Queen Mary University of London

UNIVERSITÀ DEGLI STUDI DI GENOVA

Predictive Analysis of Auditory Attention from Physiological Signals

PhyAAt: Physiology of Auditory Attention

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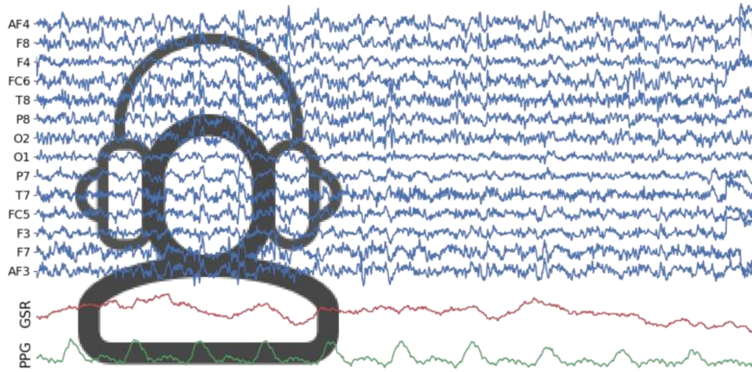


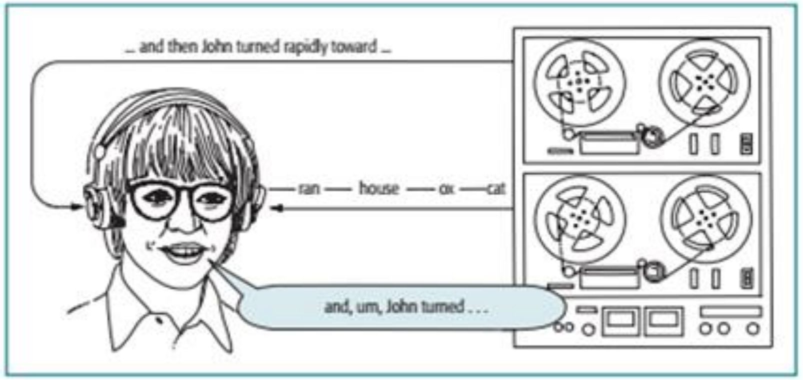
Overview

- Introduction :
  - Auditory attention & Problem formulation
- Experiment
  - Design & Procedure
- Collectect Data and Analysis
- Formulation of predictive tasks
- EEG Signal: Artifact, Rectifying, Analysis
- Performance of Predictive Tasks
  - SVM, Deeplearning : CNN
- Conclusions

Introduction

Attention : A cognitive process of selectively focusing on a discrete aspect of information, while ignoring other perceivable information

- Cognitive attention is a complex process of the brain
- Cognitive psychologist & Neuroscientist have been studying it for decades, motivated by WW-II, fighter pilots.
- Cognitive Attention : Auditory, Visual, and Task oriented
- Theories of attention (auditory) : Filter theory, Early selection and Late selection, Cognitive load theory.
- Experiment for Auditory attention : Widely used experiment setting - *dichotic listening task*.



Problem : Does auditory attention* modulates the physiology? Can it be estimated from such signals?

Experiment design

- Experiment based on *dichotic listening task*
- Stimuli
  - Generated non-semnatic (1700) stimuli from semantic (5000)

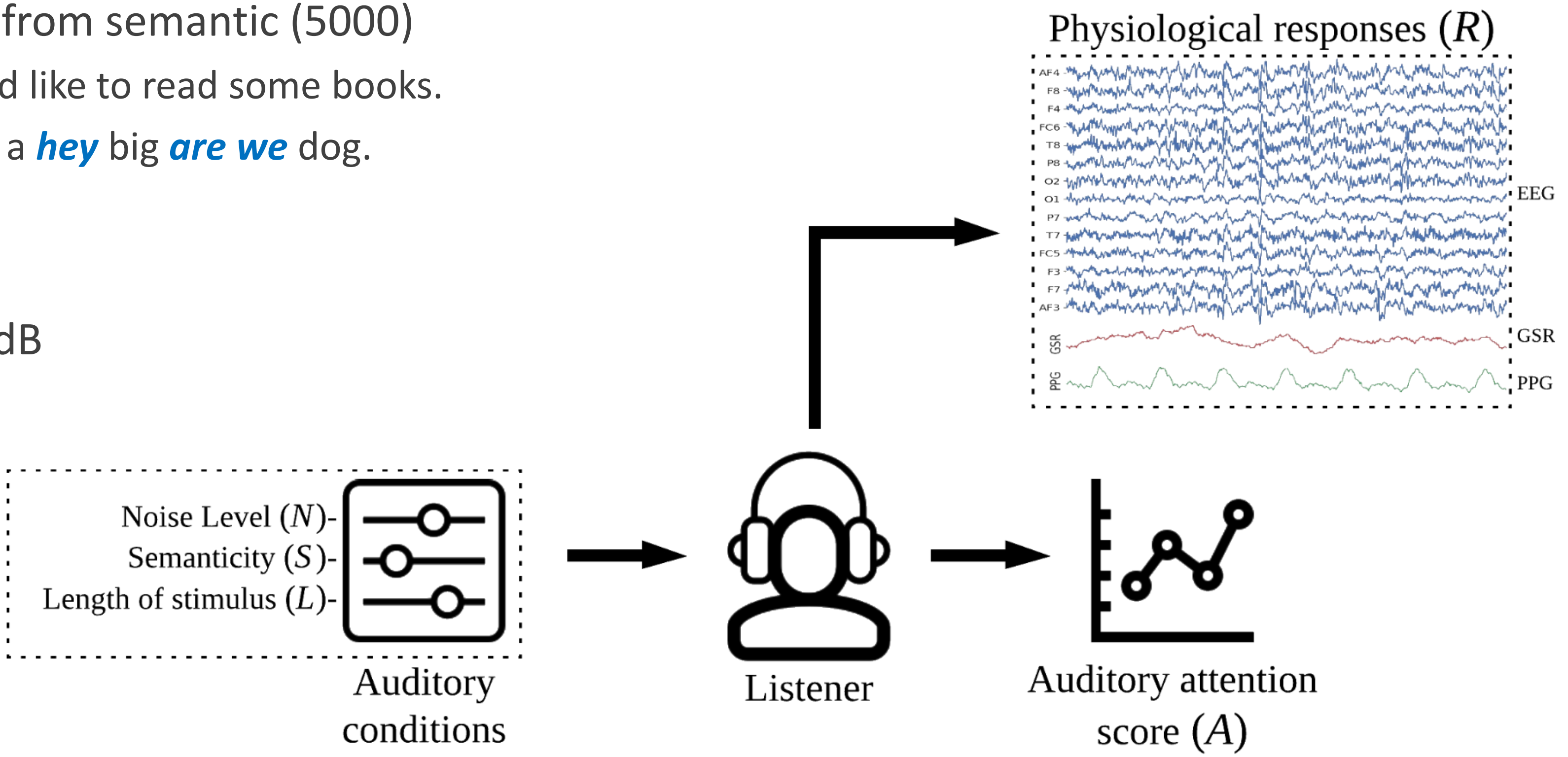
    S1 : I am going to study. S2 : I would like to read some books.

    S3 : Let's ***touch enjoyable*** go. S4 : I have a ***hey*** big ***are we*** dog.

- Auditory conditions
  - **N**: Noise levels: { -6, -3, 0, 3, 6, ∞ (*inf*) } dB
  - **S**: Semanticity: {0, 1}
  - **L**: Length of Stimulus {L1, L2, L3}

- Attention score (**A**): [0,100]
  - # correct words/ #total words in stimuli

- Physiological Responses (**R**)



Physiological signals

Three physiological signals were recorded

1. **Electroencephalogram (EEG):** 14 Channel with Emotiv Epoc, wireless device. EEG signals were filtered while recording to remove high dc

$$y_e(n) = \frac{\alpha-1}{\alpha}\left(x_e(n) - x_e(n-1) + y_e(n-1)\right), \quad \alpha = 256$$

2. **Galvanic Skin Response (GSR):** With 2 copper plates, interfaced with Arduino. Two GSR signal streams were recorded: Instantaneous and moving averaged

$$y_g(n) = \frac{1}{K}\sum_{k=0}^{K-1} x_g(n-k)$$

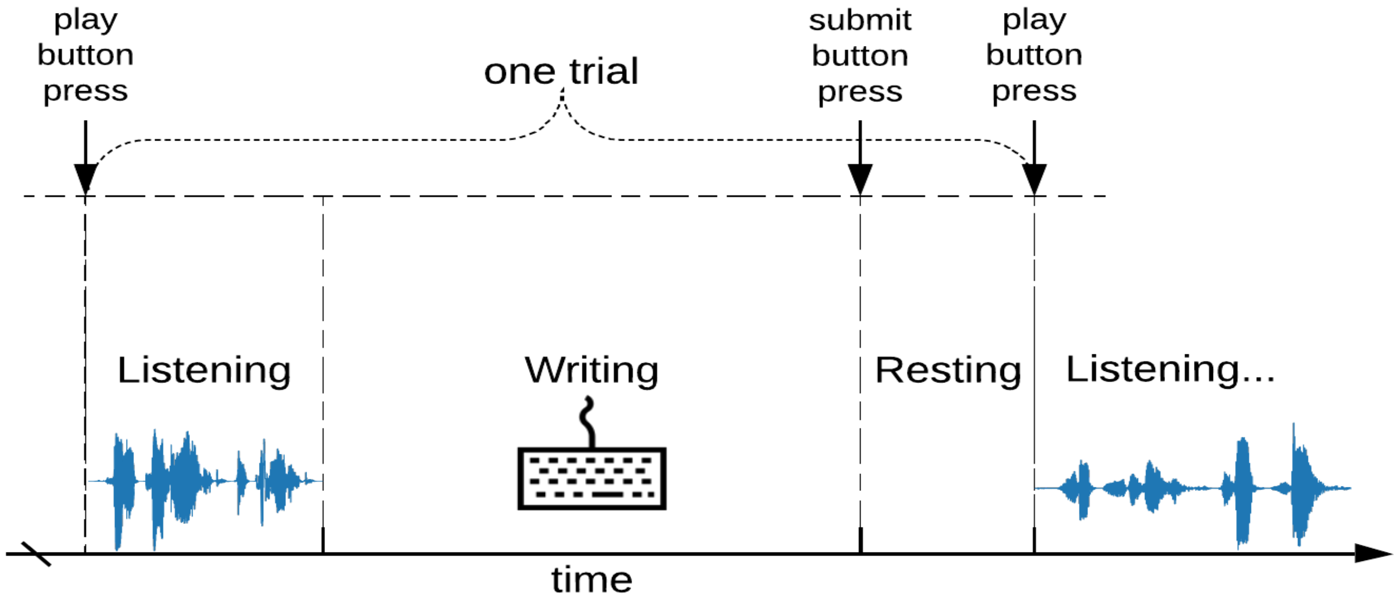
3. **Photoplethysmogram (PPG):** was recorded from Pulse sensor, interfaced with Arduino. Three streams of PPG signal were recorded , PPG signal, Beat Count (BPM), Inter Beat interval (IBI), using source code provided by manufacturer of pulse sensor

All signals were sampled at 128 Hz

Experiment procedure

- Subjects: A group of 25 non-native speakers, different nationality, and first language
- Age:16-35, Gender: 21 Male, 4 Female
- 144 trials for a subject, including all the auditory conditions
- Average time for a subject 40±10mins

-One trial:
Listening -> Writing -> Resting



Collected data

From 25 Subjects:

