# MACHINE LEARNING APPROACH TO PREDICT SUCCESSFUL MEMORY ENCODING

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# Restoring Active Memory (RAM) Project

- Four year $22.5 million grant from DARPA under BRAIN init
- Collaboration between 13 sites

- University of Pennsylvania
- **UTSW**
- Thomas Jefferson University
- Dartmouth
- Emory
- NINDS
- Mayo
- Columbia
- Boston University
- Ohio State University
- Medtronic
- Lawrence Livermore National Labs
- Blackrock Microsystems

- 190 total subjects (44 from UTSW)
    - Epilepsy patients with intracranial electrode implants

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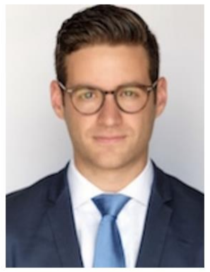
## Principal Investigator

**Dr. Bradley C Lega**

## Lab Members



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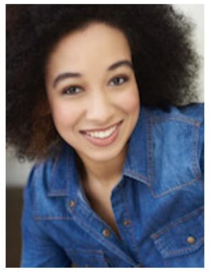
SMU master's student in Electrical Engineering



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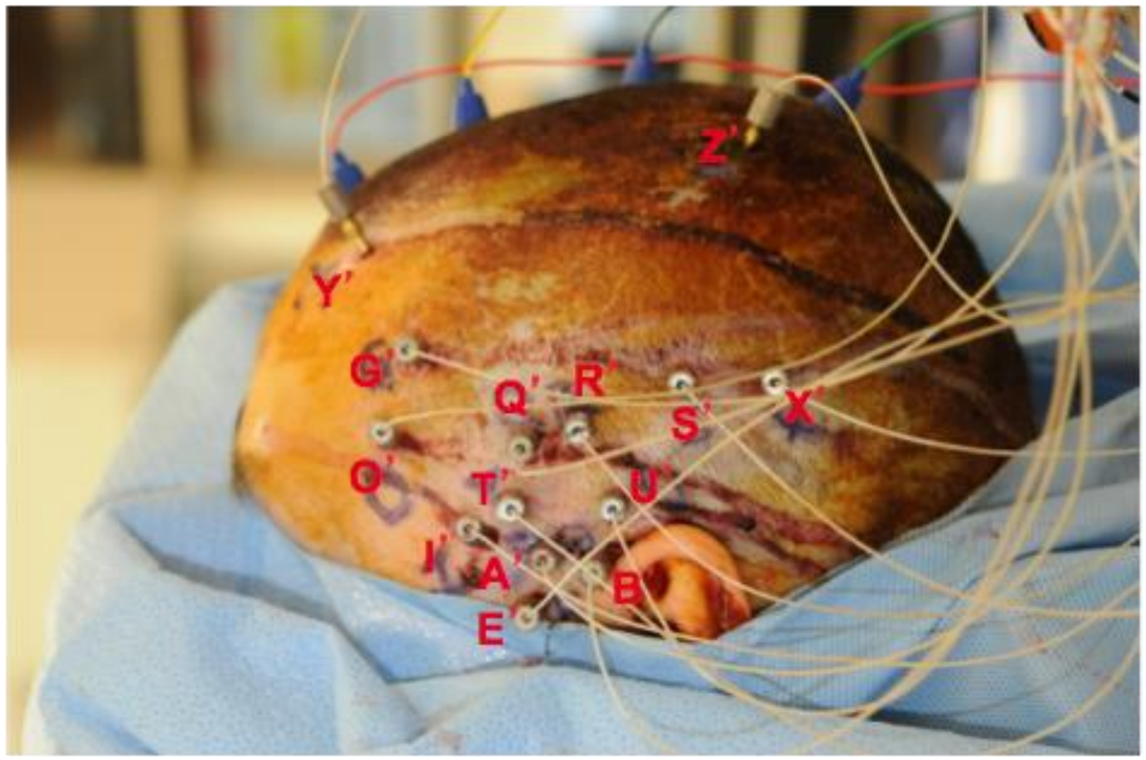
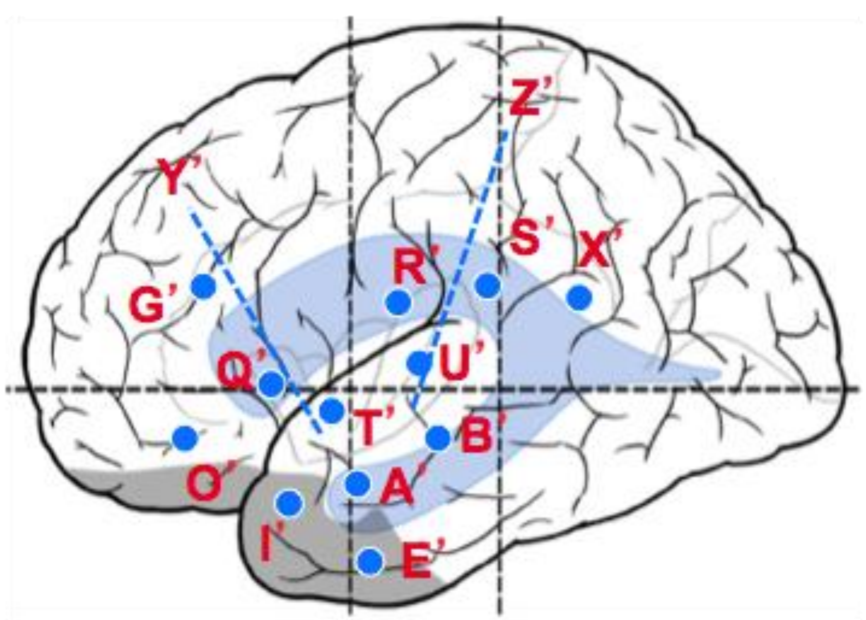
ME, Electrical Engineering, SMU, 2015
Electrical Enginger, Ph.D. Candidate, SMU, 2015

