Single-trial classification of EEG in a visual object task

Using ICA and machine learning

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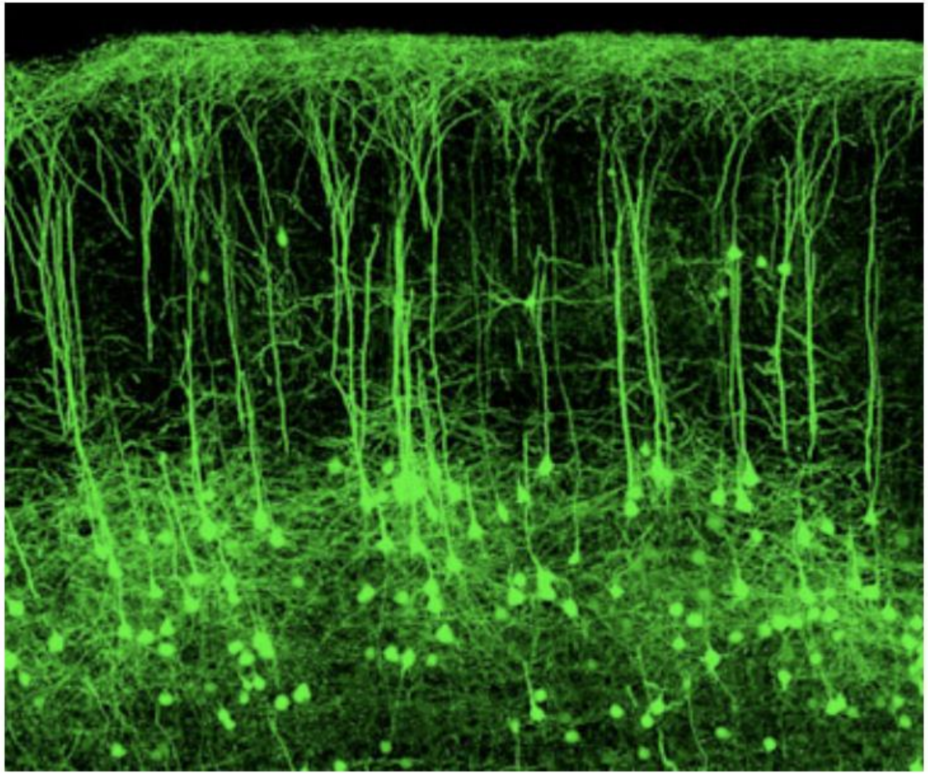
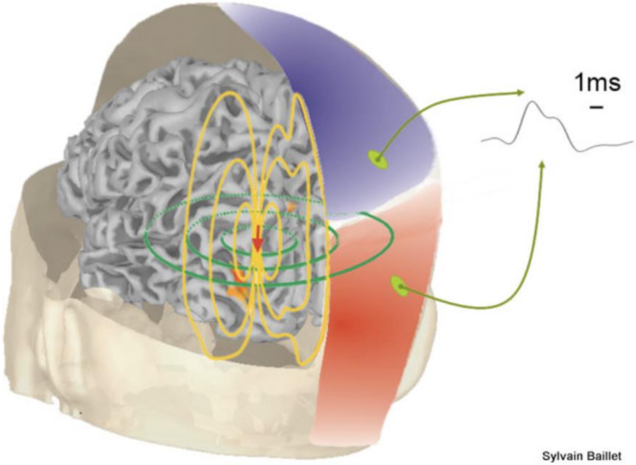
Feb 16, 2021

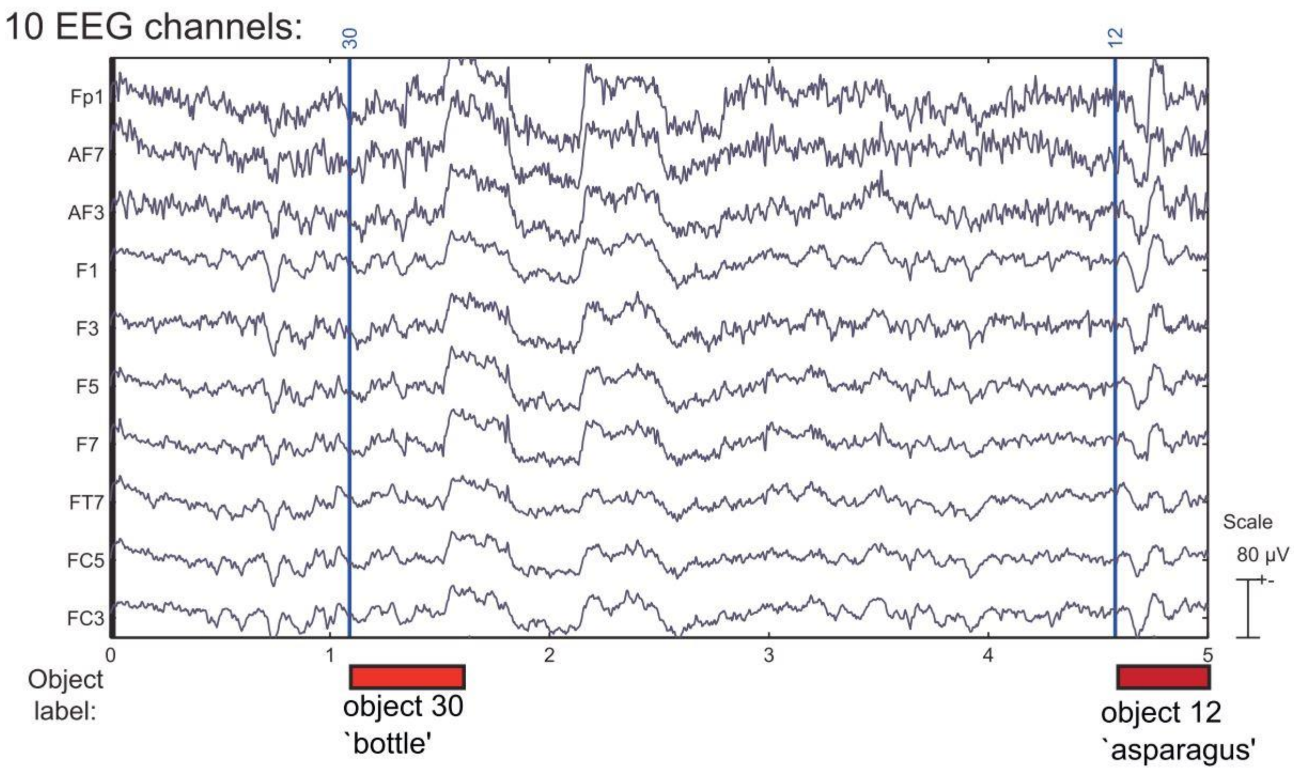
Stewart, Nuthmann, Sanguinetti, *J Neuro Meth*, **228** (2014) 1-14



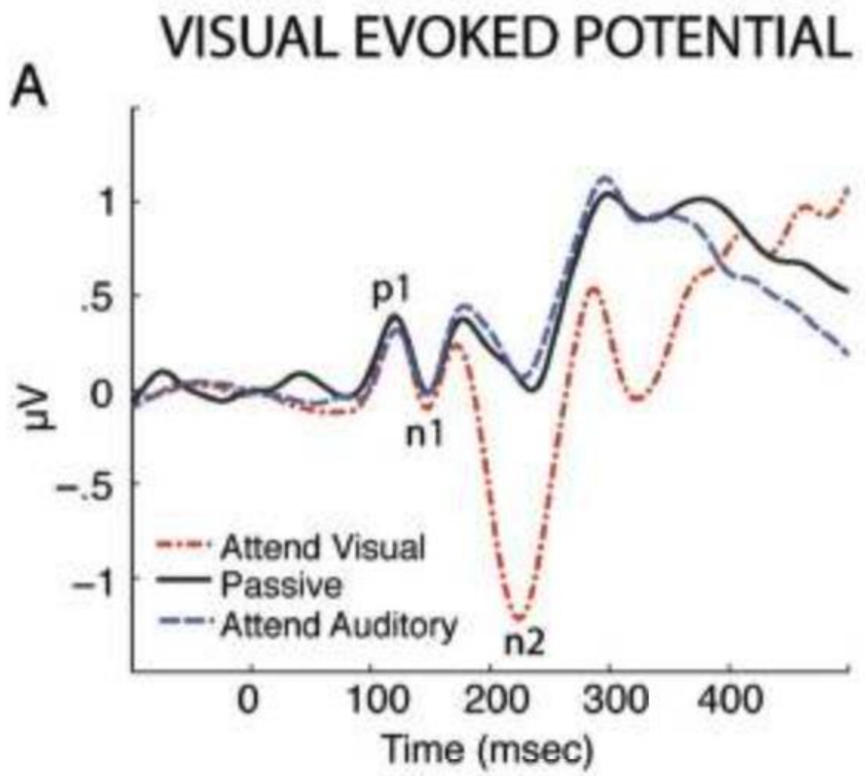
yellow fluorescent protein
Dr. Fu-Ming Zhou
https://www.uthsc.edu/neuroscience/imaging-center/