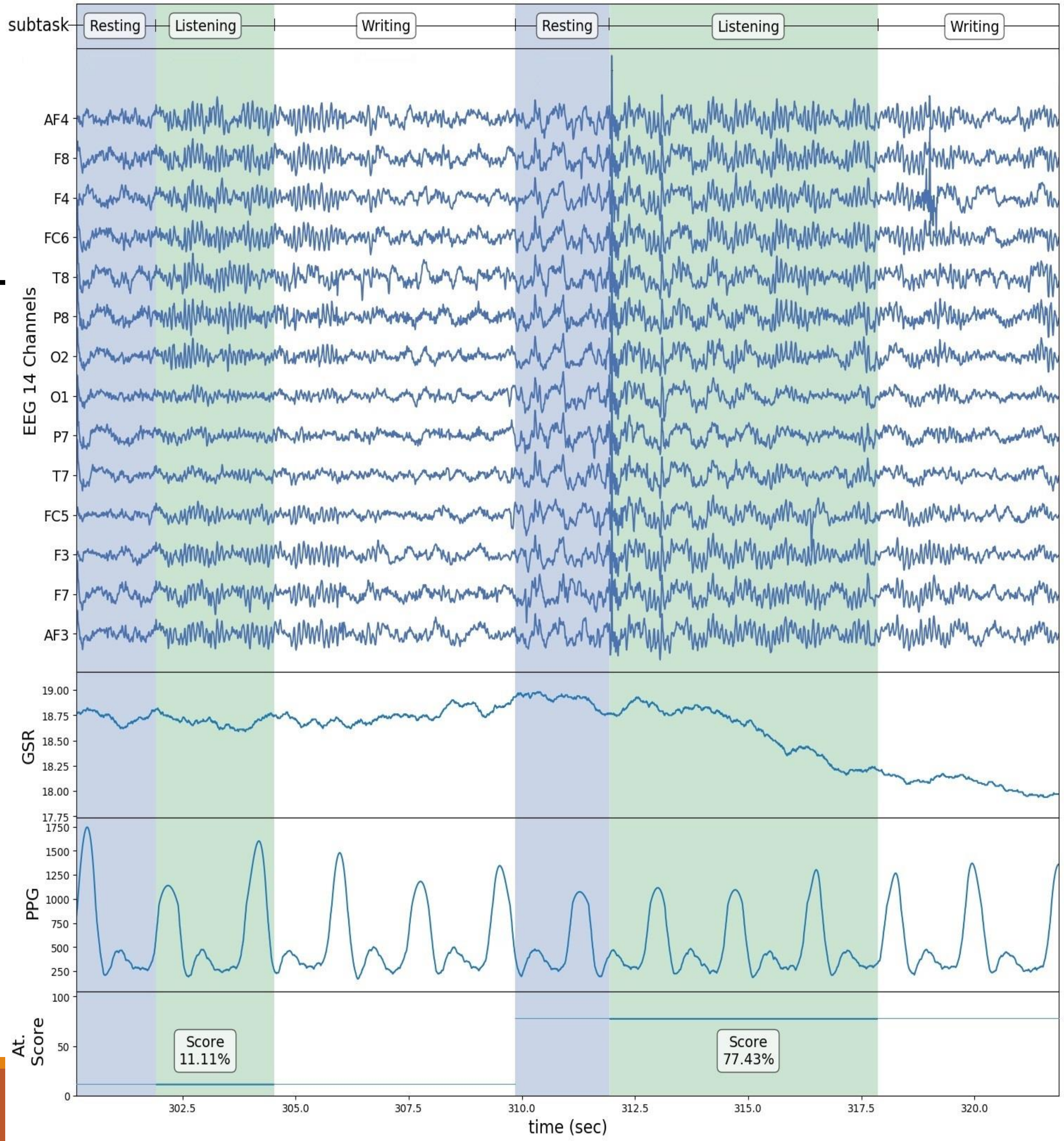
Signals: 19 signal streams at 128 Hz

- 14 Channel EEG signal
- 3 signal streams from PPG
- 2 signal streams from GSR

Labels

- State of task (T): Listening, writing, resting
- Auditory conditions (N,S,L)
- Attention score (A)

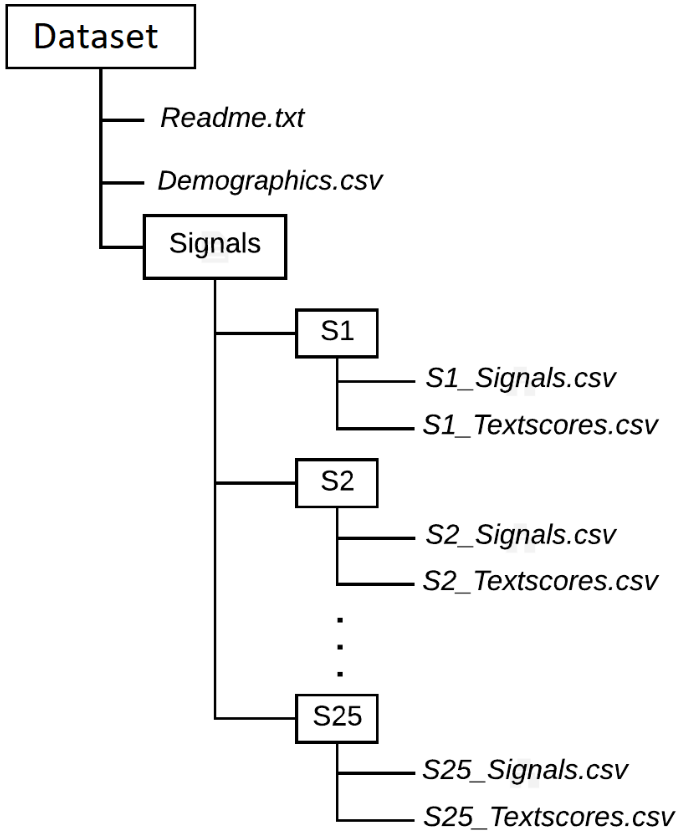
** PhyAAt: Physiology of Auditory Attention to Speech Dataset*
** https://PhyAAt.github.io*



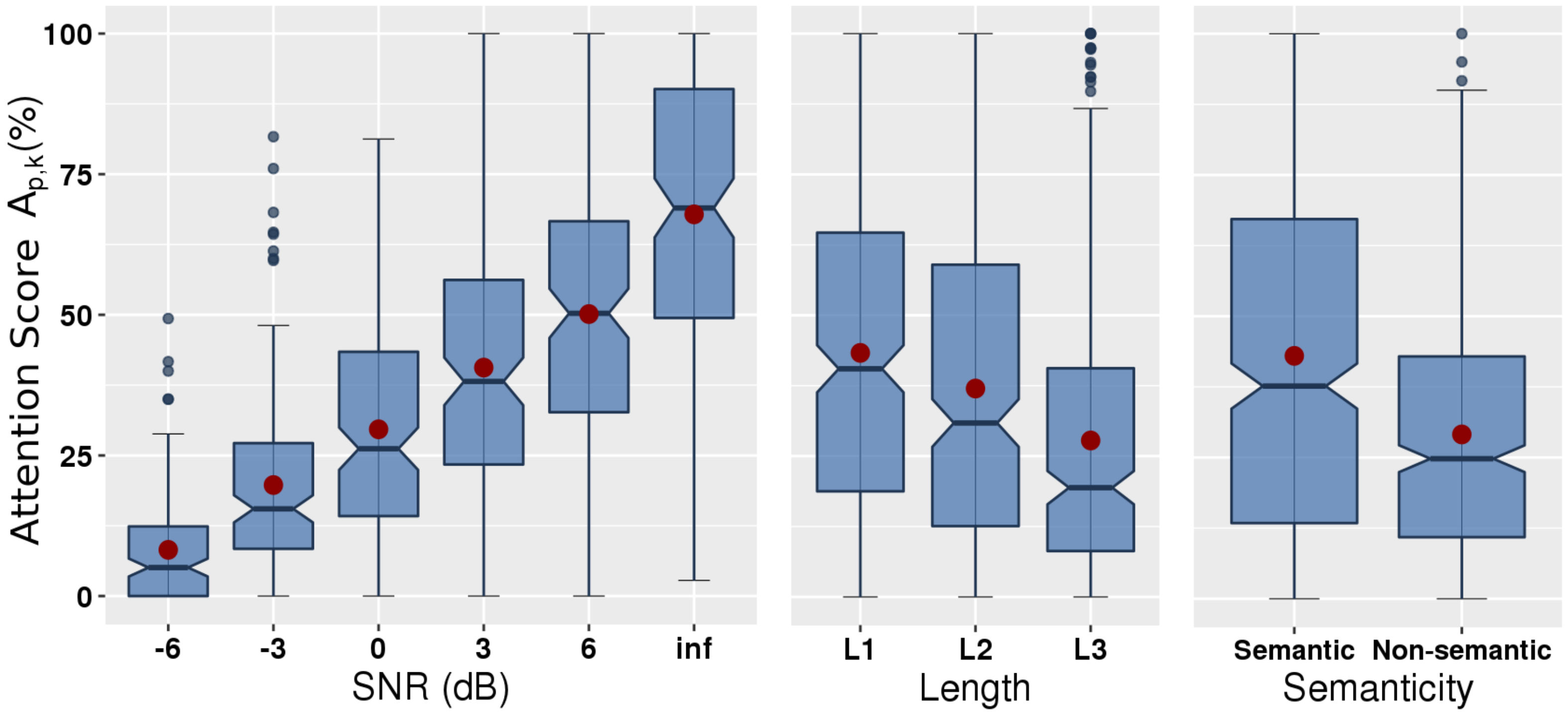
Collected data

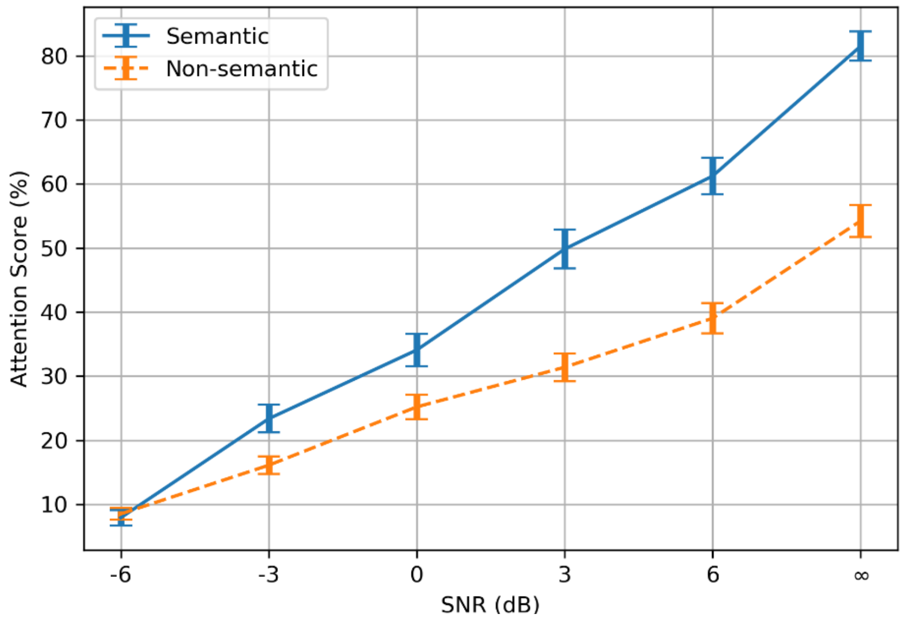
Signal Files:

•**TimeStamp** : Time stamp - normalize to start with 00 Hour
•**'AF3' ..'AF4'** : 14 Channels of EEG Signals
•**PPG** : Raw PPG signal
•**BPM** : Pulse Rate in Beats per minute
•**IBI** : Inter-Beat-Interval
•**0** : Zero (Just a divider for alignment)
•**gsrRaw** : instantaneous GSR signal
•**gsrLPF** : Lowpass GSR Signals (Moving averaged of past 100 samples)
•**Label_N**: Noise Levels [-6,-3,0,3,6,1000] dB
•**Label_S**: Semanticity Label: 0-Semantic, 1-Non-semantic
•**Label_T**: Task: 0-Listenting, 1-Writing, 2-Resting
•**CaseID** : CaseID An identifier code for experimental condition, encoded value of noise level and semanticity



Analysis of attention scores

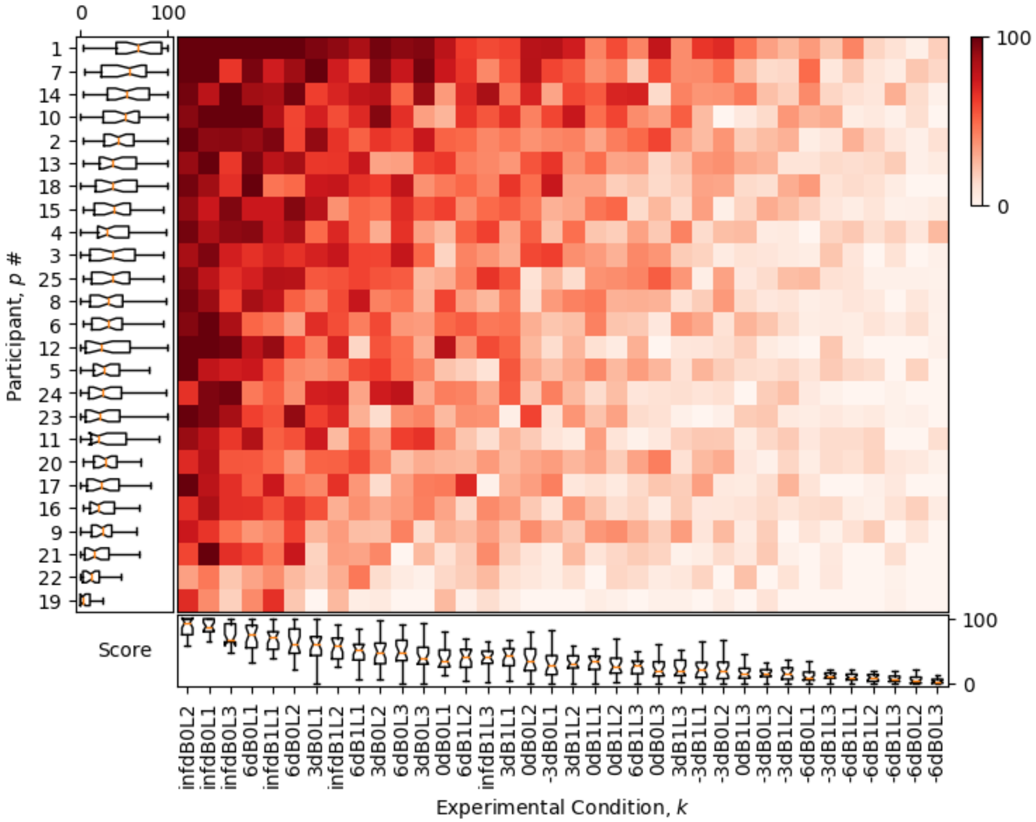


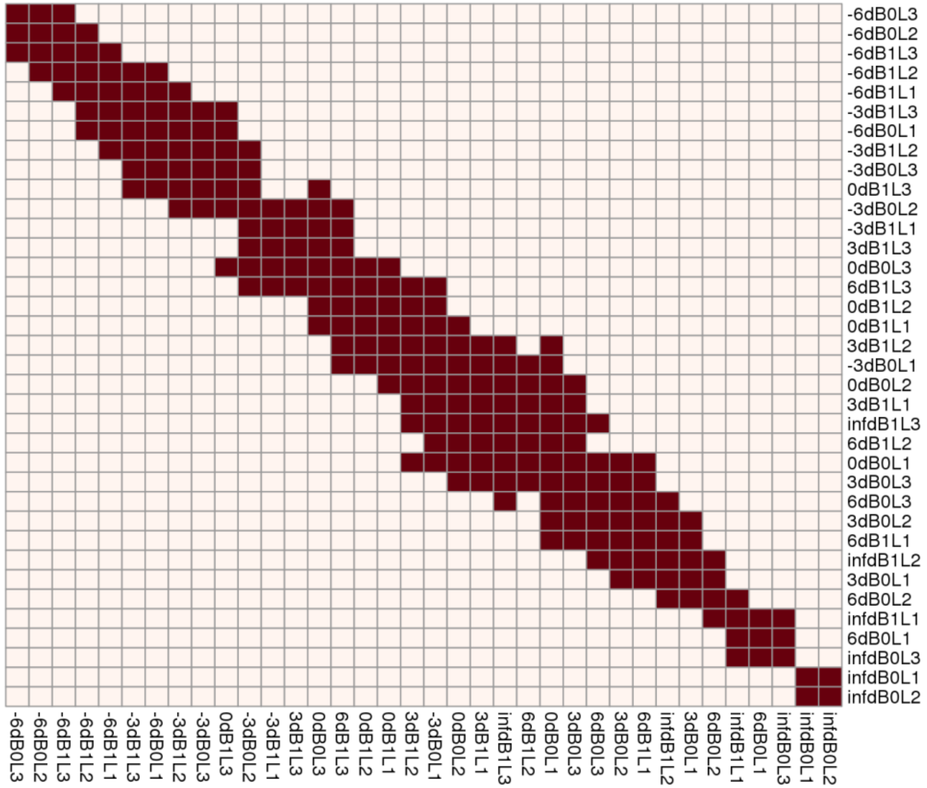


**Article: Analysis of Factors Affecting the Auditory Attention of Non-native Speakers, Electronic Journal of e-Learning*

Analysis of attention scores

Individual analysis and comparing different experimental groups





**Article: Analysis of Factors Affecting the Auditory Attention of Non-native Speakers, Electronic Journal of e-Learning*

Formulation of predictive tasks

T1: Attention score prediction

$A \approx f_A(R)$

$A' = f_A(R)$

by solving

$$min_{f_A} \mathcal{E}(f_A)$$

where $\mathcal{E}(f_A)$ is expected risk

$$\mathcal{E}(f_A) = E[\mathcal{L}(A, f_A(R))]$$

and is $\mathcal{L}(.,.)$ loss function and $E[.]$ is expectation operator.