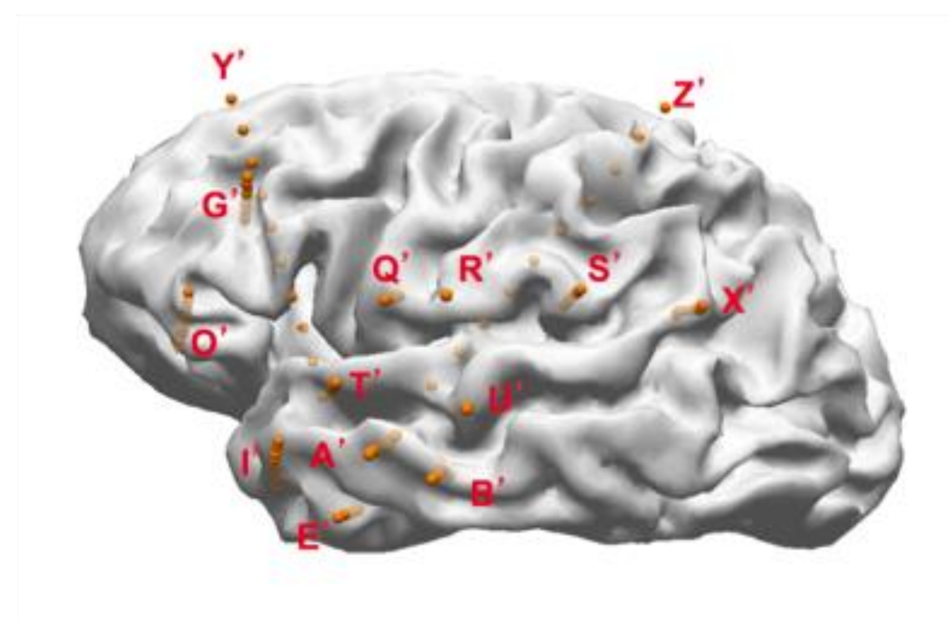
Constance Kemp

Program Coordinator

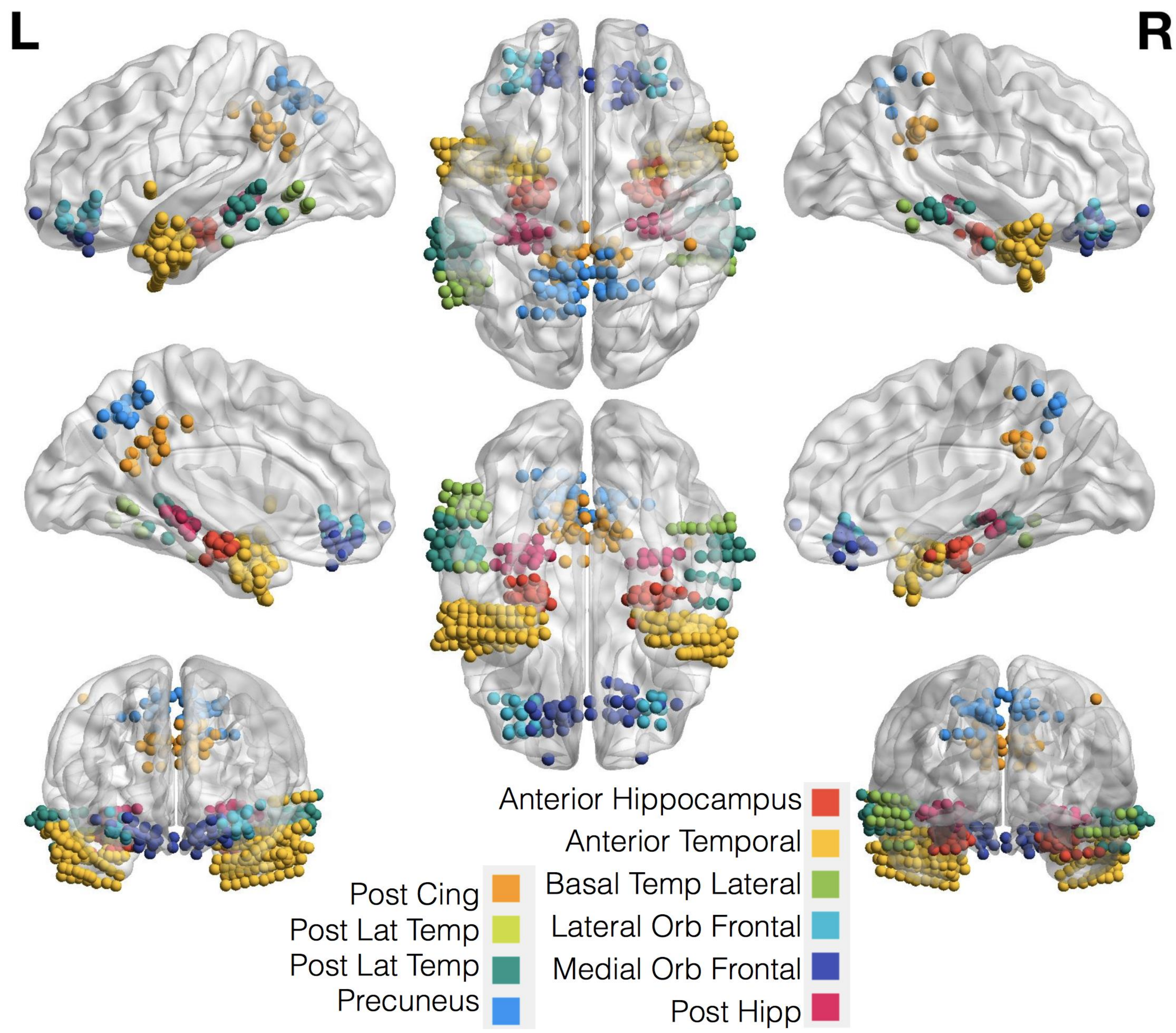
# Stereo EEG Intracranial Depth Recording