Single time trace of voltage signal at particular surface scalp locations



- Different stim presented in a sequence
- Continuous brain signal can be broken up into "trials," all starting at t=0 of stim presented
- We can focus analysis on particular "channel" location that has largest SNR for a given brain phenomenon we care about
- Visual task uses neurons in back of the brain (occipital cortex)



Lenartowicz et al. *J Cog Neuro* (2014)

- If we AVERAGE many trials, we can reduce increase SNR
- But only capture truly time-locked signal
- Different tasks can have different time-locked brain response
- **But averaging can remove some real signal (consider averaging time-points of ocean waves)**
- **NO WAVES (unless perfectly time-locked)**

Averaging removes any signal that is NOT perfectly time-locked to trial start

http://passyworldofmathematics.com/mathematics-of-ocean-waves-and-surfing/

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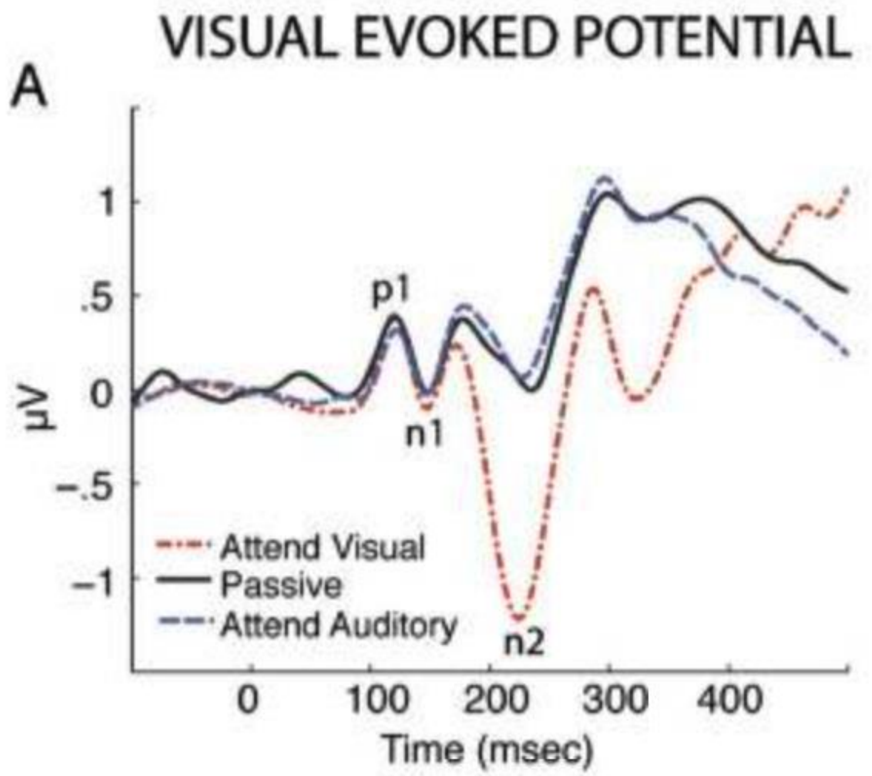

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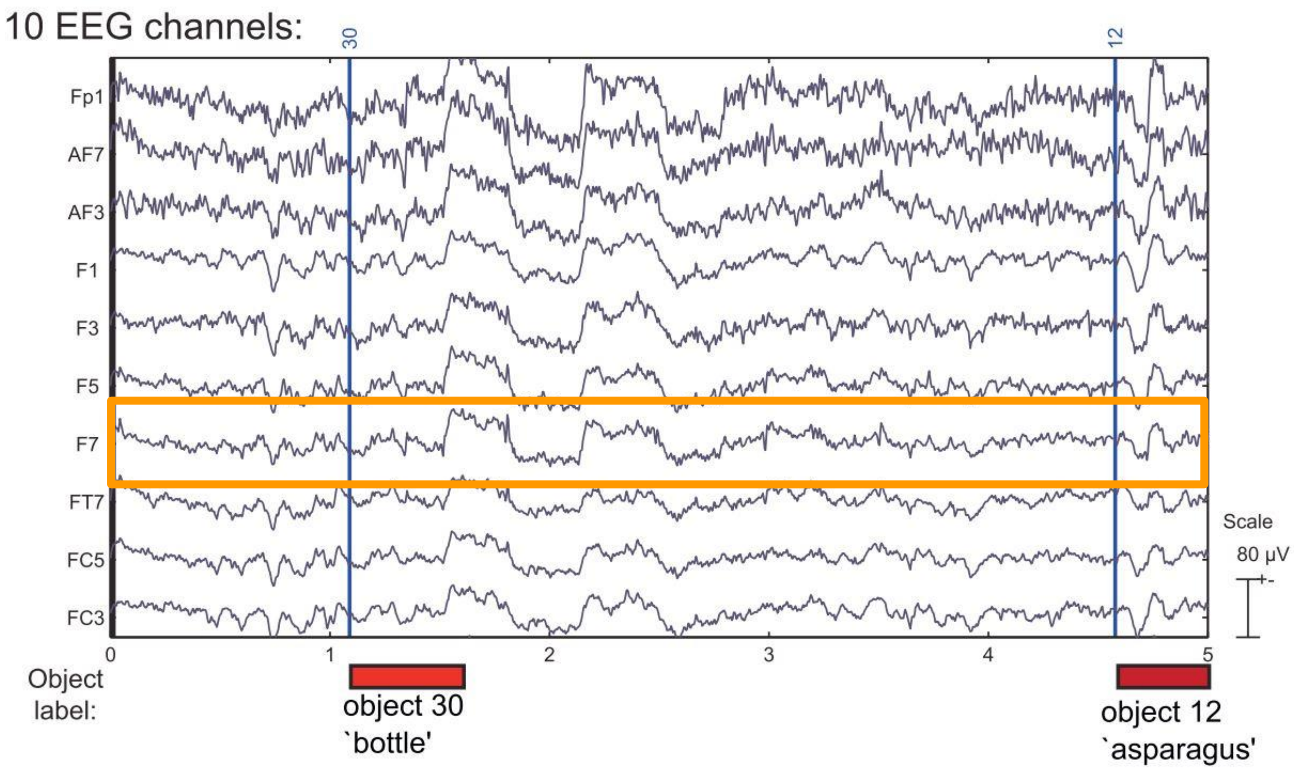
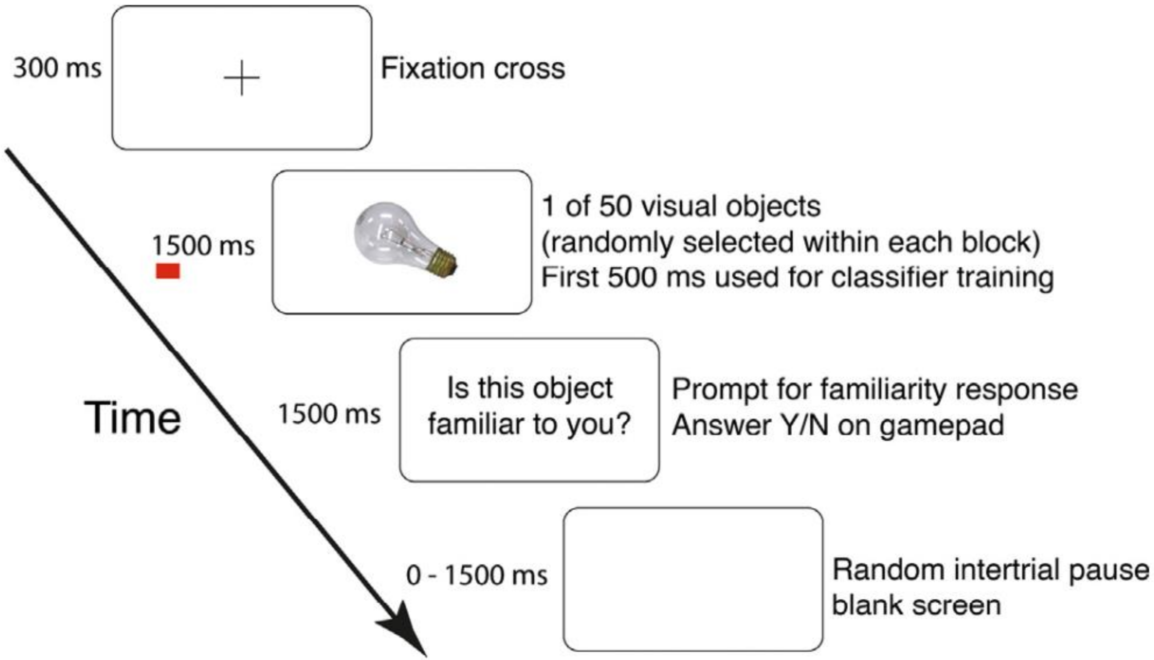
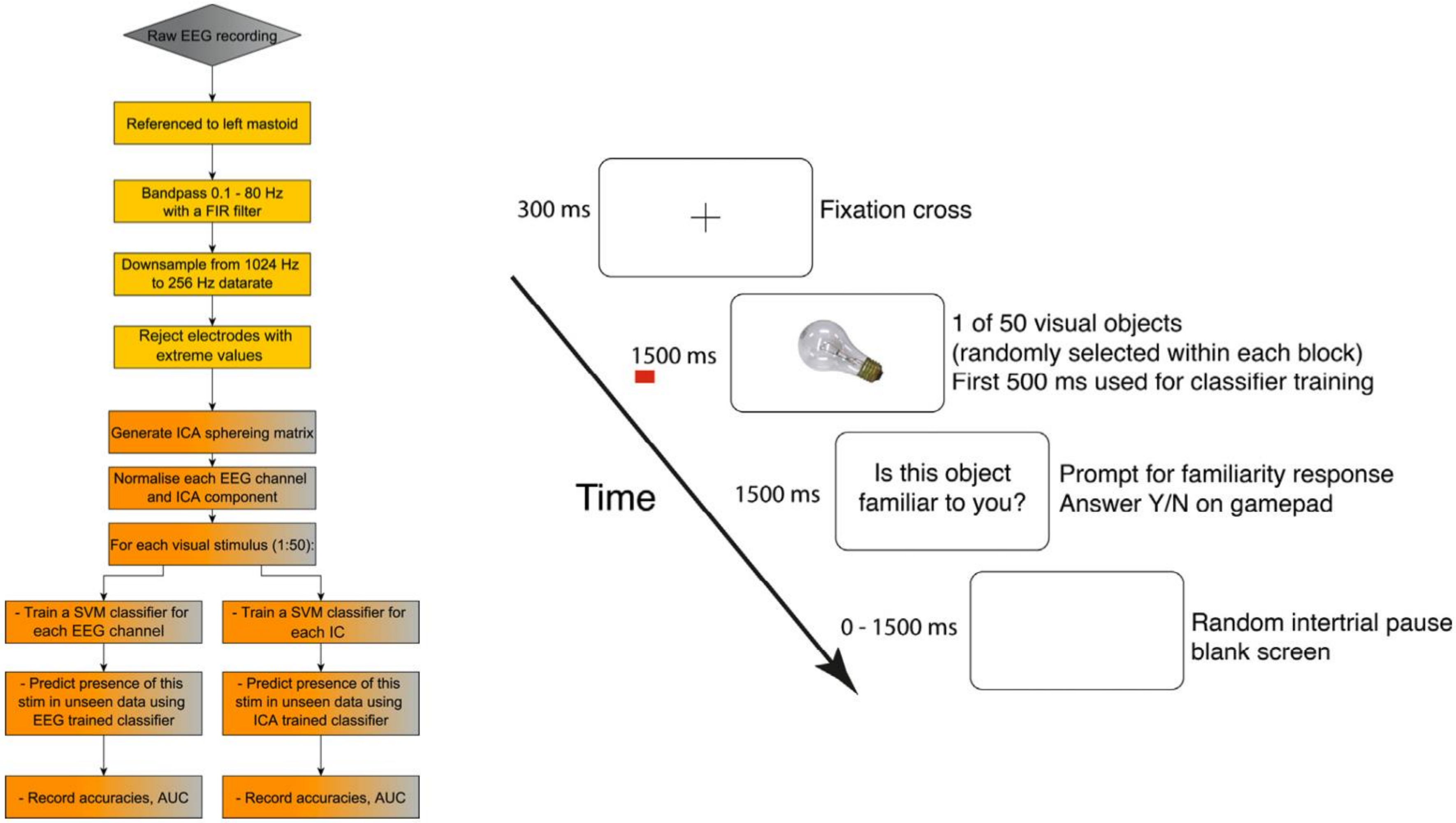
Measure brain signal voltages and analyze INDIVIDUAL TRIALS for common signal