T2: Noise level prediction

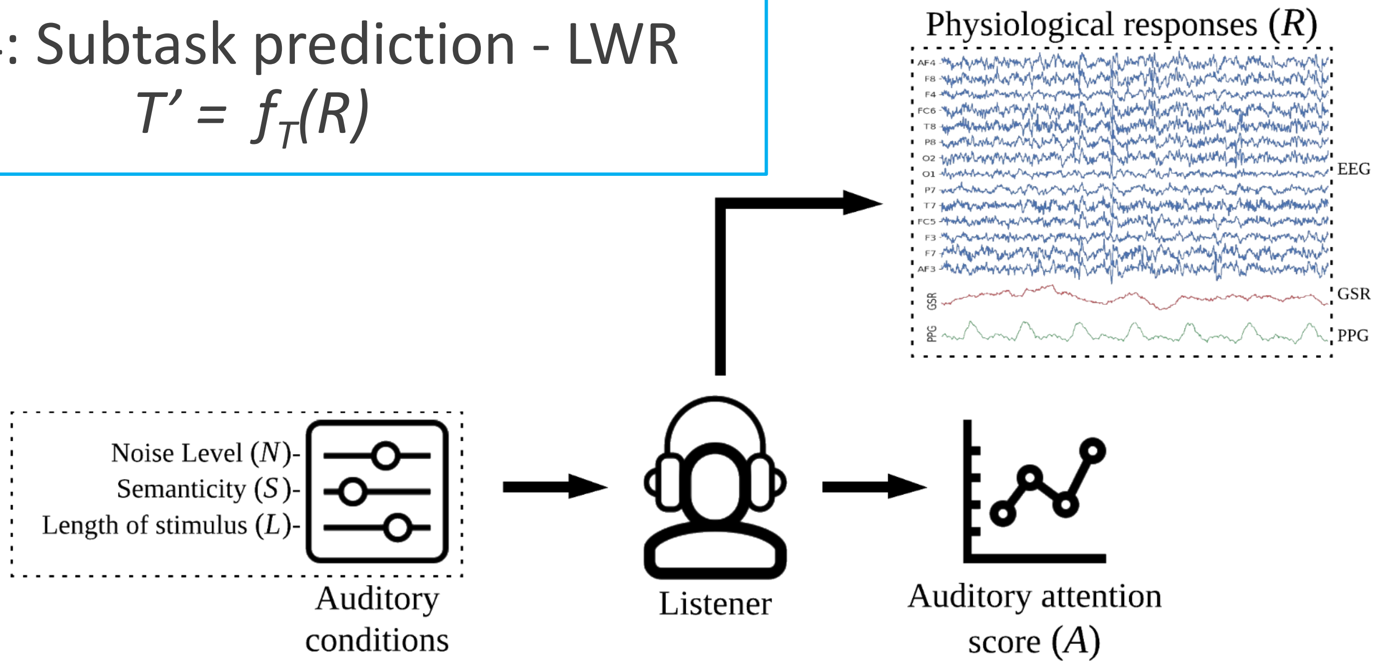
$N' = f_N(R)$

T3: Semanticity prediction

$S' = f_S(R)$

T4: Subtask prediction - LWR

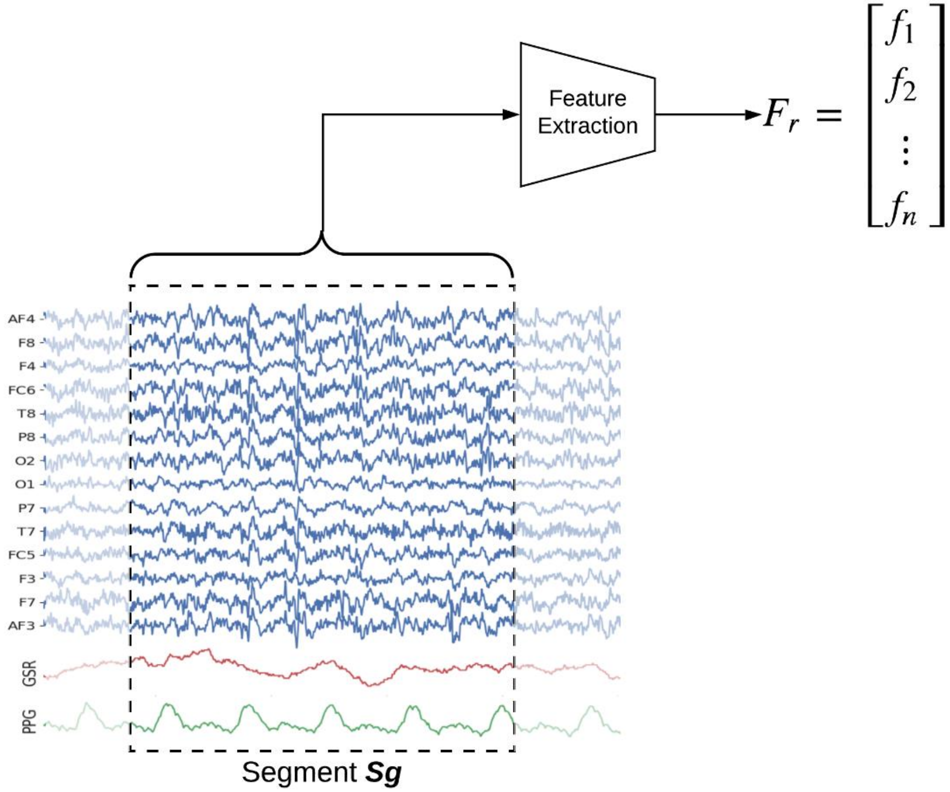
$T' = f_T(R)$



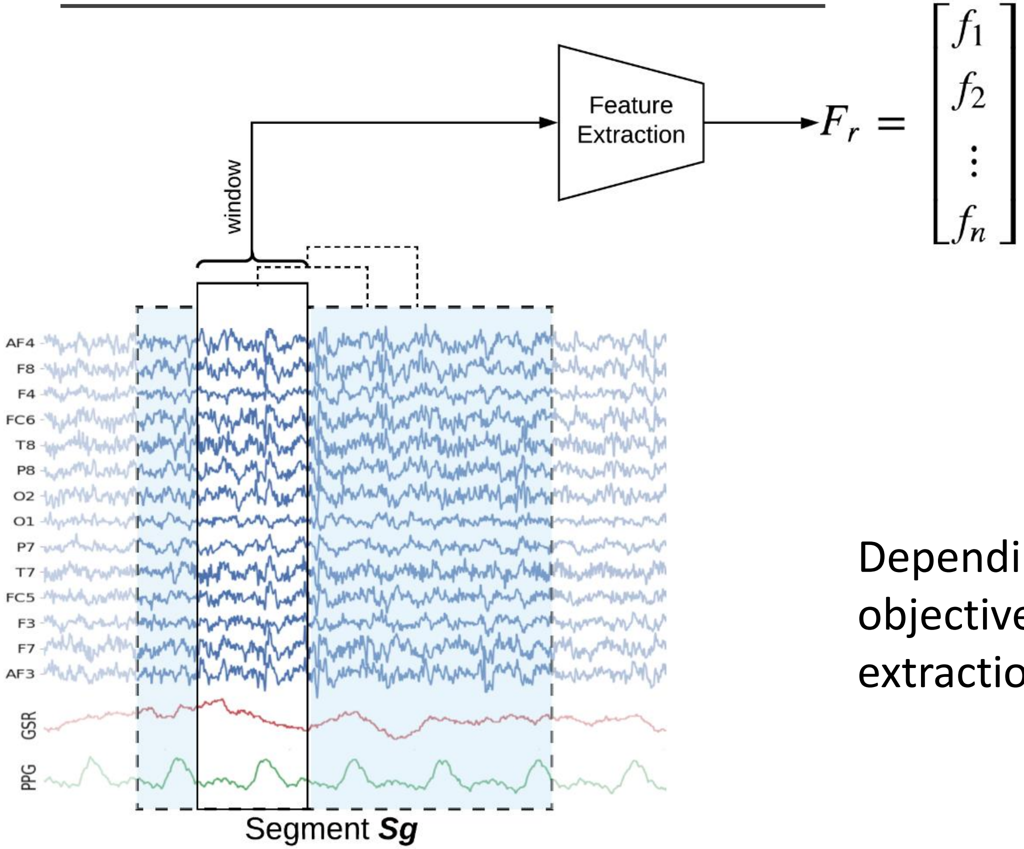
Feature extraction: $R \rightarrow F_r$

Feature extraction framework (procedure)

Segment-wise feature extraction



Window-wise feature extraction

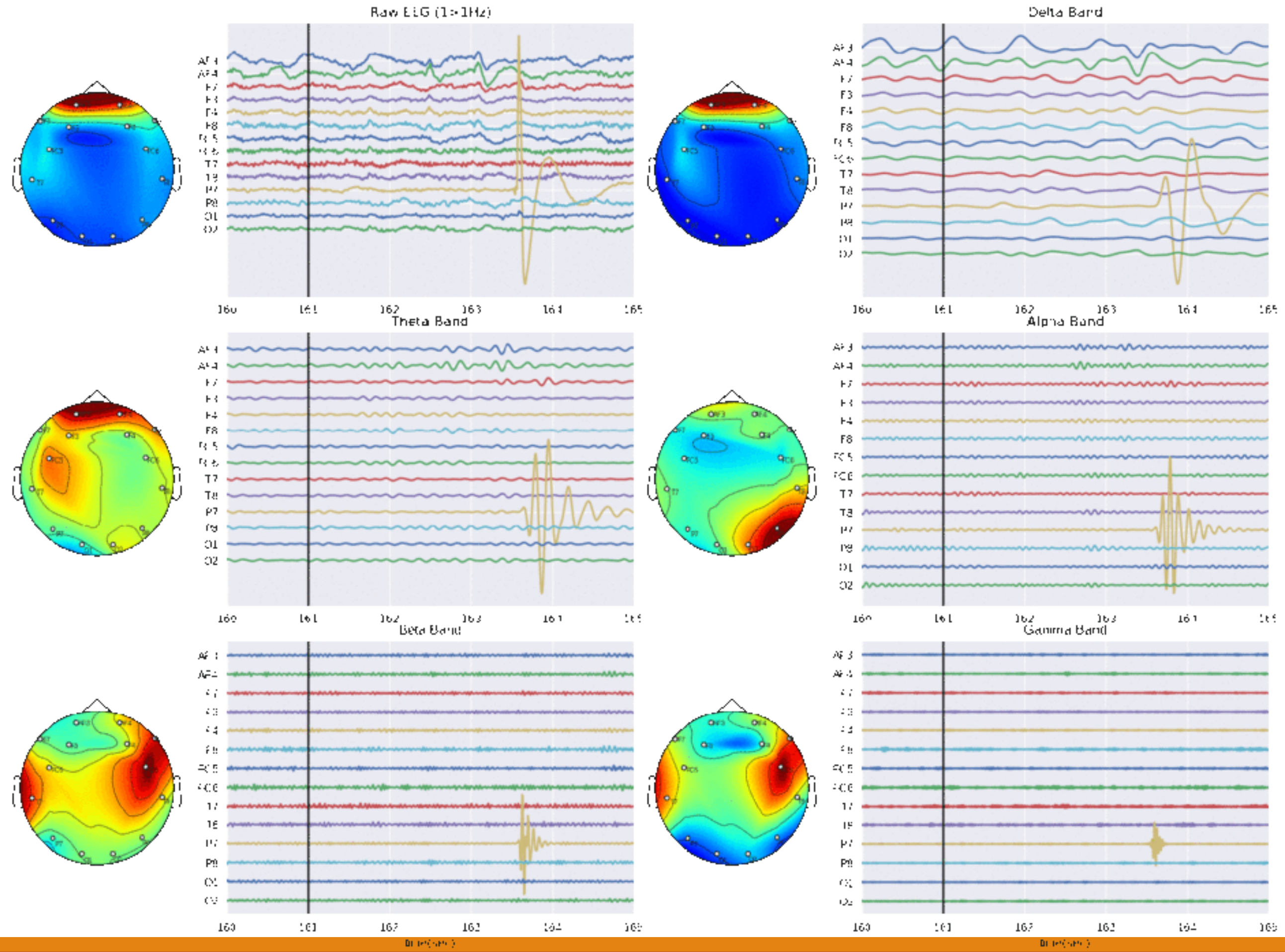


Depending on the task and objective, different feature extraction method is used

Analysis of EEG signals

Frequency Bands of EEG Signal:

- Delta : 0.1 – 4 Hz
- Theta : 4 – 8 Hz
- Alpha : 8 – 14 Hz
- Beta : 14 – 30 Hz
- Gamma (Low) : 30-47 Hz
- Gamma (High): 47-64 Hz



Before We use EEG, we have an issue:
Artifacts in EEG

Predictive modelling: Baseline

Before any further processing

Features:
- 84 features from EEG (14 x 6), power in each frequency band
- 10 features from GSP and PPG, mean and standard deviation

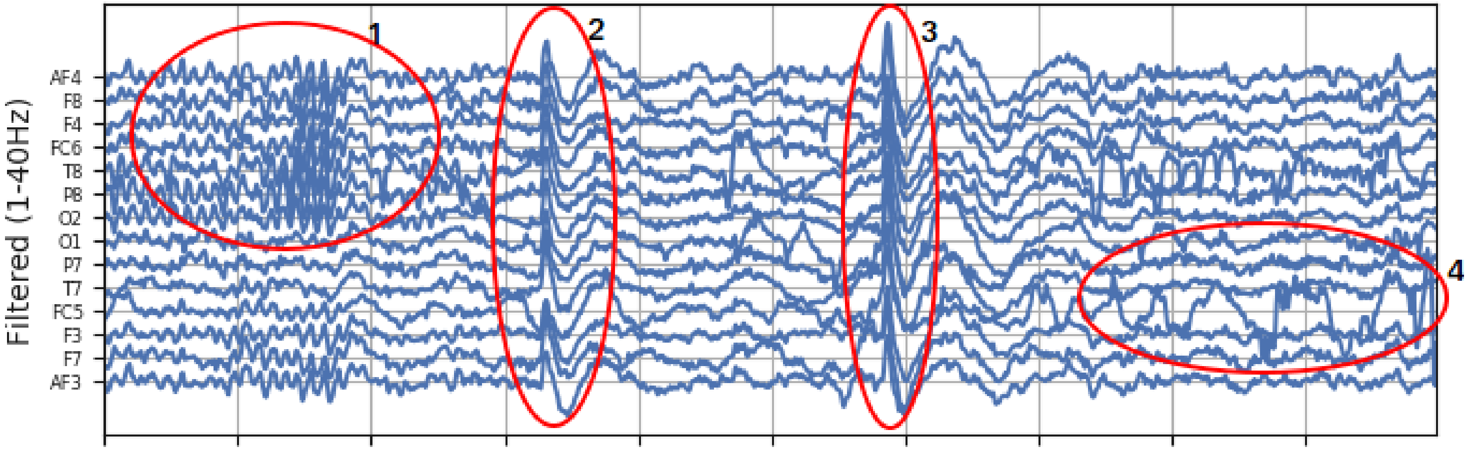
Models:
- Classification: Support Vector Machine with RBF kernel
- Regression : Huber Regression

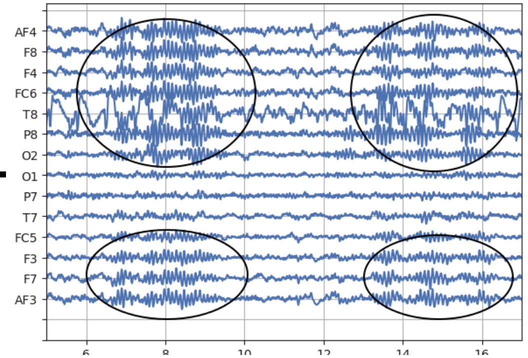
Performance Measure
- Accuracy for classification
- Mean Absolute Error (MAE) for regression
- 10-fold cross validation