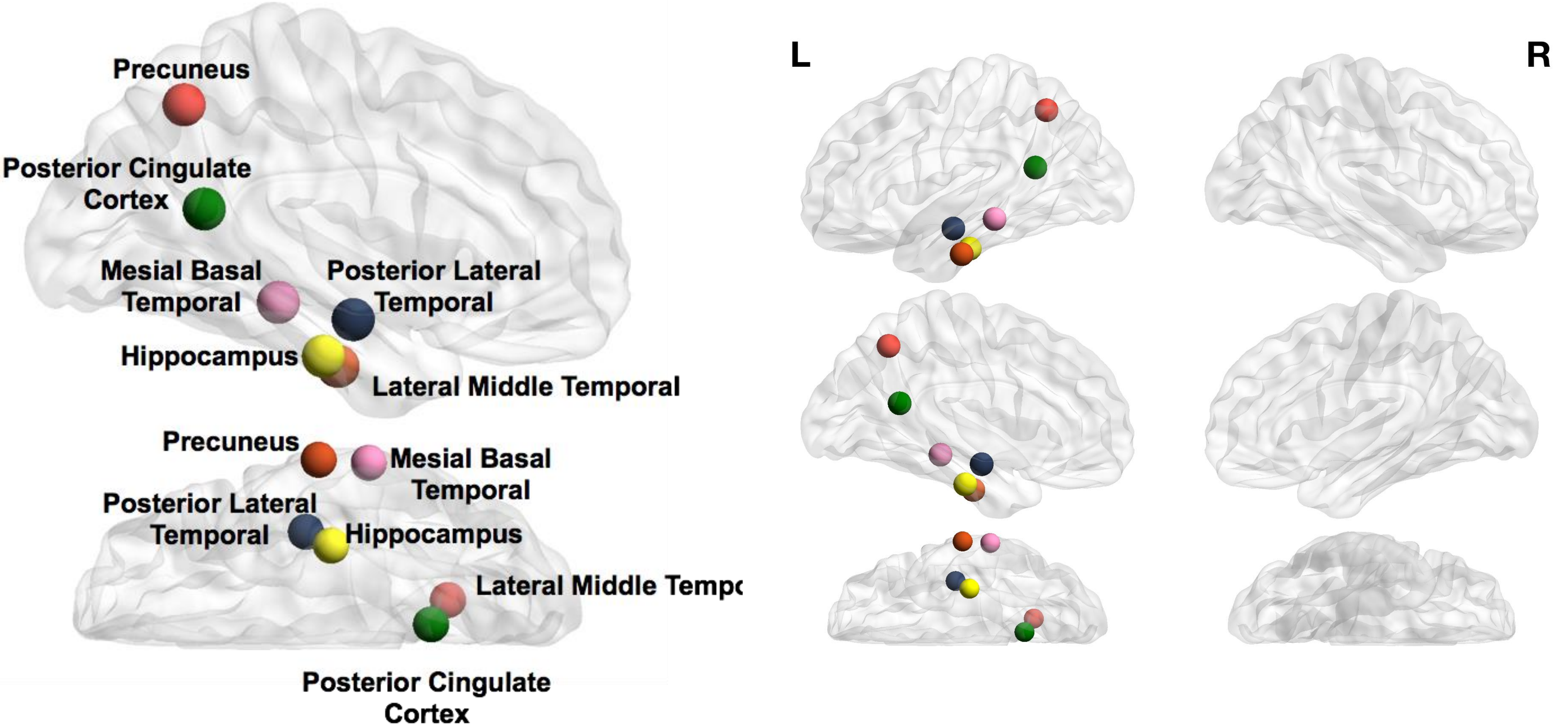



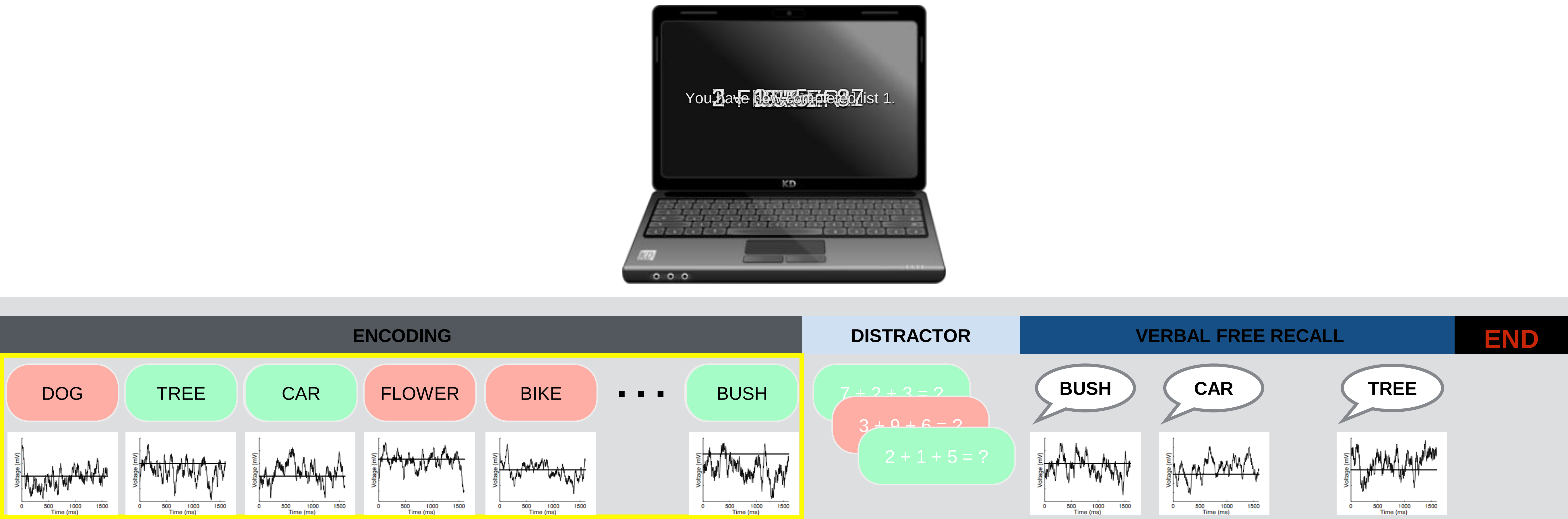
# Electrode Localization



# Regions of Interest

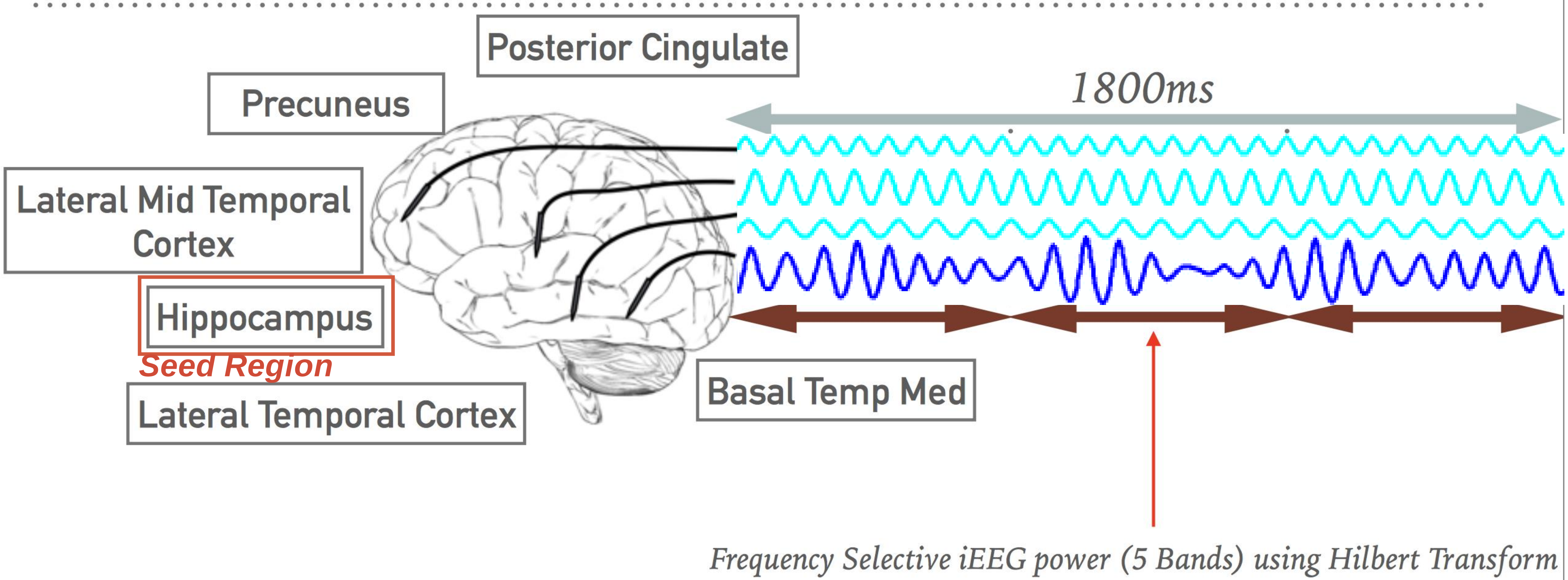



***Seed Region : Hippocampus***




Able to compare neural activation patterns during the **encoding** of words that are later remembered with patterns during **encoding** of words that are not remembered