- Break signal up into many trials
- KEEP each trial separate, as an independent measurement
- Use Machine Learning (SVM) to categorize signatures that are common across different trials of the same type.
- BOTTLE and ASPARAGUS are both OBJECT VISUAL stim

Measure brain signal voltages and analyze INDIVIDUAL TRIALS for common signal





Raw EEG recording
Referenced to left mastoid
Bandpass 0.1 - 80 Hz with a FIR filter
Downsample from 1024 Hz to 256 Hz datarate
Reject electrodes with extreme values
Generate ICA sphereing matrix
Normalise each EEG channel and ICA component
For each visual stimulus (1:50):
- Train a SVM classifier for each EEG channel
- Train a SVM classifier for each IC
- Predict presence of this stim in unseen data using EEG trained classifier
- Predict presence of this stim in unseen data using ICA trained classifier
- Record accuracies, AUC
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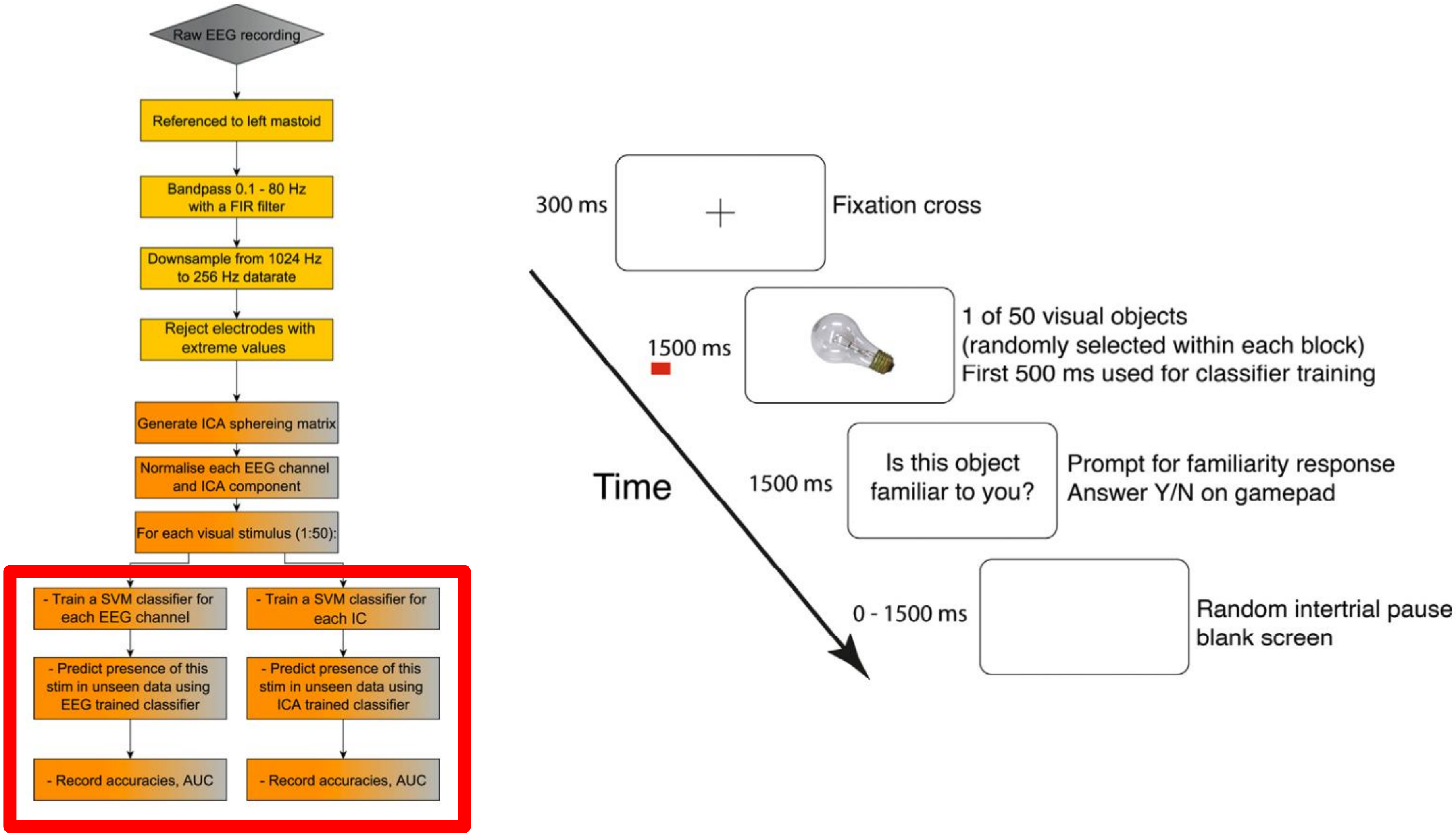
300 ms
Fixation cross
1500 ms
1 of 50 visual objects
(randomly selected within each block)
First 500 ms used for classifier training
Time
1500 ms
Is this object familiar to you?
Prompt for familiarity response
Answer Y/N on gamepad
0 - 1500 ms
Random intertrial pause
blank screen