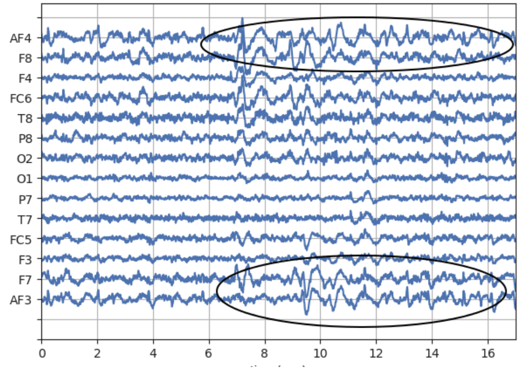
Task	Accuracy/MAE	
	Train	**Test**
1. Attention Score^a : *Regr.*	8.920	37.234
2. Noise level^b : 3 *classes*	0.625	0.493
3. Semanticity^b : 2 *classes*	0.753	0.396
4. LWR^b : 3*classes*	0.797	0.704

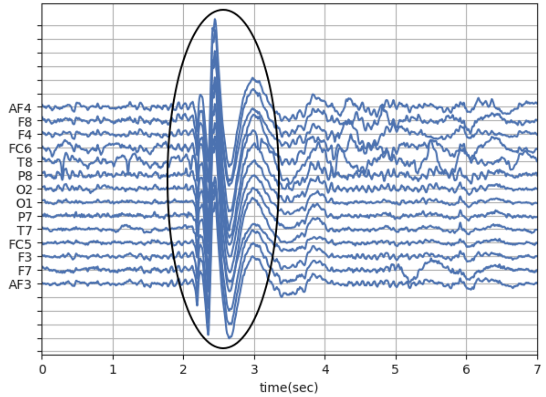
^{a}Huber Regression($epsilon = 1.35$)
^{b}SVM (RBF)

Artifacts in EEG





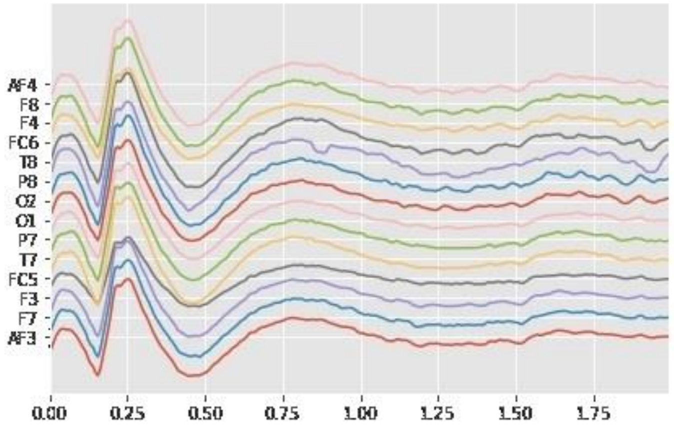


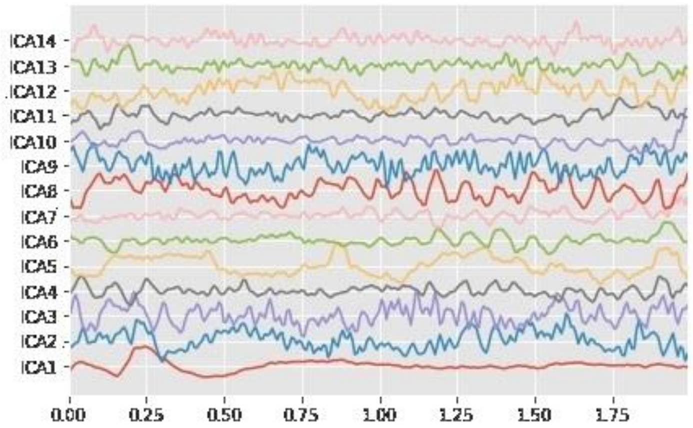


1: Muscular Artifacts
2 and 3 : Motion artifact
4: Ocular artifact

Artifact removal algorithms

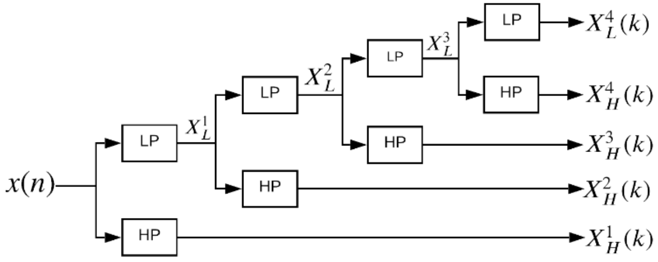
Blind Source Separation – ICA based approach



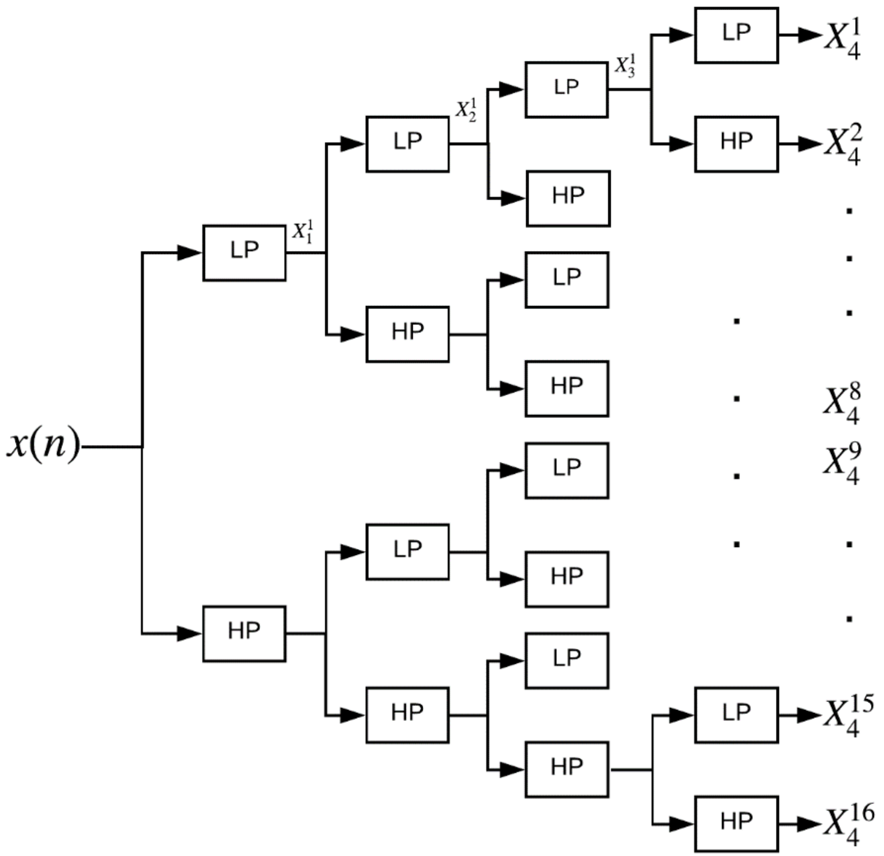


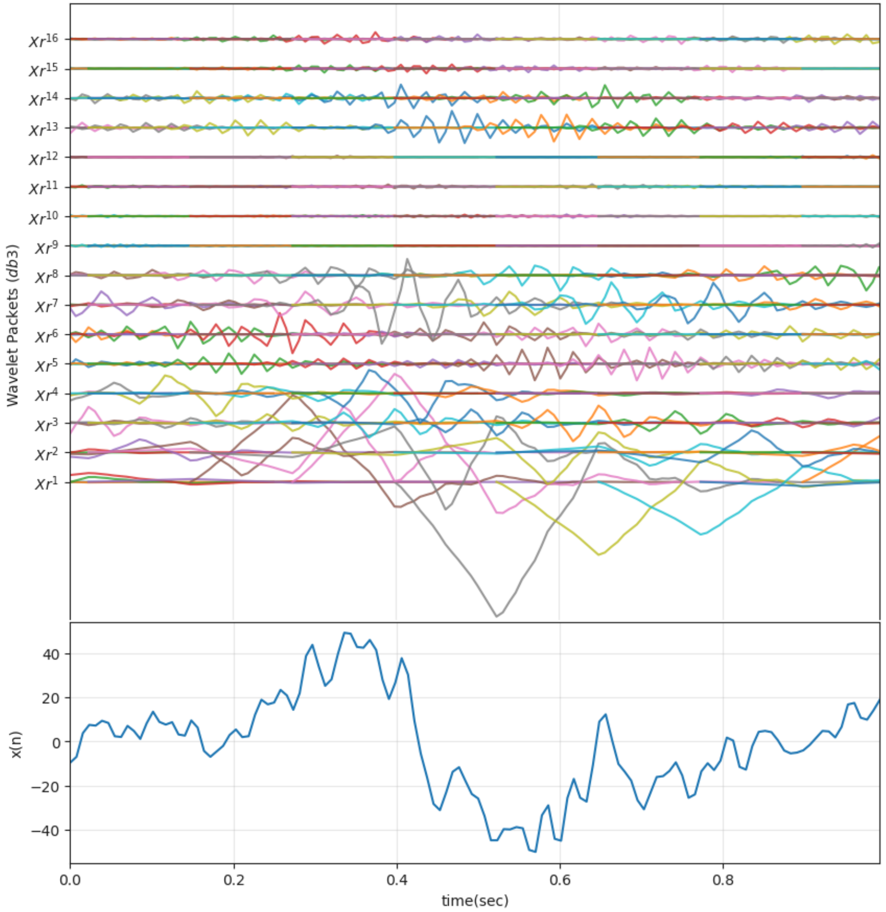
Wavelet based approach: hard thresholding

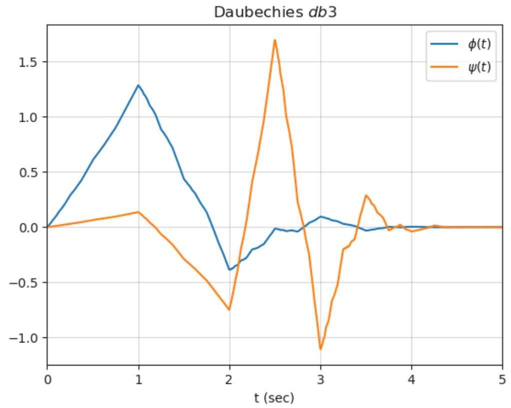
- Global threshold: $\theta = \hat{\sigma}\sqrt{2logN}$ $\hat{\sigma} = \frac{median(|w|)}{0.6745}$
- Statistical threshold: $\theta = 1.5\ SD(w)$



Wavelet Packet Decomposition (WPD)