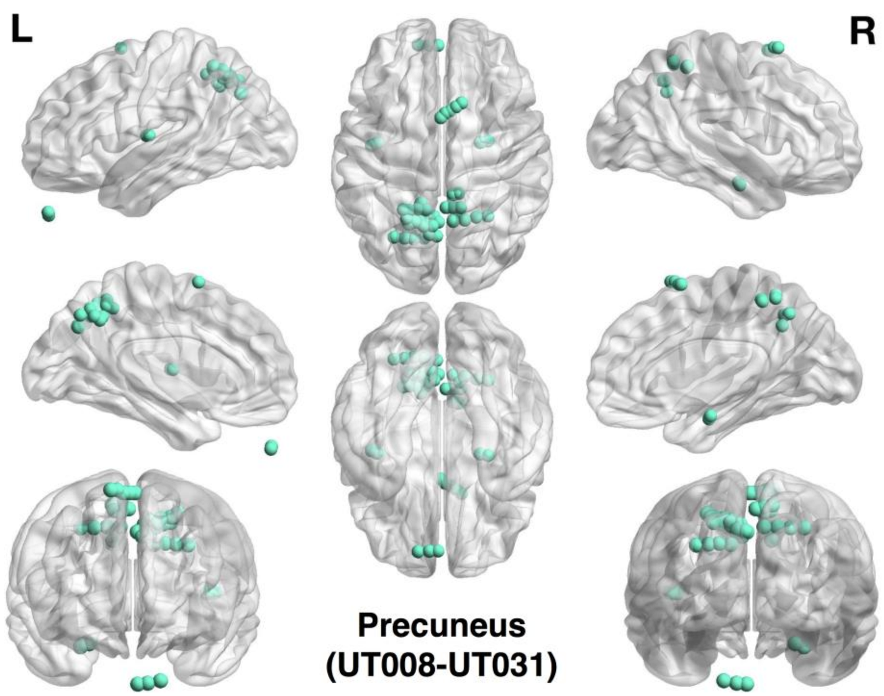
# DATA ACQUISITION AND PREPROCESSING : POWER DATA



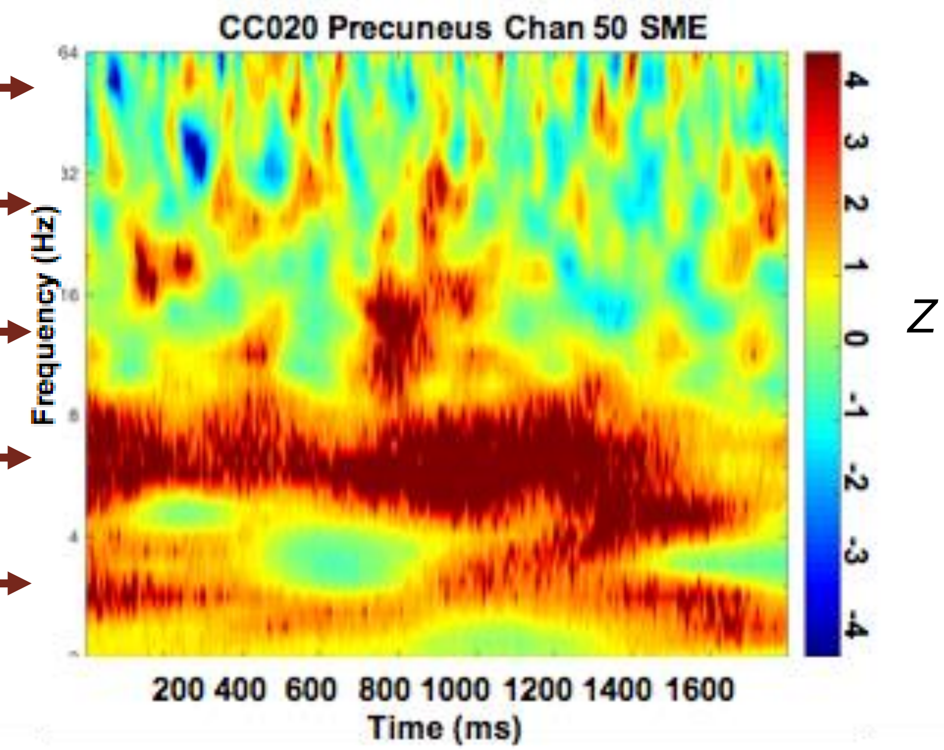

Delta: 2-4Hz
Theta: 4-9Hz
Alpha : 9-16Hz
Beta :16-32Hz
Gamma: 32-55Hz

Data : Events x Frequency(5 Bands) x Time(3 Windows) x 6 Regions )

# Intracranial EEG Power Spectrogram



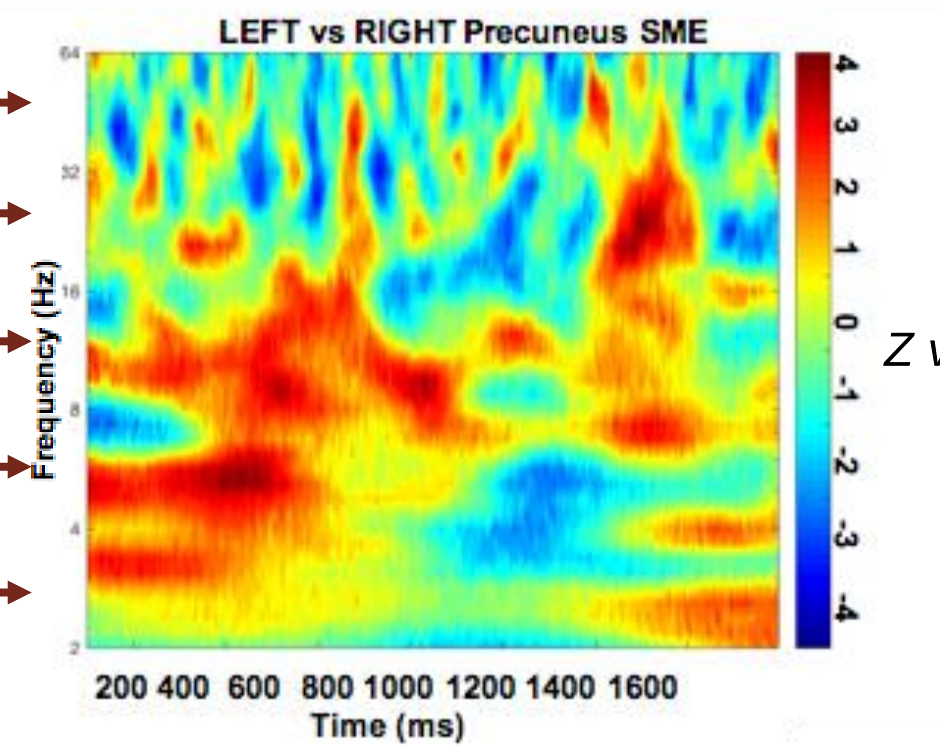

*Gamma(25-55Hz)*
*Beta (16-25 Hz)*
*Alpha (9-16Hz)*
*Theta (5-9Hz)*
*Delta (2-5Hz)*




*Z values*

**Figure 2a : Single Channel Precuneus SME**

*Gamma(25-55Hz)*
*Beta (16-25 Hz)*
*Alpha (9-16Hz)*
*Theta (5-9Hz)*
*Delta (2-5Hz)*



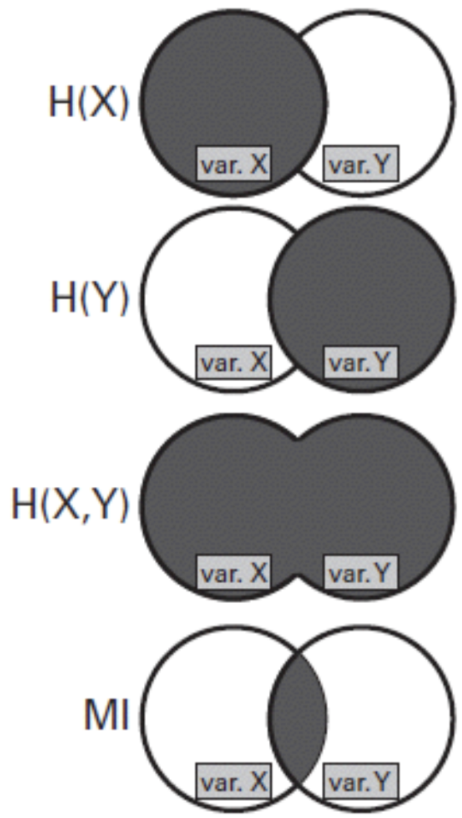

*Z values*

**Figure 2b: Left vs Right Precuneus SME**

# DATA SET : MUTUAL INFORMATION DATA (ALL SIX REGIONS)

- *The MI values are **Z-normalized** and the are averaged across channel pairs.*
- *The max positive and **negative** lags across each event is chosen to be the predictor for 'recall' and 'non-recall' for all 6 regions of interest.*

