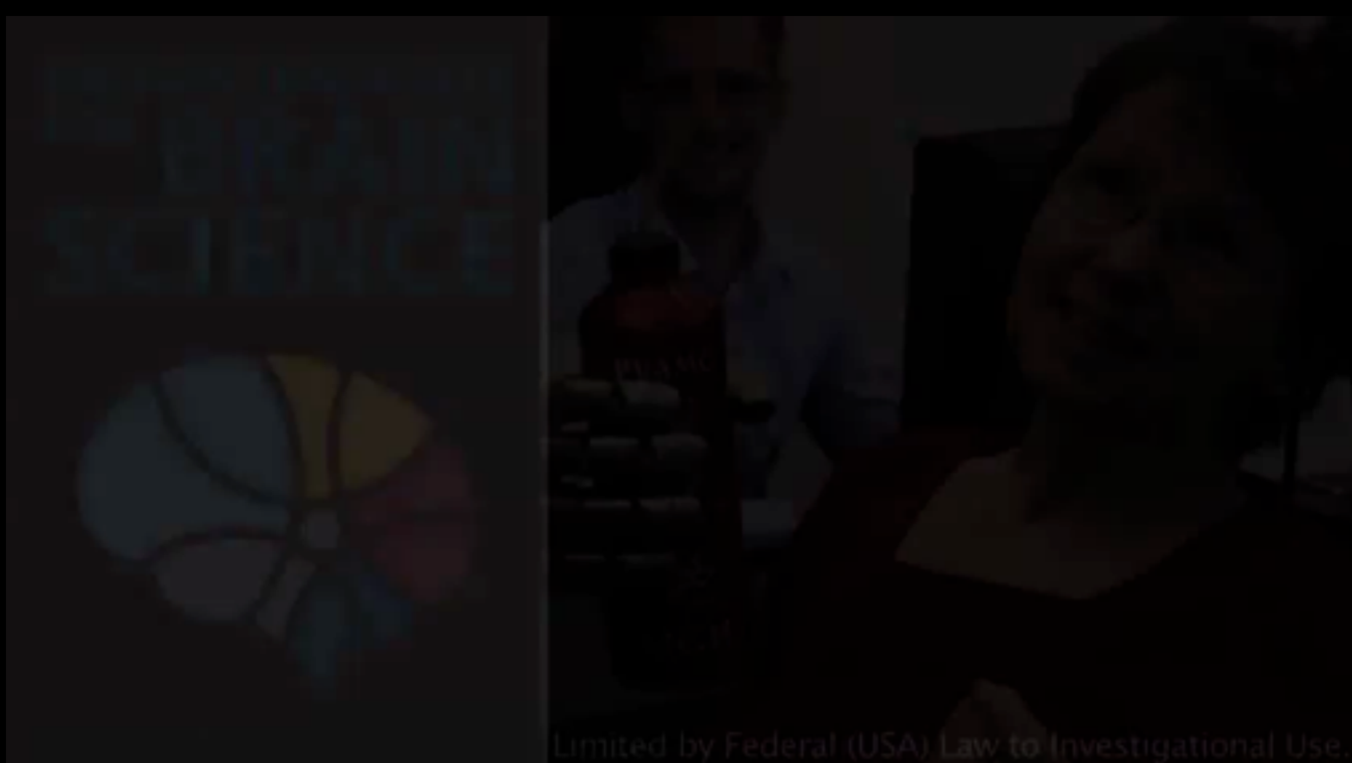
Brain-computer interface



c-VEP BCI

Brain-Computer Interface based on code-modulated visual evoked potentials

EBERHARD KARLS UNIVERSITÄT TÜBINGEN



Controlling An Avatar By Thought Using Real-Time fMRI

The End