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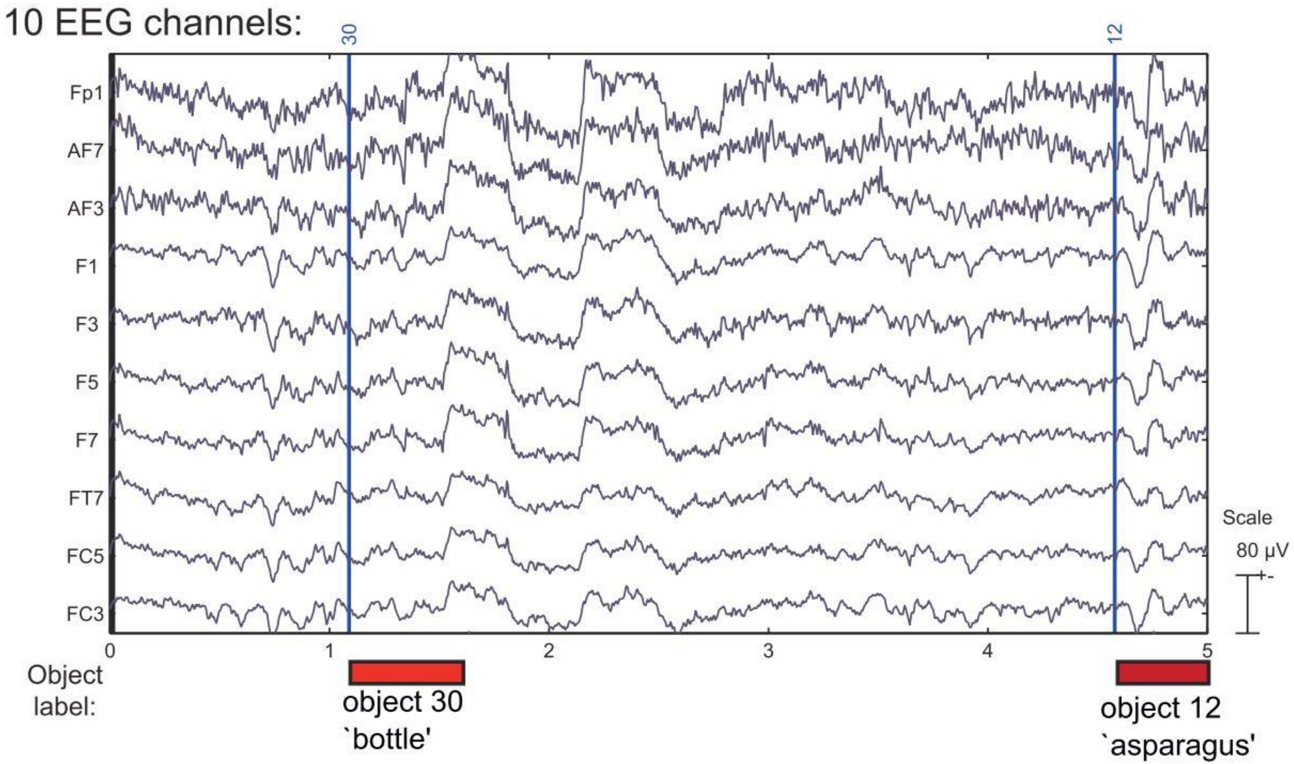
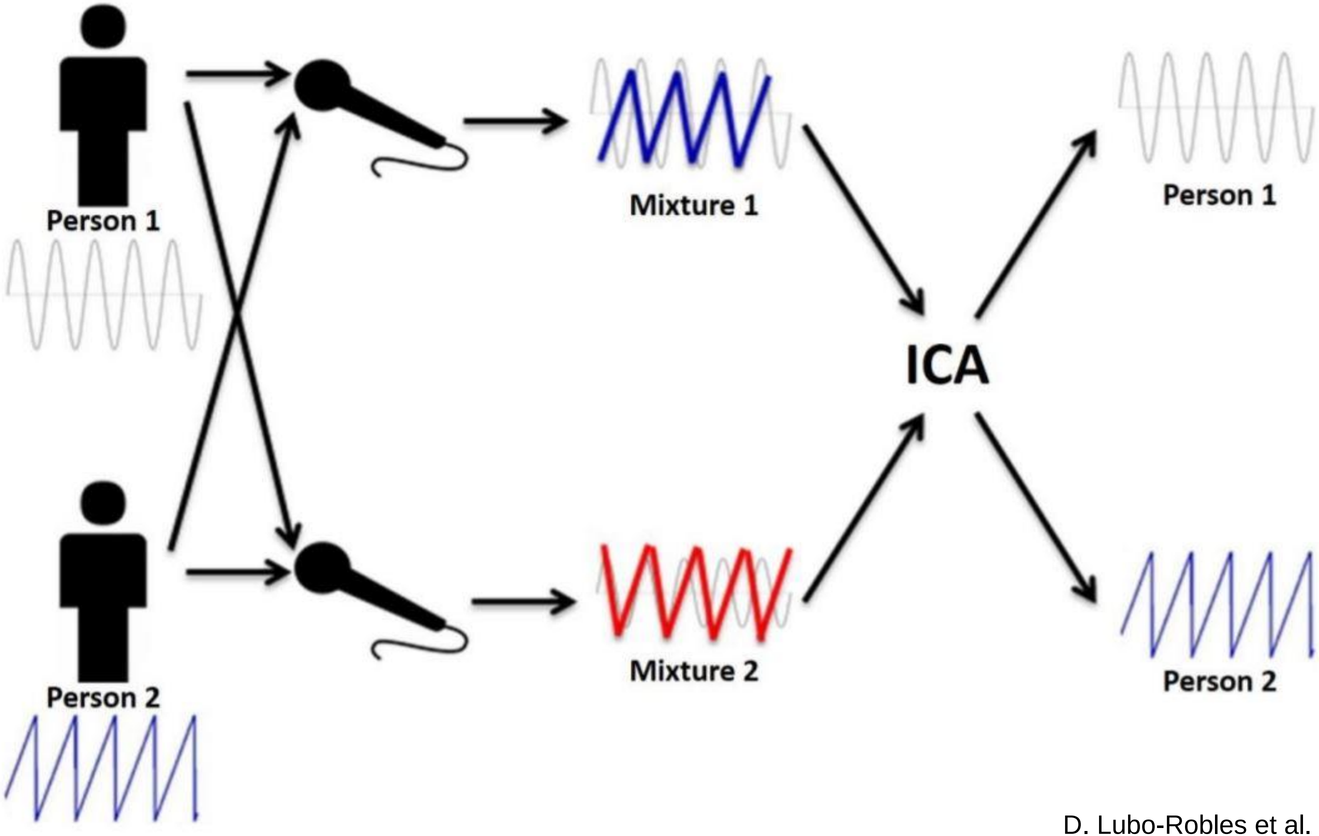
EEG Channels During Visual Stimulus



- Why do the recordings look so correlated?
- What do they do with all of this redundant information?