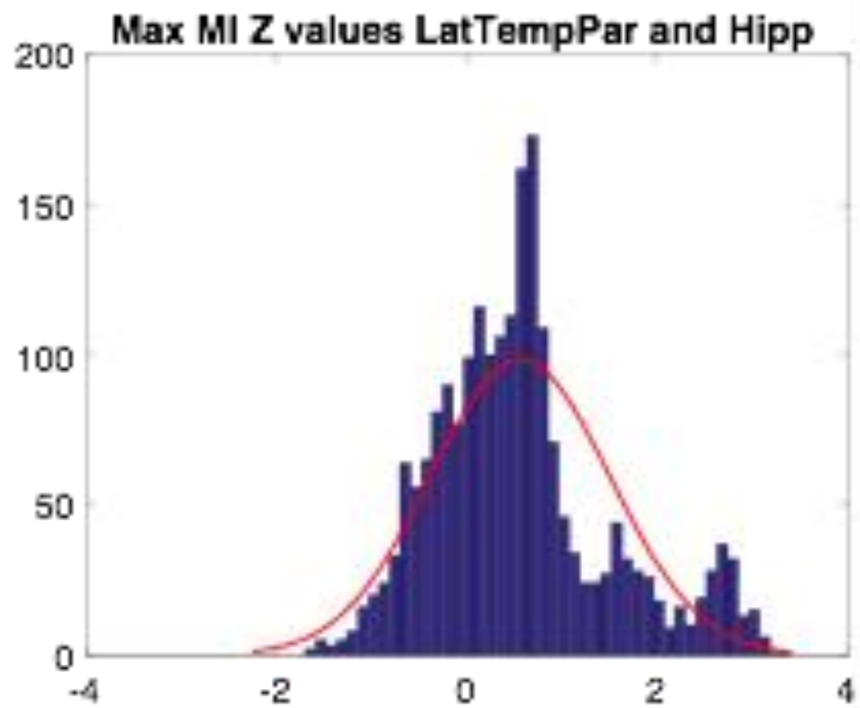
$$I(X;Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$$




$$MI(X,Y) = H(X) + H(Y) - H(X,Y)$$

*Data : Events x ChannelPairs(Seed: HIPP) x TimeLags ( -200ms to 200ms)*

# Mutual Information (Lagged)



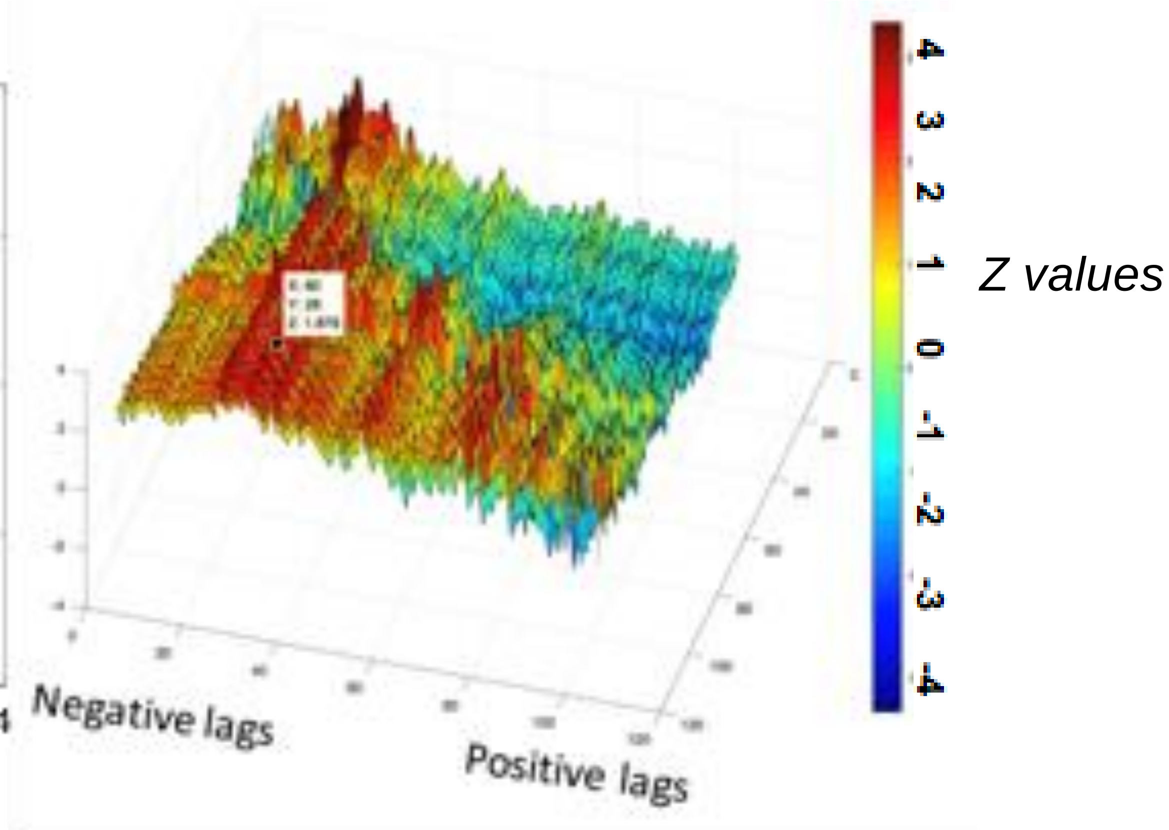




Figure 3a : Max MI Z Val Distribution

- Max MI Z Values are Normally Distributed.
- Precuneus leads the Hippocampus by 112ms.