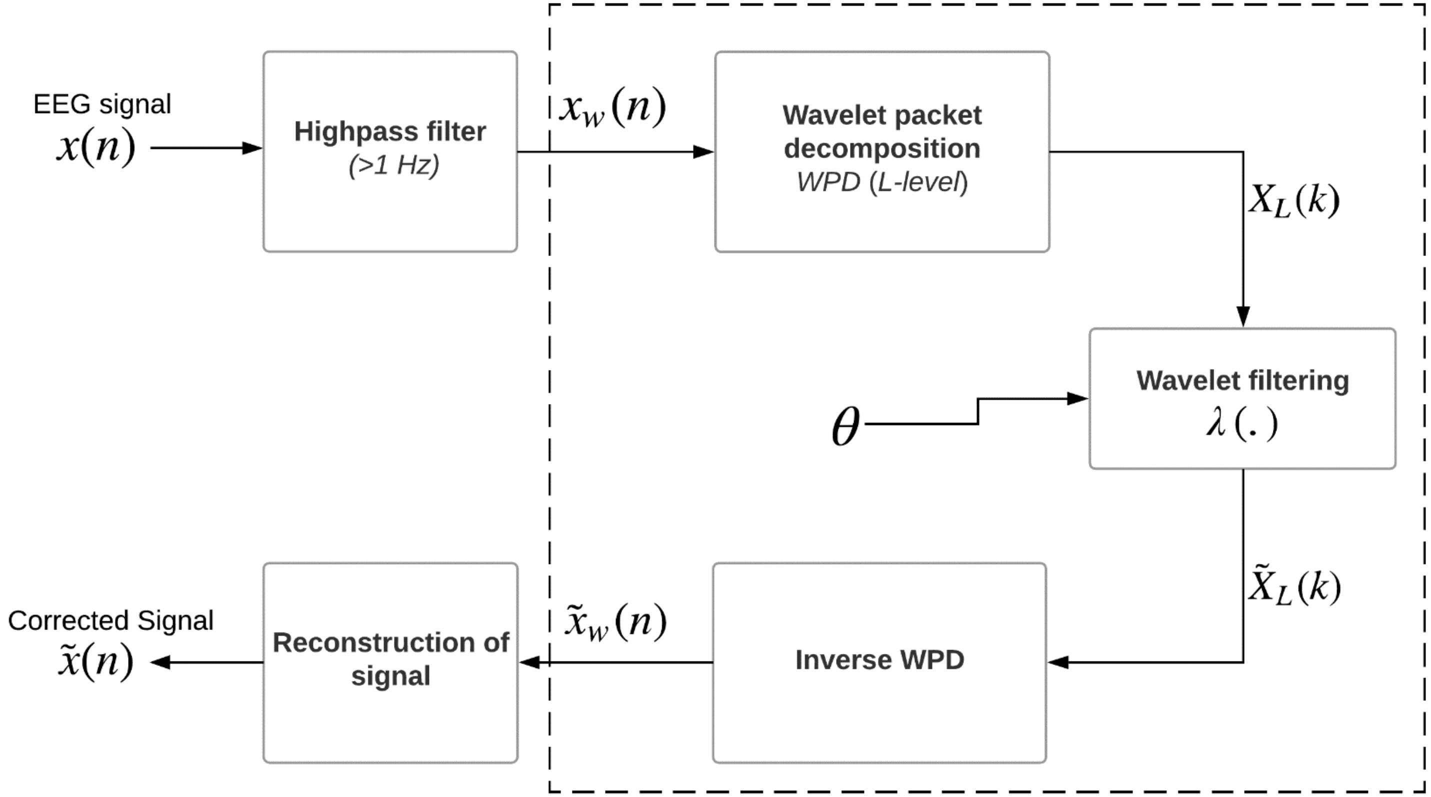
WPD based artifact removal algorithm

Approach

$$x(n) = \sum_{i,k} X_j^i(k)\psi_j^i(n - 2^j k)$$

$$X_j^i(k) = \langle x(n), \psi_j^i(n - 2^j k)\rangle$$

$$\tilde{x}(n) = \sum_{i,k} \lambda\left(X_j^i(k)\right)\psi_j^i(n - 2^j k)$$



$$x(n) = s(n) + v(n)$$

$$X_j^i(k) = S_j^i(k) + V_j^i(k)$$

Modes of wavelet filtering

Elimination

$$\lambda_e(w) = \begin{cases} w & if\ |w| \leq \theta_\alpha \\ 0 & else \end{cases}$$

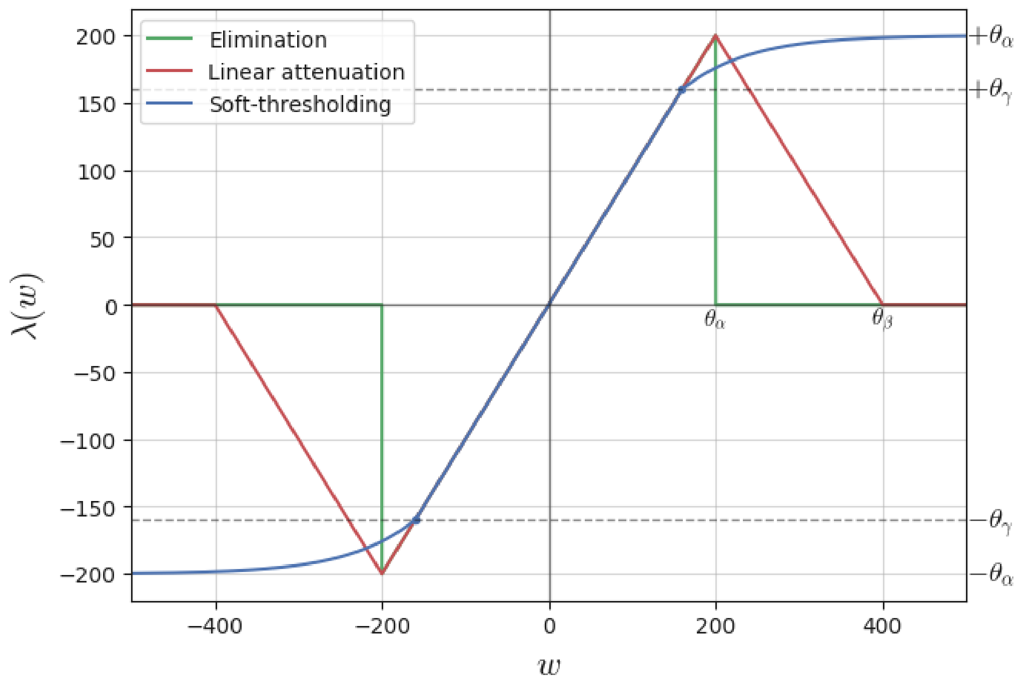
Linear Attenuation

$$\lambda_a(w) = \begin{cases} w & if\ |w| \leq \theta_\alpha \\ sgn(w)\theta_\alpha\left(1 - \dfrac{|w| - \theta_\alpha}{\theta_\beta - \theta_\alpha}\right) & if\ \theta_\alpha < |w| \leq \theta_\beta \\ 0 & otherwise \end{cases}$$

Soft-thresholding

$$\lambda_s(w) = \begin{cases} w & if\ |w| < \theta_\gamma \\ \dfrac{1 - e^{-\alpha w}}{1 + e^{-\alpha w}}\theta_\alpha & else \end{cases}$$

$$\alpha = -\frac{1}{\theta_\gamma}\log\frac{\theta_\alpha - \theta_\gamma}{\theta_\alpha + \theta_\gamma}$$

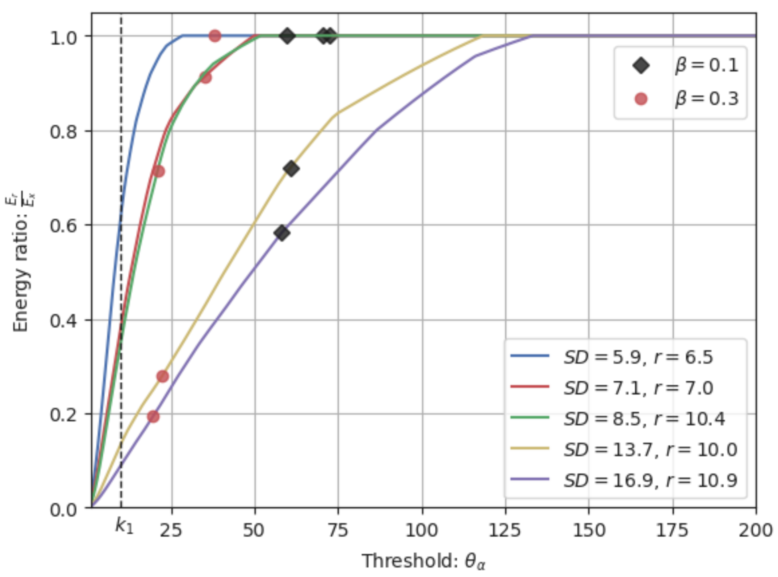


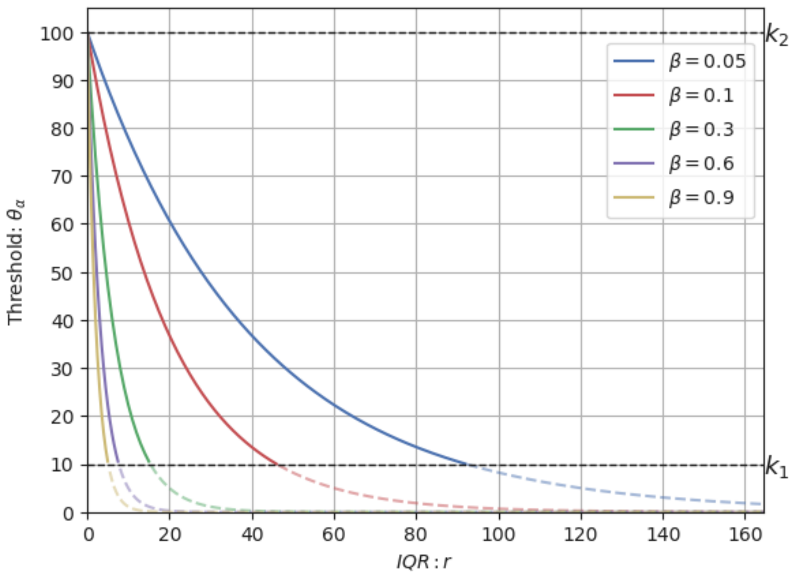
Threshold selection

Based on interquartile range (r)

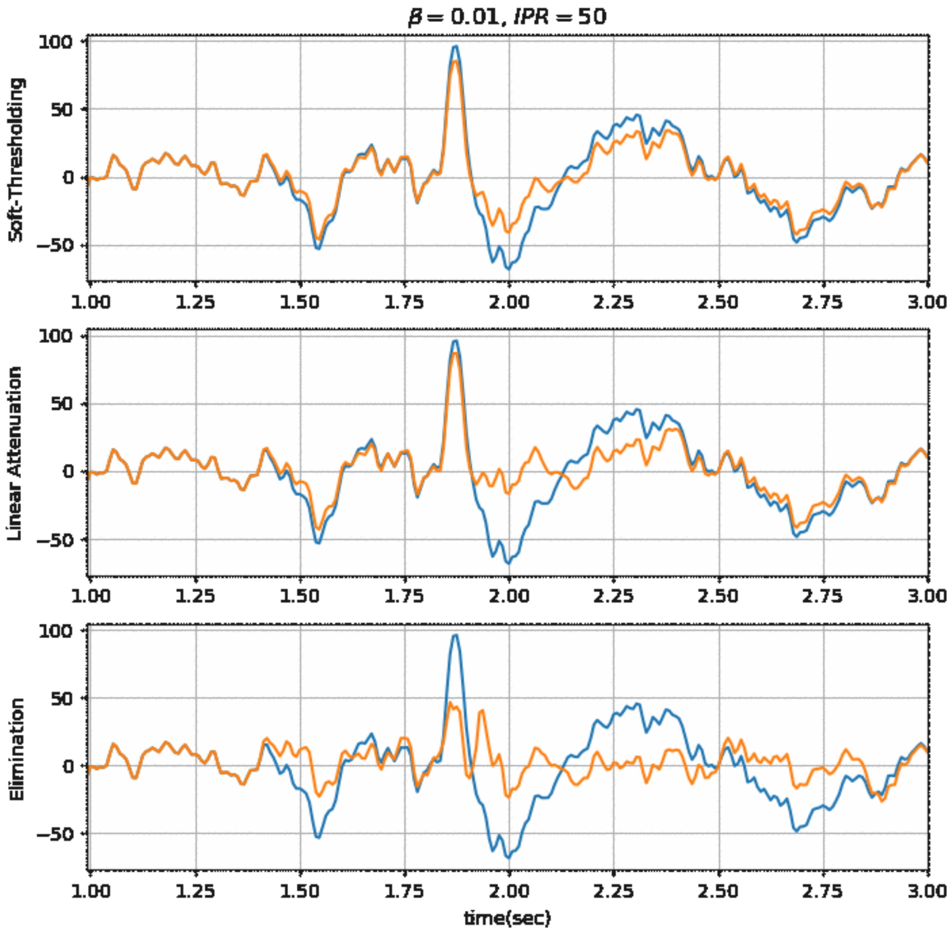
$$\theta_\alpha = f_\beta(r) = \begin{cases} k_2 exp\left(-\beta \frac{100}{k_2}\frac{r}{2}\right) & if \quad r \geq -\frac{2k_2}{100\beta} log(k_1/k_2) \\ k_1 & otherwise \end{cases}$$

$$Pr\left(max|S_j| > f_\beta(r)\right) \to 0, \quad r \to \infty$$





Summarized algorithm



Algorithm 1 Tunable algorithm for artifact removal from EEG signal using wavelet decomposition