Independent Component Analysis (ICA) and The Cocktail Party Problem



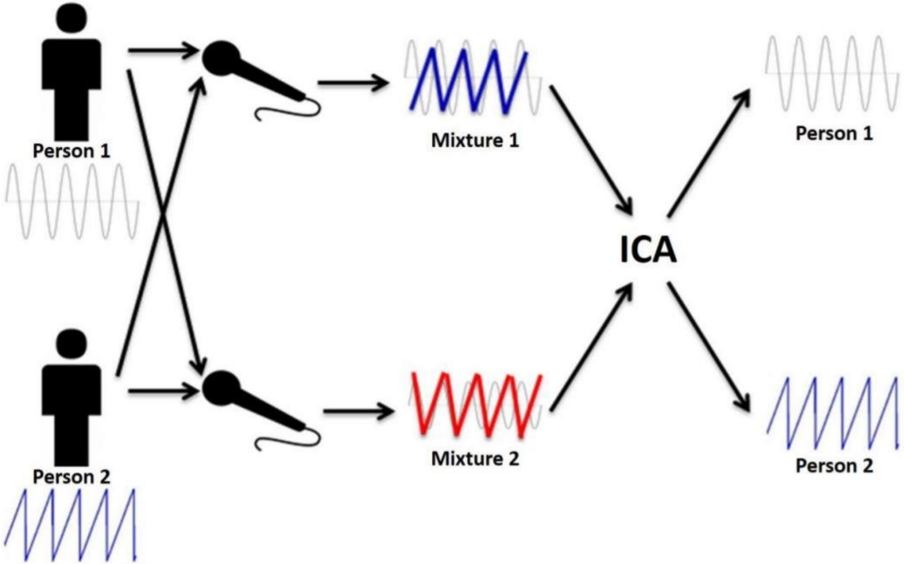
D. Lubo-Robles et al. 2018

Independent Component Analysis (ICA) and The Cocktail Party Problem

In this case:

person 1, 2 = independent brain processes

mixtures 1, 2 = EEGs



Independent Component Analysis (ICA)

Feature space of the observed data (EEGs)

$$\begin{pmatrix} x_1 \\ \vdots \\ x_N \end{pmatrix} \xrightarrow{\text{Unmixing Matrix } (\mathbf{W})} \begin{pmatrix} s_1 \\ \vdots \\ s_N \end{pmatrix}$$

Feature space of the independent sources (brain processes)

$$\mathbf{s} = \mathbf{W}\mathbf{x}$$

- Assumes all source features in **s** are independent.
- Requires at least as many microphones as talkers: len(**x**) >= len(**s**)

Independent Component Analysis (ICA)

Feature space of the observed data (EEGs)

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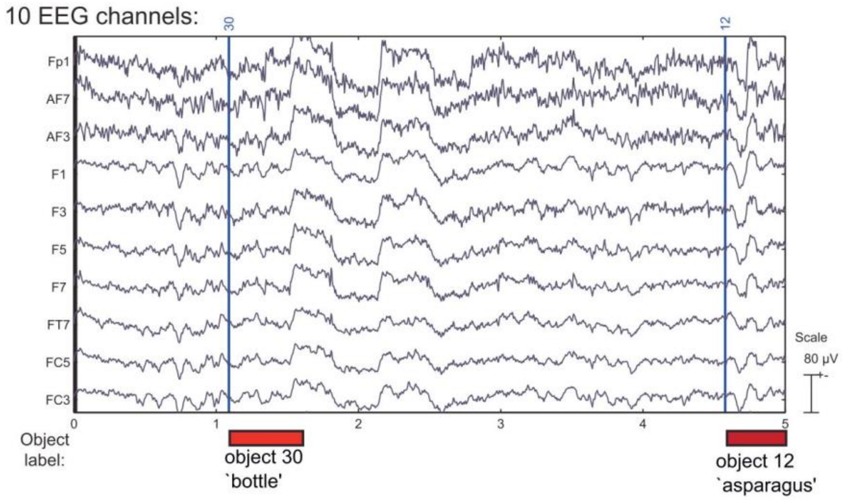
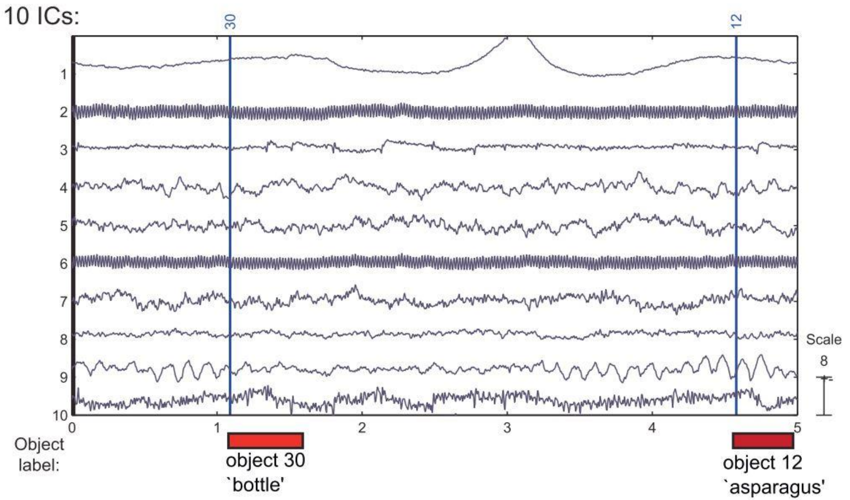
Feature space of the independent sources (brain processes)

$$\mathbf{s} = \mathbf{W}\mathbf{x}$$

- The Infomax algorithm is used to compute the independent sources.
- **W** is determined by minimizing the mutual information between components in **s**.
- This makes the new features as "independent" as possible.
- ICA does not identify the number of sources or their amplitudes.

Before and After Independent Component Analysis (ICA)

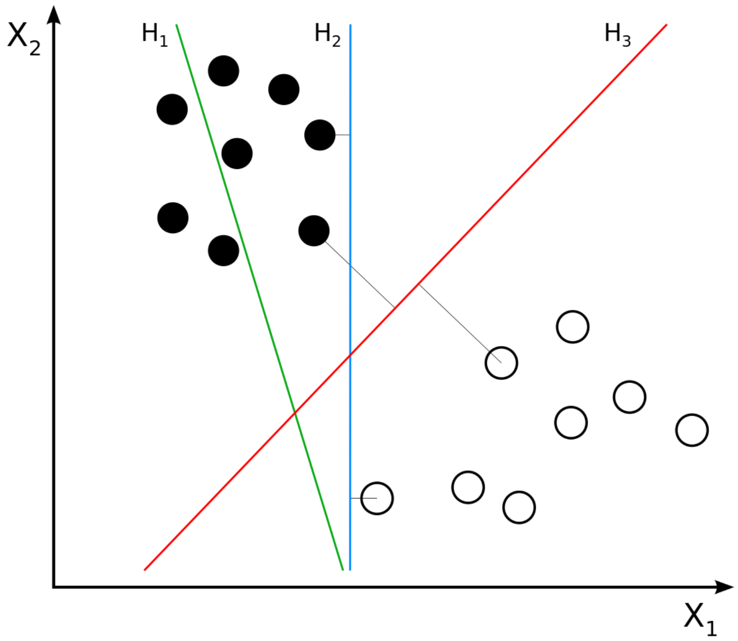




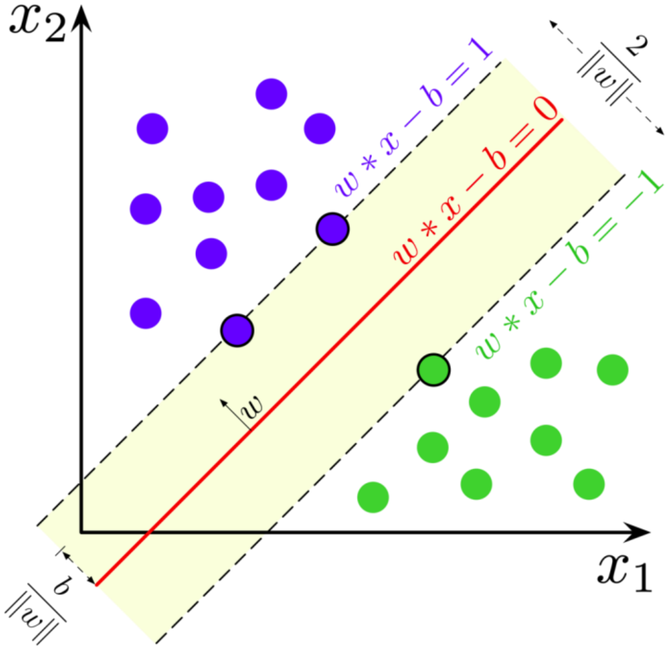
- Some of the independent components (IC) may be isolated measurements of the brain activity of interest.
- Other ICs may just be “noise” from other electrical activity in the brain/heart/muscles, not relevant to the experiment. [and 60Hz line noise from electronics!]