# Machine Learning Data

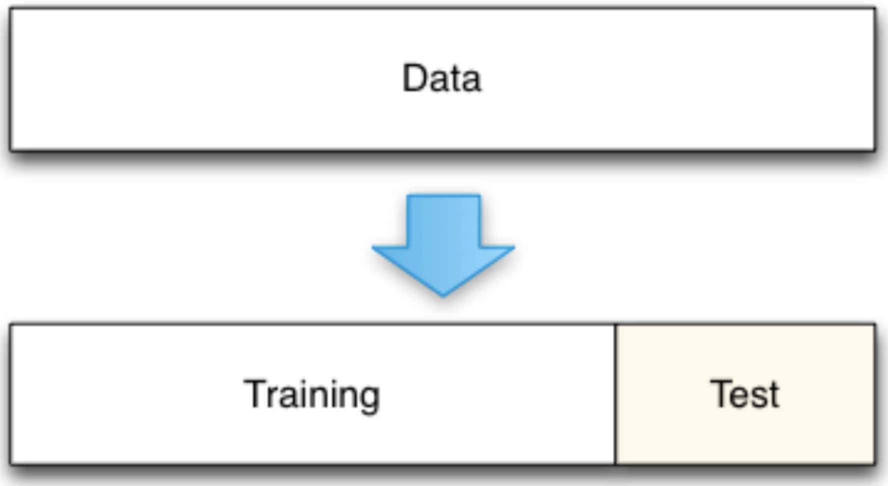
**Features**

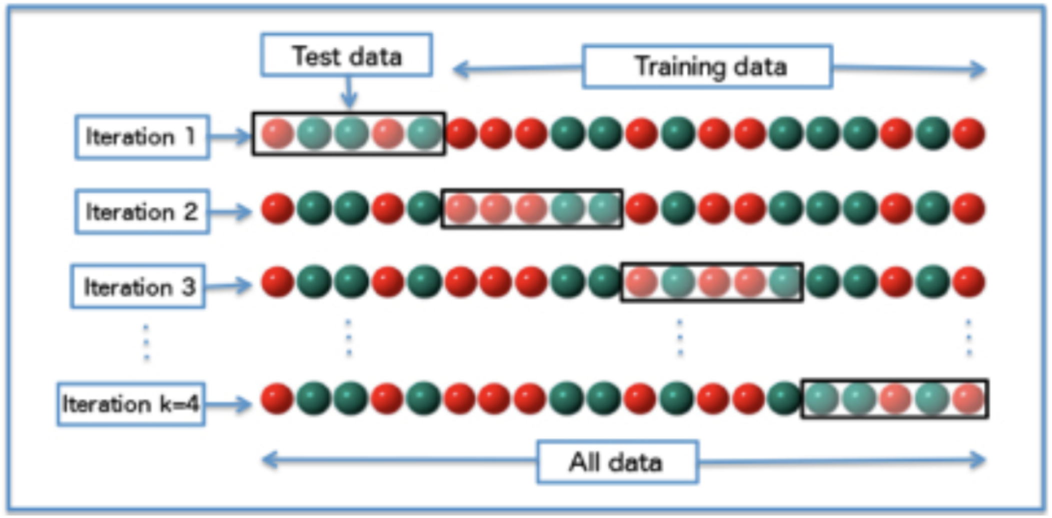
**Events (Trials)**

| Power Region 1 | Power Region 2 | Power Region 3 | Power Region 4 | Power Region 5 | Power Region 6 | MI Region 6 | MI Region 6 | MI Region 6 | MI Region 6 | MI Region 6 | MI Region 6 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | |
| Recall | | | | | | | | | | | |
| Recall | | | | | | | | | | | |
| Recall | | | | | | | | | | | |
| NonRecall | | | | | | | | | | | |
| NonRecall | | | | | | | | | | | |
| NonRecall | | | | | | | | | | | |
| … | | | | | | | | | | | |

Data : Events x Frequency(5 Bands) x Time(3 Windows) x 6 Regions )

# CROSS VALIDATION TECHNIQUES



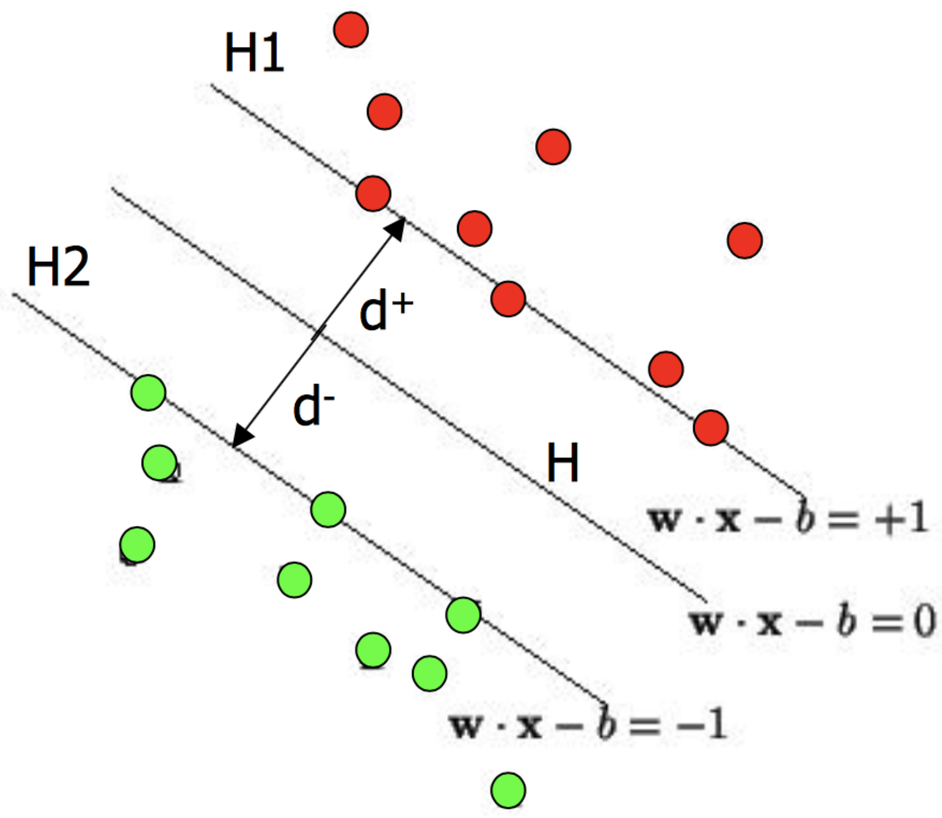

- *HoldOut Validation : 70 % : Training , 30 % : Testing*
- *k-Fold CrossValidation : Divide Dataset into k-partitions*

# Support Vector Machines

Define the hyperplane H such that:

$\mathbf{x}_i \bullet \mathbf{w}+b \geq +1$ when $y_i = +1$

$\mathbf{x}_i \bullet \mathbf{w}+b \leq -1$ when $y_i = -1$




H1 and H2 are the planes:

H1: $\mathbf{x}_i \bullet \mathbf{w}+b = +1$

H2: $\mathbf{x}_i \bullet \mathbf{w}+b = -1$

The points on the planes H1 and H2 are the Support Vectors

d+ = the shortest distance to the closest positive point

d- = the shortest distance to the closest negative point

The <u>margin</u> of a separating hyperplane is $d^+ + d^-$.

# Support Vector Machines

## We now must solve a <u>quadratic</u> programming problem

- Problem is: <u>minimize</u> $||\mathbf{w}||$, **s.t.** discrimination boundary is obeyed, i.e., min $f(x)$ s.t. $g(x)=0$, where

  $f$: $\frac{1}{2}\,||w||^2$ and

  $g$: $\mathbf{y_i(x_i \bullet w)\text{-}b = 1}$ **or** $\mathbf{[y_i(x_i \bullet w)\text{-}b] - 1 = 0}$

This is a **<u>constrained optimization problem</u>**

Solved by Lagrangian multipler method

# Support Vector Machines

## In general

Gradient max of $f$

constraint condition $g$

$L(x,\alpha) = f(x) + \sum_i \alpha_i g_i(x)$ a function of $n+m$ variables

$n$ for the $x's$, $m$ for the $\alpha$. Differentiating gives $n+m$ equations, each set to 0. The $n$ eqns differentiated wrt each $x_i$ give the gradient conditions; the $m$ eqns differentiated wrt each $\alpha_i$ recover the constraints $g_i$