Input: Single channel EEG signal $x(n)$

Output: Corrected EEG signal $\tilde{x}(n)$

Parameters choice :

Wavelet family:(say *db3*), window size: N samples

Bounds on threshold θ_α: $[k_1, k_2]$ (say [10, 100] or [0.1, 1.0])

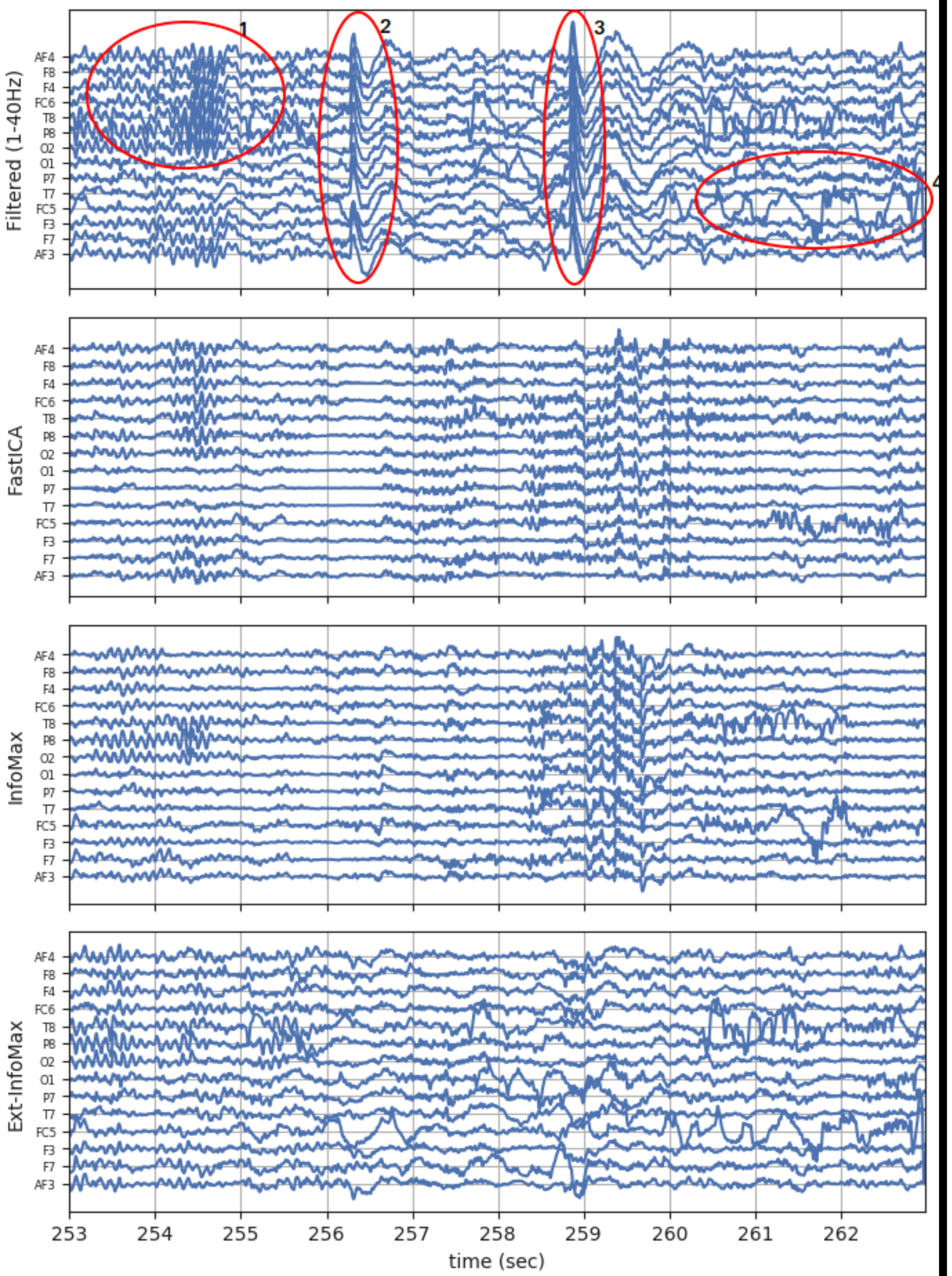
Wavelet filtering mode: $\lambda_e(\cdot)$, $\lambda_a(\cdot)$, or $\lambda_s(\cdot)$ and corresponding θ_β ($\theta_\beta = 2\theta_\alpha$) or θ_γ ($\theta_\gamma = 0.8\theta_\alpha$)

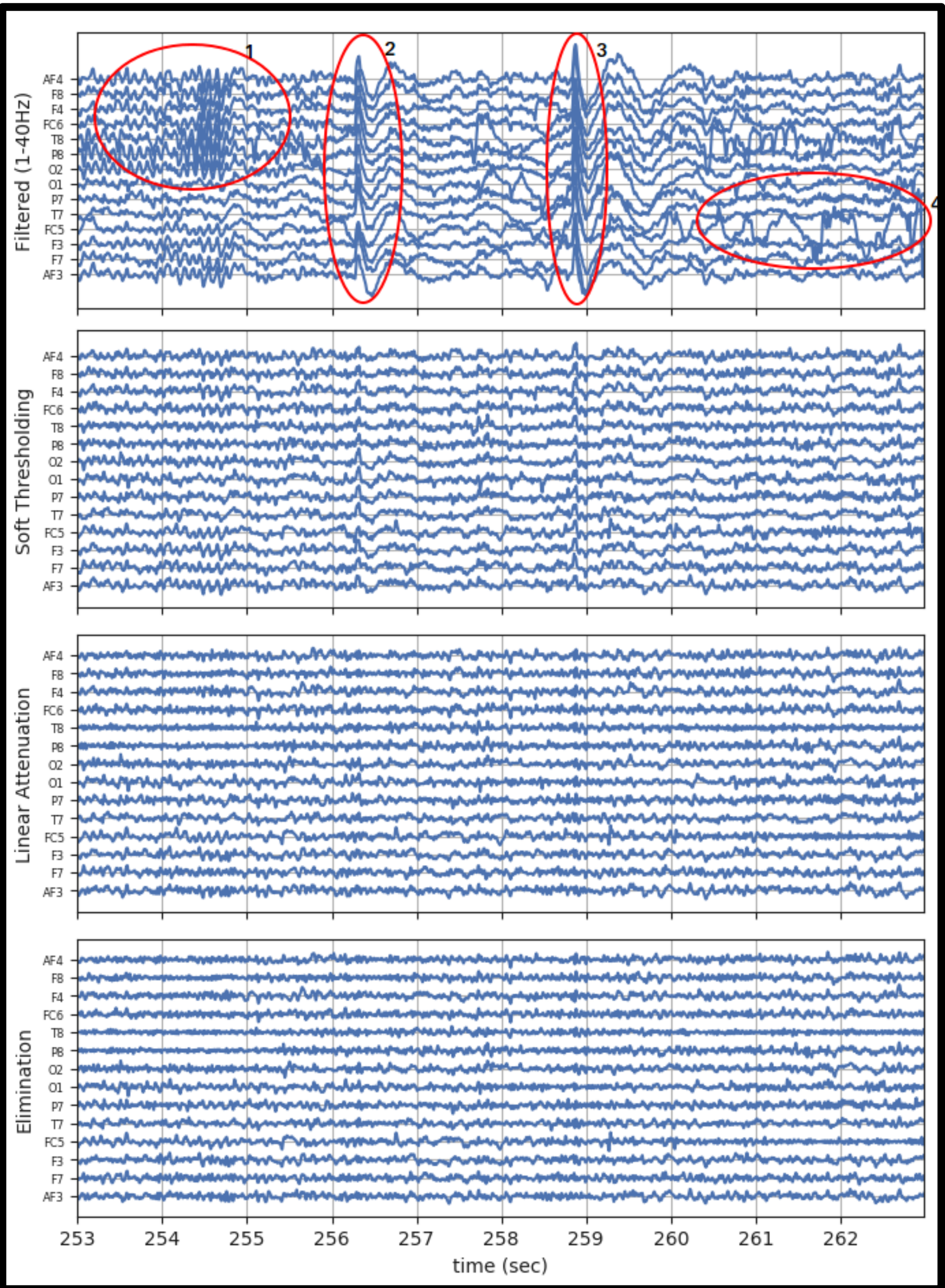
Threshold selection parameter: β (say 0.1), IPR (say 50%)

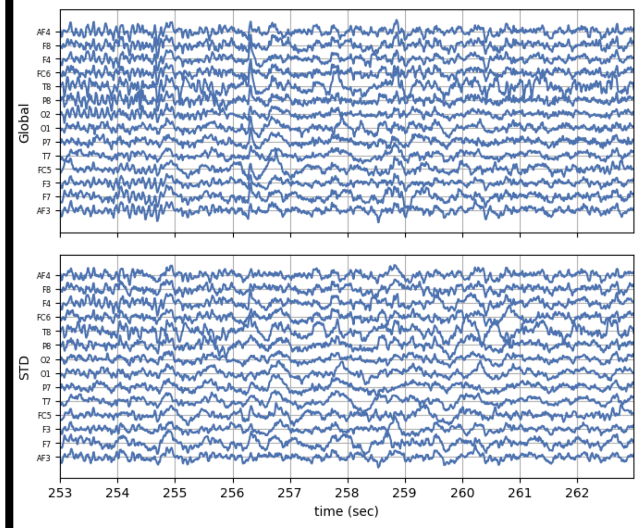
Procedure:

1: Filter the input signal $x(n)$ with high pass filter of cut-off frequency 1 Hz: $x_f(n) \leftarrow x(n)$
2: **while** all windows of $x_f(n)$ are extracted **do**
3: Extract a window of signal with 50% overlapping: $x_w(n) \leftarrow x_f(n)$
4: Compute L-level WPD: $X_L \leftarrow WPD(x_w(n))$
5: Compute θ_α
6: Apply wavelet filtering: $\tilde{X}_L \leftarrow \lambda(X_L)$
7: Reconstruct signal with IWPD: $\tilde{x}_w(n) \leftarrow IWPD(\tilde{X}_L)$
8: Synthesize the entire signal with overlapping add method: $\tilde{x}(n) \leftarrow \tilde{x}_w(n)$...