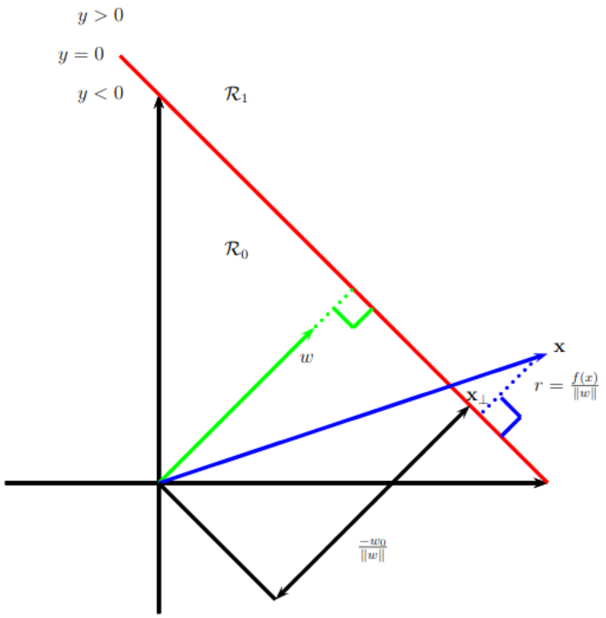
Support-Vector Machine (SVM)

- Supervised learning for classification and regression
- Non-probabilistic, linear, binary classifier (in most basic form)
- Finds p-1 dimensional hyperplane which divides N points with p features according to their classifications



SVM Hard Margin Cost Function





$$f(\mathbf{x}) = \mathbf{w}^T\mathbf{x} - b$$

$$\mathbf{x} = \mathbf{x}_\perp + r\frac{\mathbf{w}}{\|\mathbf{w}\|}$$

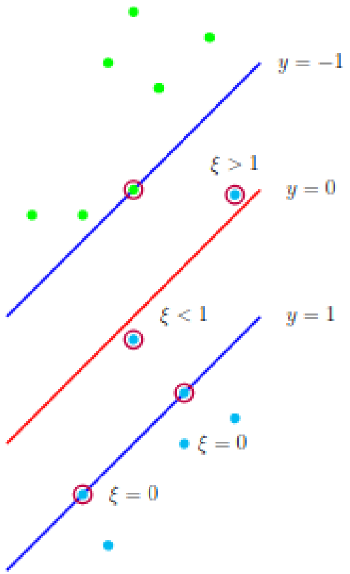
$$f(\mathbf{x}) = \mathbf{w}^T\mathbf{x}_\perp - b + r\frac{\mathbf{w}^T\mathbf{w}}{\|\mathbf{w}\|} = r\|\mathbf{w}\| \Rightarrow r = \frac{f(\mathbf{x})}{\|\mathbf{w}\|}$$

$$\max\left(\frac{1}{\|\mathbf{w}\|}\min\left(\tilde{y}_n f(\mathbf{x}_n)\right)\right),\ \tilde{y}_n f(\mathbf{x}_n) > 0\ \forall\ n$$

$$J = \frac{1}{2}\|\mathbf{w}\|^2$$

SVM Soft Margin Cost Function

$$J = \frac{1}{2}||w||^2 + C\sum_n \xi_n, \;\; \tilde{y}_n f(\mathbf{x}_n) \geq 1 - \xi_n$$



• No longer require every point to lie on the correct side of the decision boundary
• The value of ξ corresponds to how extremely the boundary is violated
• C is a parameter which must be fixed somehow

Dual Problem and Kernel Trick

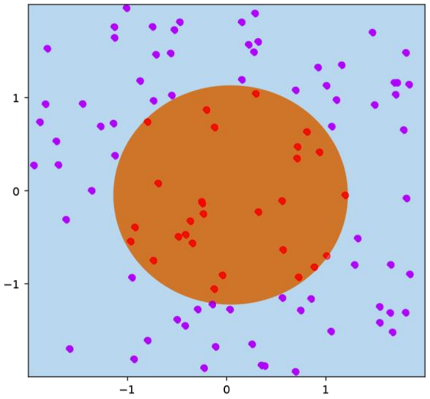
$$\mathcal{L} = \frac{1}{2}||\mathbf{w}||^2 - \sum_n \alpha_n \left(\tilde{y}_n f(\mathbf{x}_n) - 1\right)$$

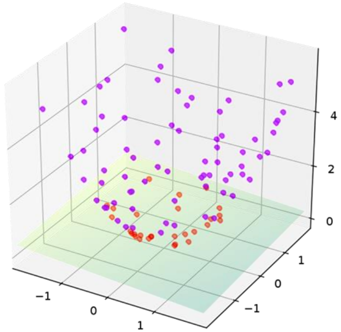
Minimize wrt w,b and maximize wrt α

$$\mathcal{L}' = -\frac{1}{2}\sum_{i,j} \alpha_i \alpha_j \tilde{y}_i \tilde{y}_j \mathbf{x}_i^T \mathbf{x}_j + \sum_n \alpha_n$$

After setting partial derivatives wrt w, b equal to zero

$$\alpha_n \geq 0, \ \sum_n \alpha_n \tilde{y}_n \ = 0$$

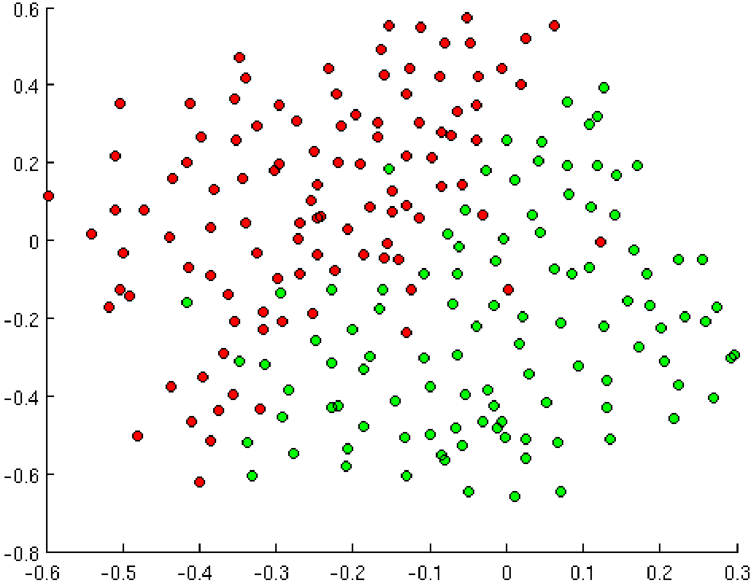




$$\varphi(a,b) = (a, b, a^2 + b^2)$$
$$k(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i \cdot \mathbf{x}_j + ||\mathbf{x}_i||^2 ||\mathbf{x}_j||^2$$