In our case, $f(x)$: $\frac{1}{2}\|\mathbf{w}\|^2$ ; $g(x)$: $y_i(\mathbf{w}.x_i + b) - 1 = 0$ so Lagrangian is

$$L = \tfrac{1}{2}\|\mathbf{w}\|^2 - \Sigma\alpha_i[y_i(\mathbf{w}.x_i + b) - 1]$$

# Support Vector Machines

## Lagrangian Formulation

- In the SVM problem the Lagrangian is

$$L_P \equiv \tfrac{1}{2}\|\mathbf{w}\|^2 - \sum_{i=1}^{l} \alpha_i y_i (\mathbf{x}_i \cdot \mathbf{w} + b) + \sum_{i=1}^{l} \alpha_i$$

$$\alpha_i \geq 0, \forall i$$

- From the derivatives = 0 we get

$$\mathbf{w} = \sum_{i=1}^{l} \alpha_i y_i \mathbf{x}_i, \sum_{i=1}^{l} \alpha_i y_i = 0$$

# Logistic Regression

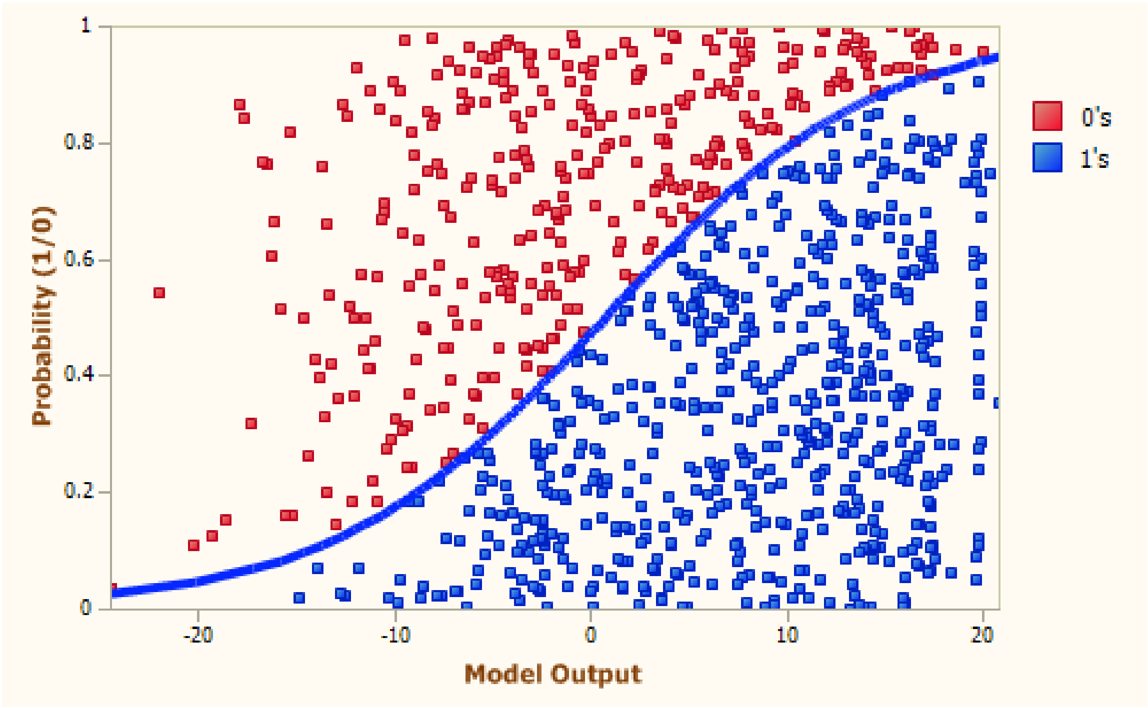



**Figure: Sigmoid function, or logistic function**

- Logistic regression is a regression model where there is a binary dependent variable (DV) where it can take only two values, such as pass/fail, win/lose, alive/dead or healthy/sick.
- Its activation function is expressed as follows :

$$S(t) = \frac{1}{1+e^{-t}}$$

Where, $t = \beta_0 + \beta_1 x$

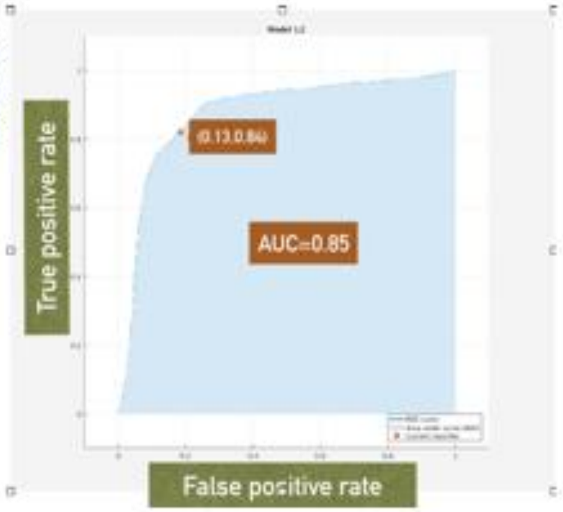
and

$$F(x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x)}}$$

Binary Classifier : Probabilistic Model

## SVM Classifier : (quadratic) Combined Subjects

- The ROC shows that the SVM model predicts recall performance with an of AUC =0 .85
- Recall Accuracy = 84 %

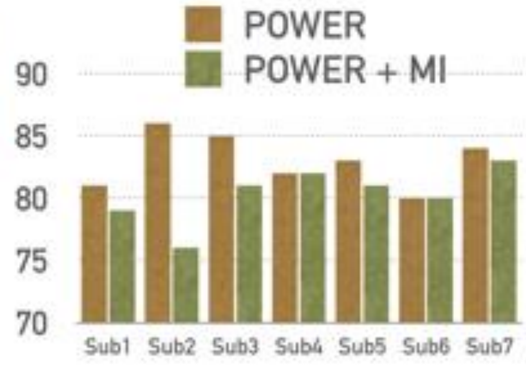



## Logistic Regression Classifier : Combined Subjects

- The ROC shows that the logistic Regression model predicts recall performance with an of AUC =0 .75
- Recall Accuracy = 0.75 %


## SVM Classifier : (quadratic) Individual Subjects

- The Bar plots shows that the SVM model predicts recall performance with an average of 82 % accuracy across all subjects.
- Power gives similar prediction results compared to than choosing Power + MI




## Logistic Regression Classifier : Individual Subjects

- The Bar plots shows that the logistic model predicts recall performance with an average of 76 % accuracy across all subjects.
- Power gives similar prediction results compared to than choosing Power + MI

# Cross Validation Error

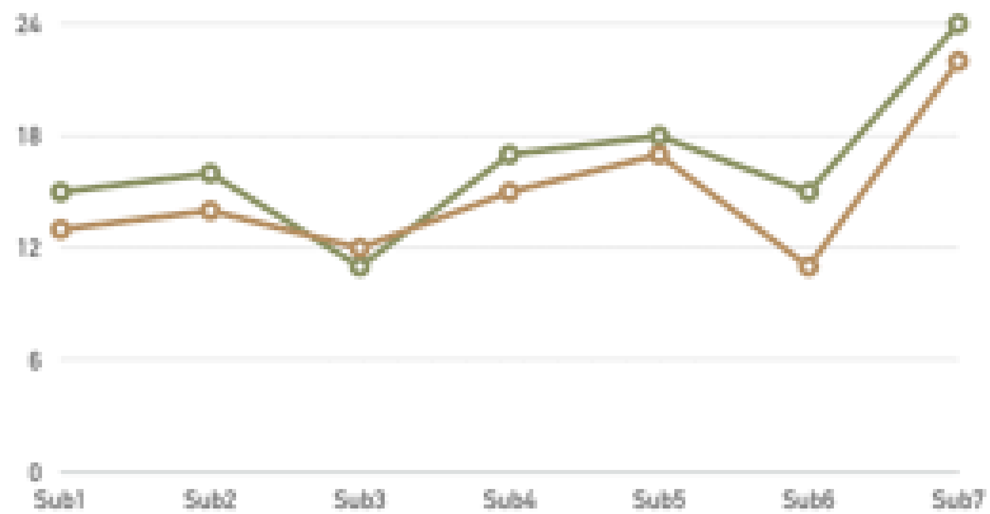



**Figure a :K-Fold Loss (Support Vector Machines Classifier)**

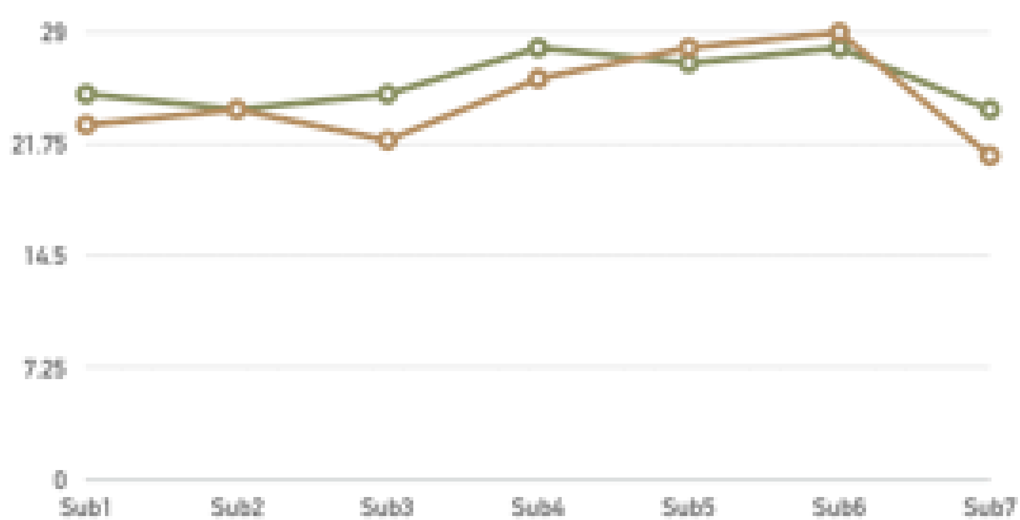



**Figure b :K-Fold Loss (Logistic Regression Classifier)**

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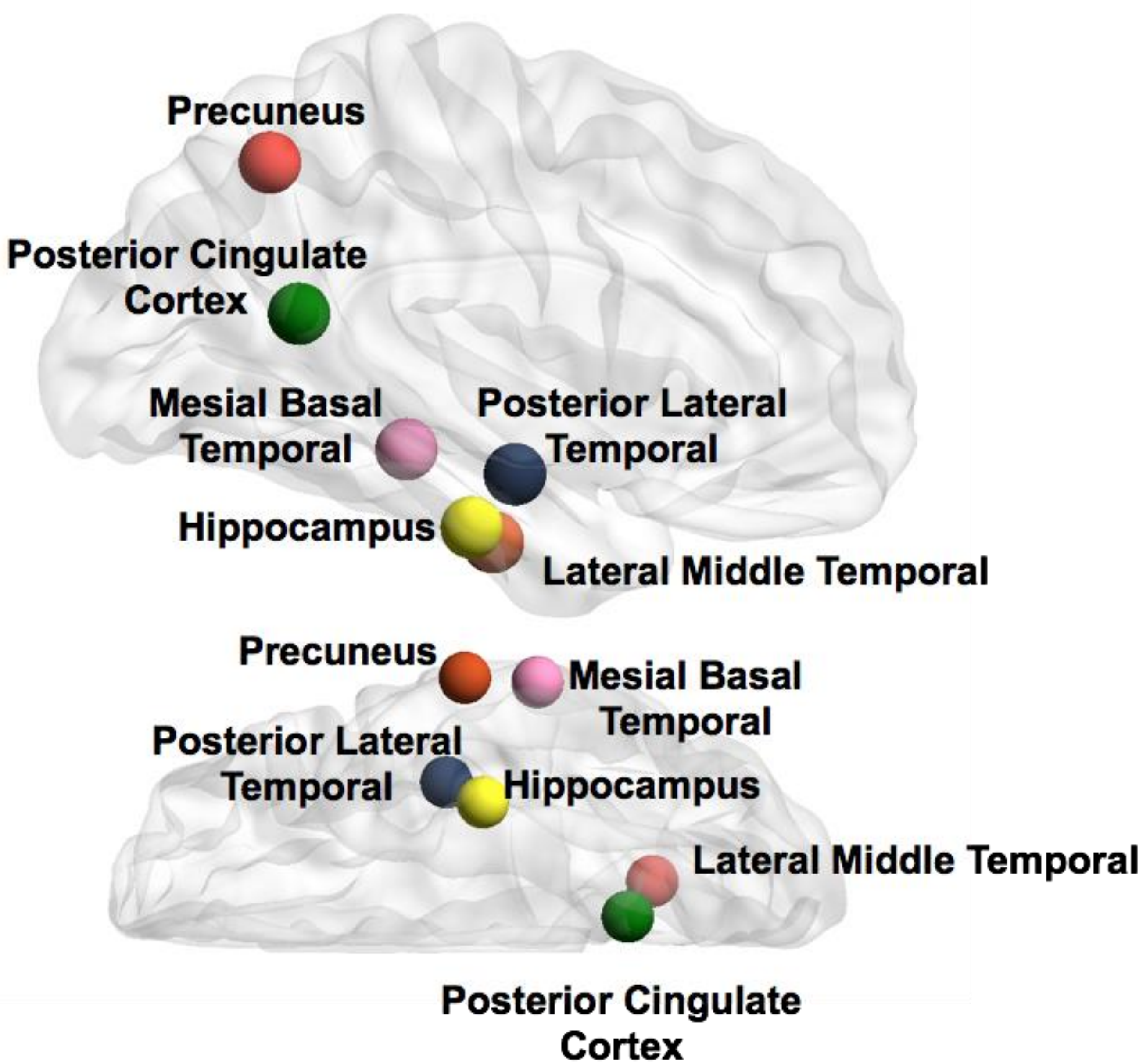


## Classification Summary (Leave one Region Out)

Table 1 :Classification Summary (Leave one Region Out)

| Region Excluded Out | AUC | Recall % |
|---|---|---|
| Basal Temp Mesial | 0.85 | 83 % |
| Lateral Temporal Cortex | 0.82 | 82% |
| Lateral Middle Temporal Cortex | 0.83 | 81% |
| Precuneus | 0.79 | 78% |
| Posterior Cingulate | 0.79 | 78% |
| Hippocampus | 0.75 | 73% |

- From this Table above, it can be observed that the prediction accuracy and classifier AUC value reduces when we a generate a classifier without "Hippocampus" Region.

# Future Work

- **Estimation of important predictors from iEEG Power and Mutual Information to improve the classifier performance.**

- **Adding more Connectivity based predictors to the existing models**

**Thank You !**