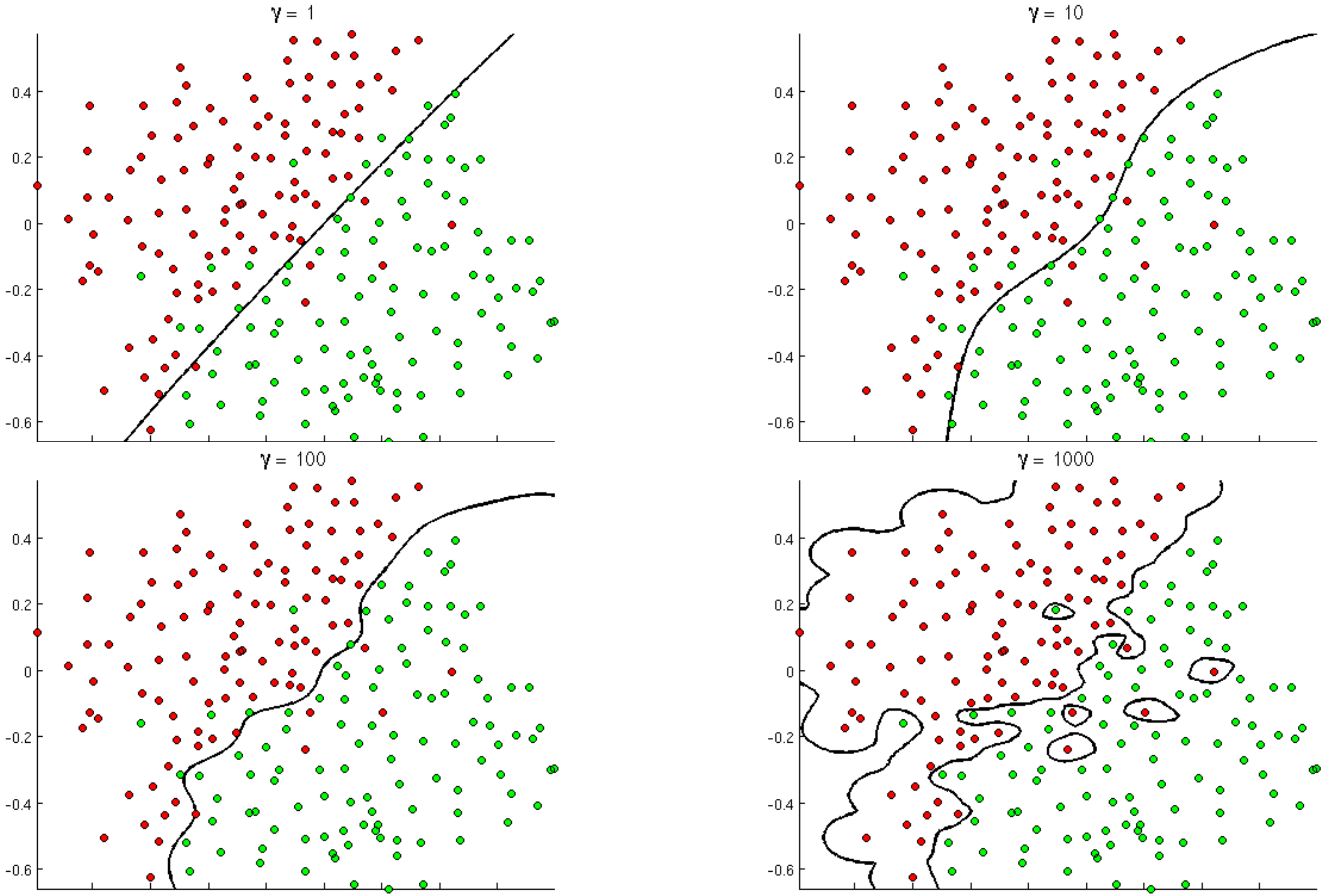
Radial Basis Function

$$k(\mathbf{x}_i, \mathbf{x}_j) = \exp\left[-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2\right]$$

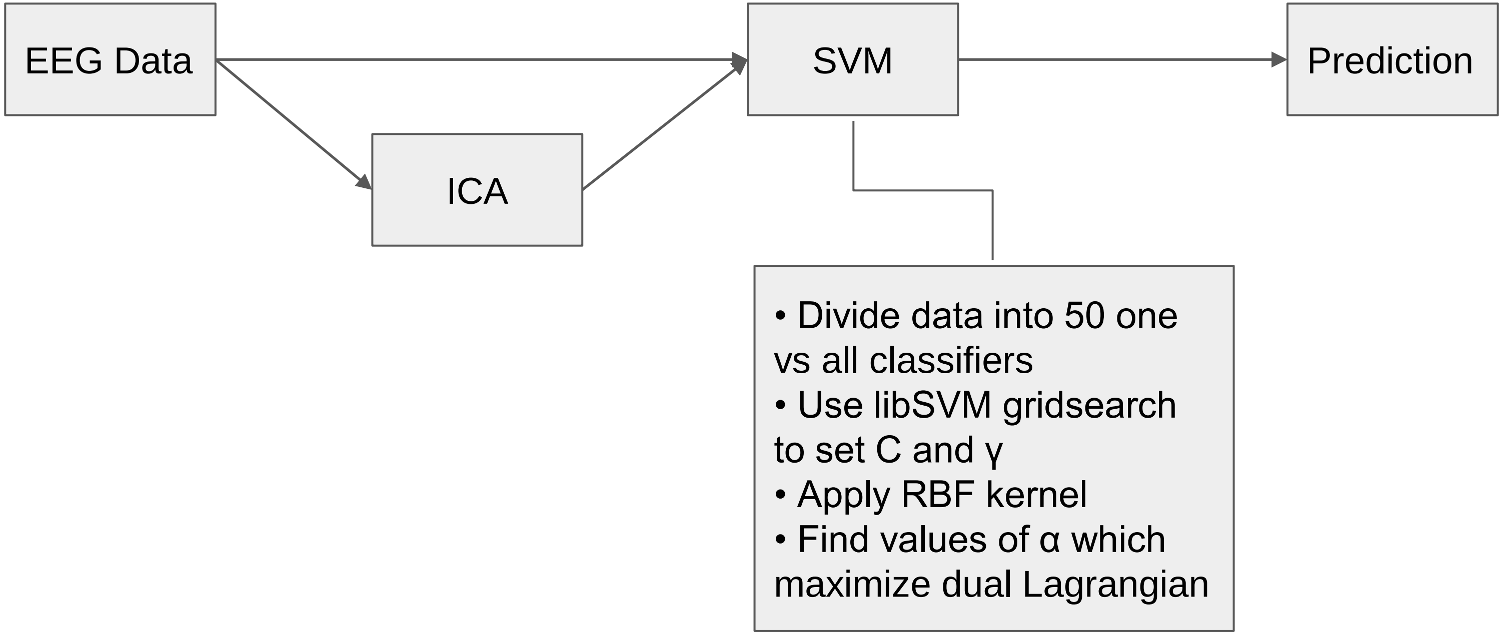


- Acts as a similarity measure
- Used in a wide variety of applications
- Introduces new parameter γ

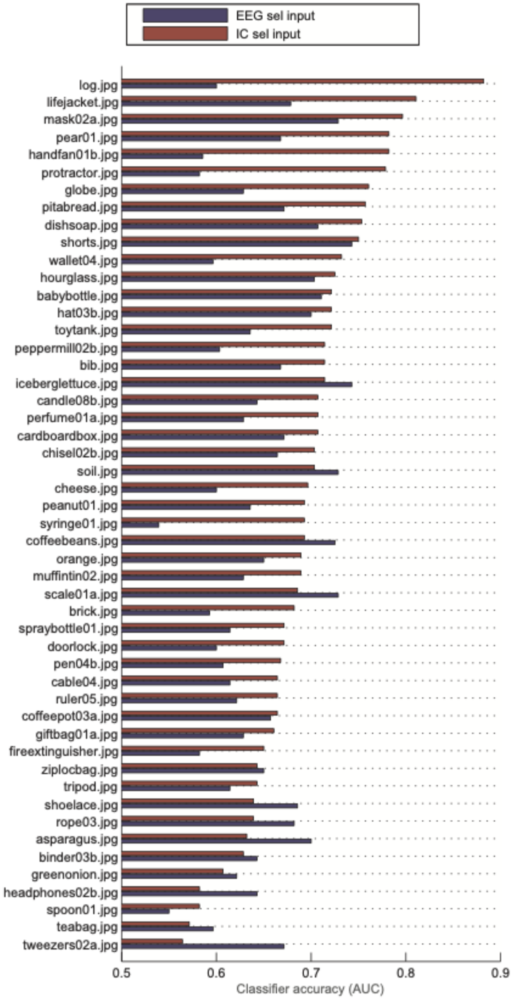
Radial Basis Function



Application of SVMs to EEG Data



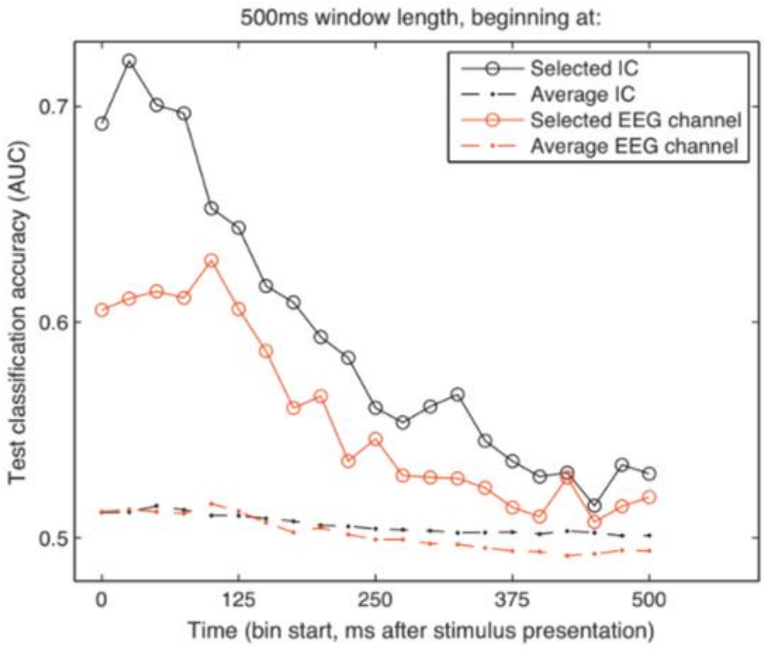
Conclusions



- able to correctly classify object present/object absent scenarios with 87% accuracy

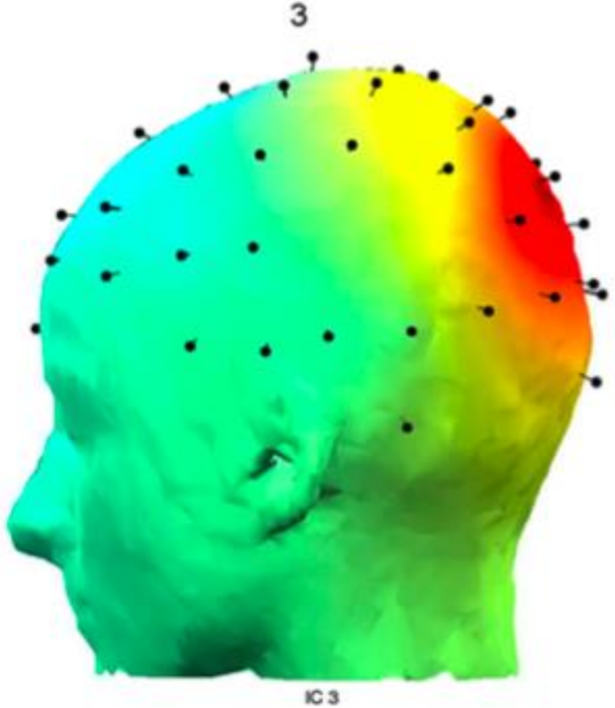
- IC performed better than individual EEG channels

Conclusions

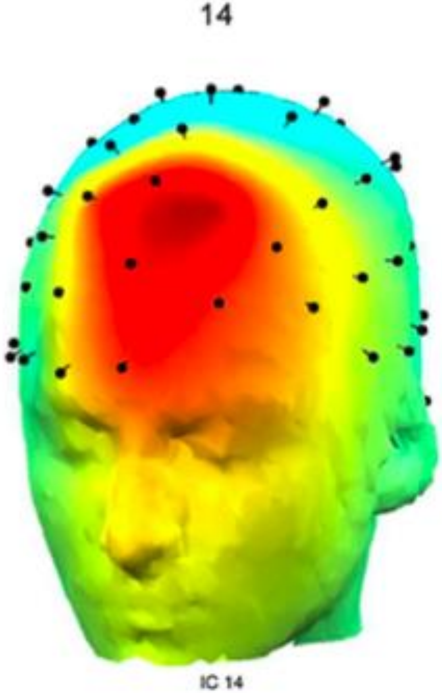


- single selected channel inputs were better for classifying data than using all of the EEG signals/all of the ICs

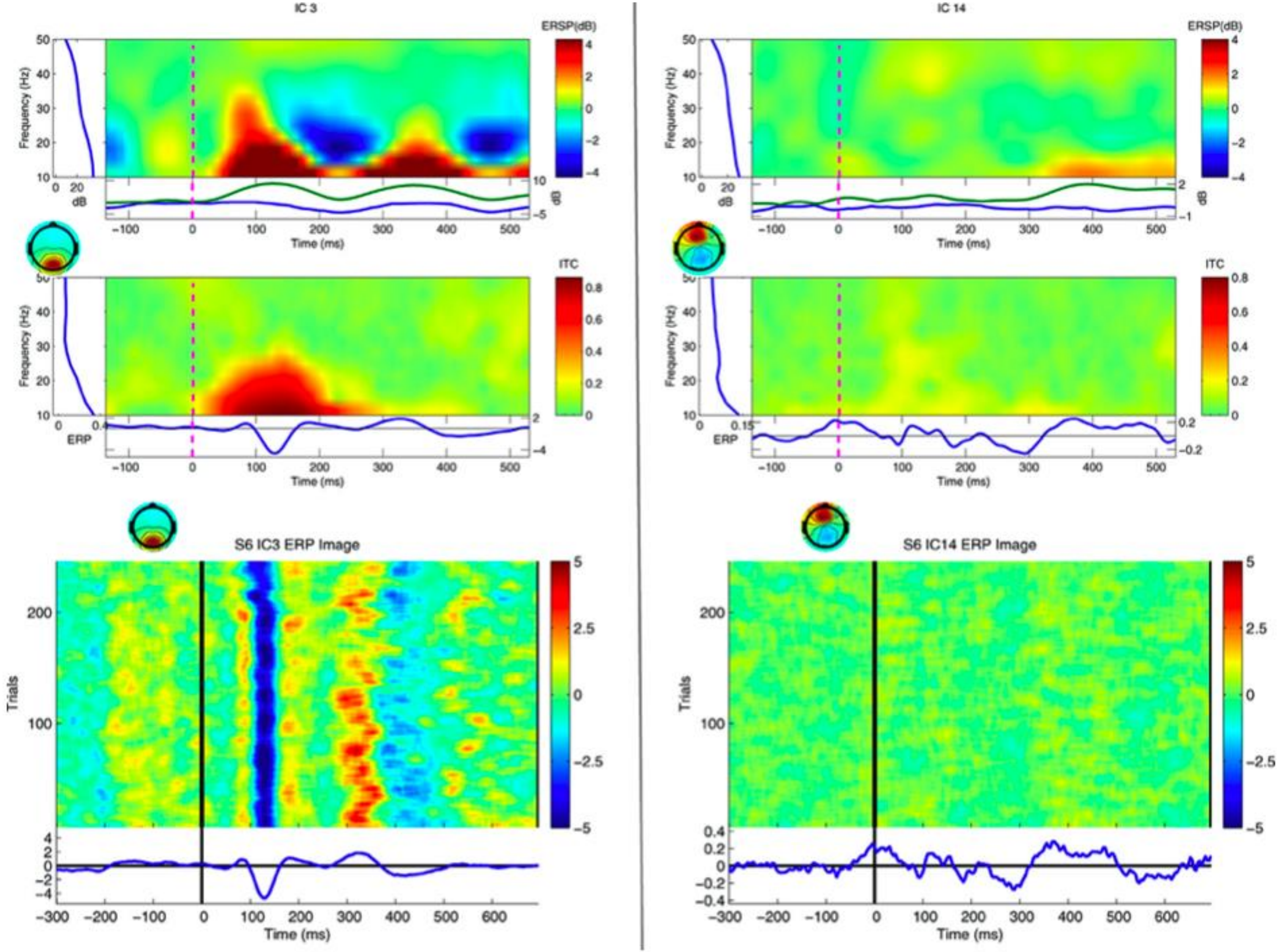
High accuracy IC
0.91 AUC



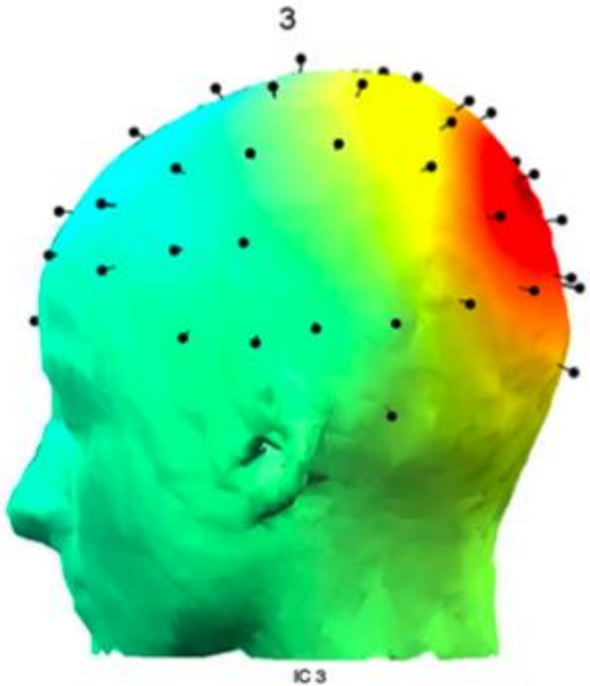
Low accuracy IC
0.51 AUC



Additional Slides


IC 3
IC 14
ERSP(dB)
ITC
Frequency (Hz)
Time (ms)
dB
ERP
S6 IC3 ERP Image
S6 IC14 ERP Image
Trials

High accuracy IC
0.91 AUC



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