Results: Visual inspection







Results: Performance of predictive tasks

After applying artifact removal algorithm

- Extracting power spectral features: Total power in 6 frequency band, for each channel, 84 features, using segment-wise
- Models: Support Vector Machine with RBF, C=1 and Huber regression
- Data of one subject with 10-Fold cross validation

Method		LWR Accuracy		Sementicity Accuracy		Noise Level Accuracy		Attention score MAE	
		Tr	*Ts*	*Tr*	*Ts*	*Tr*	*Ts*	*Tr*	*Ts*
Filtered signal (baseline)		0.797	0.704	0.753	0.396	0.625	0.493	8.920	37.234
ICA	FastICA	0.793	0.701	0.785	0.424	0.592	0.493	8.153	37.176
	InfoMax	0.828	0.722	0.833	0.458	0.644	0.472	8.509	38.490
	Ext. InfoMax	0.859	0.752	0.898	0.542	0.682	0.444	7.206	36.790
WPD:	Soft-Thr.	0.899	0.766	0.939	0.597	0.802	0.493	7.798	36.893
$IPR = 50$,	Lin. Atten.	0.884	0.780	0.892	0.556	0.731	0.486	8.482	38.435
$\beta = 0.6$	Elimination	0.887	0.778	0.892	0.549	0.748	0.507	7.475	33.322
WPD:	Soft-Thr.	0.892	0.782	0.934	0.576	0.804	0.493	8.479	38.899
$IPR = 50$,	Lin. Atten.	0.891	0.769	0.910	0.500	0.773	0.493	7.304	**32.746**
$\beta = 0.9$	Elimination	0.883	0.782	0.944	0.583	0.792	**0.514**	8.002	34.891
WPD:	Soft-Thr.	0.894	0.782	0.936	0.583	0.793	0.507	8.235	41.825
$IPR = 70$,	Lin. Atten.	0.888	0.773	0.924	0.493	0.781	0.500	7.481	**33.908**
$\beta = 0.6$	Elimination	0.895	**0.796**	0.957	**0.611**	0.818	**0.514**	8.174	35.811
WPD:	Soft-Thr.	0.895	**0.792**	0.934	0.597	0.792	0.500	8.557	39.828
$IPR = 70$,	Lin. Atten.	0.892	0.780	0.927	0.514	0.781	0.507	7.701	34.474
$\beta = 0.9$	Elimination	0.894	0.787	0.958	**0.611**	0.809	0.507	7.768	35.542

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Automatic and tunable algorithm for EEG artifact removal using wavelet decomposition with applications in predictive modeling during auditory tasks

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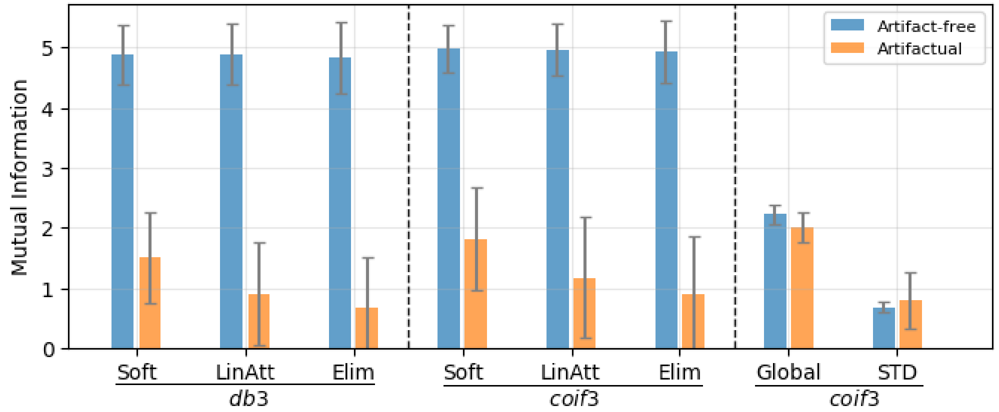
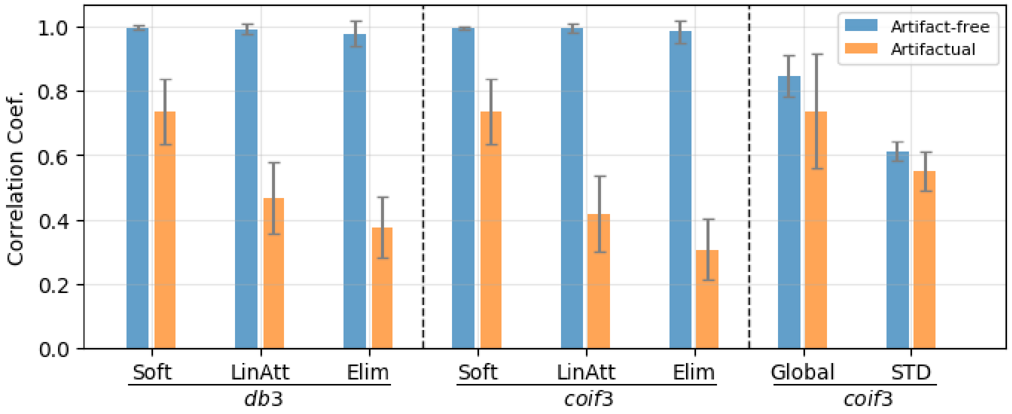
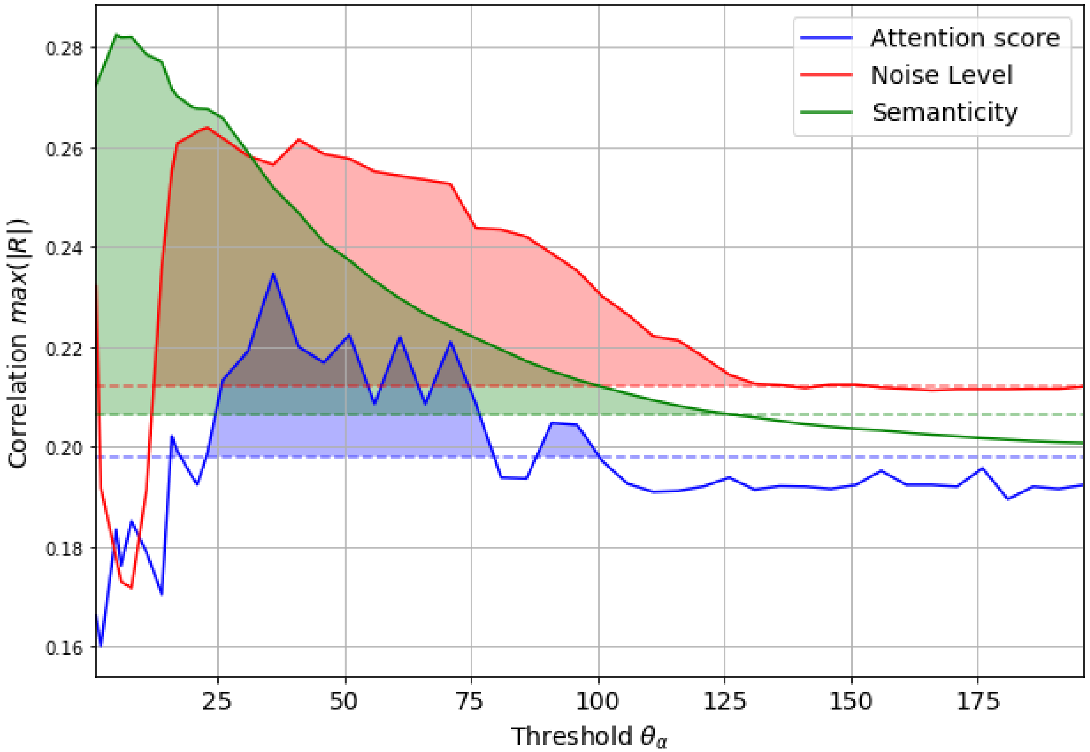
Results: Others



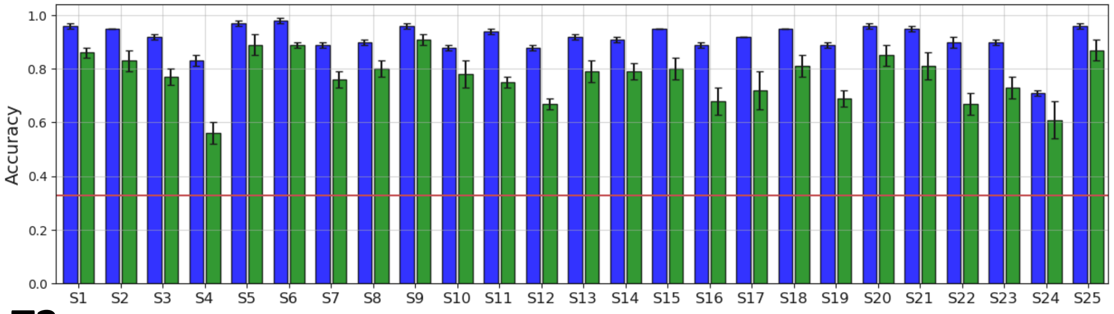




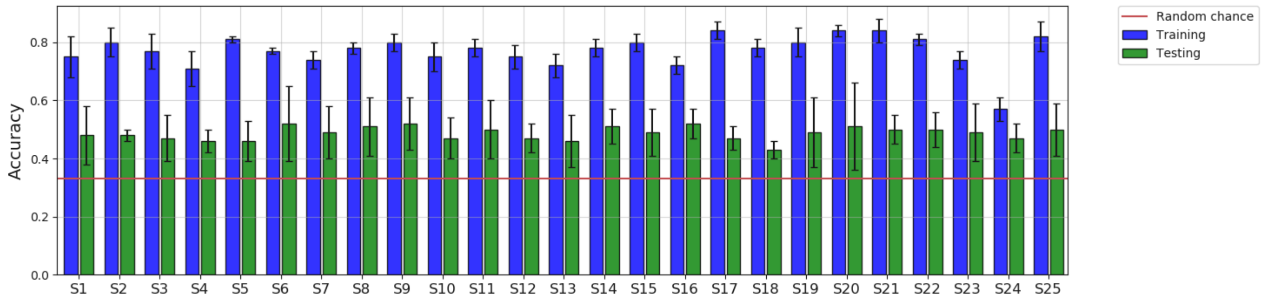
Predictive Tasks: All the subjects

Performance of all the subjects in different tasks, using a model (SVM) and spectral features

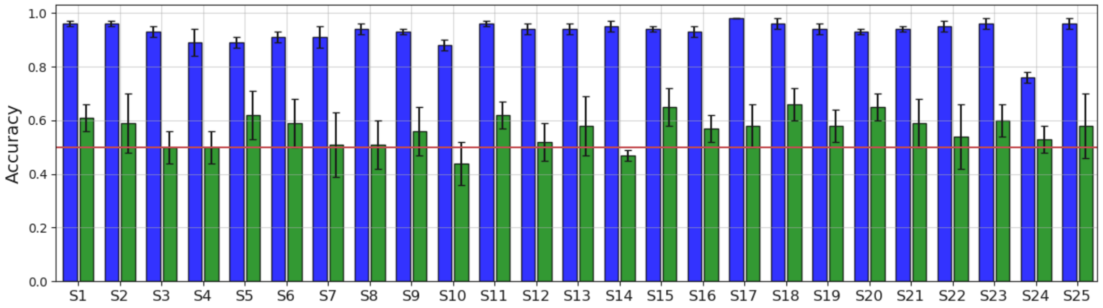
T4



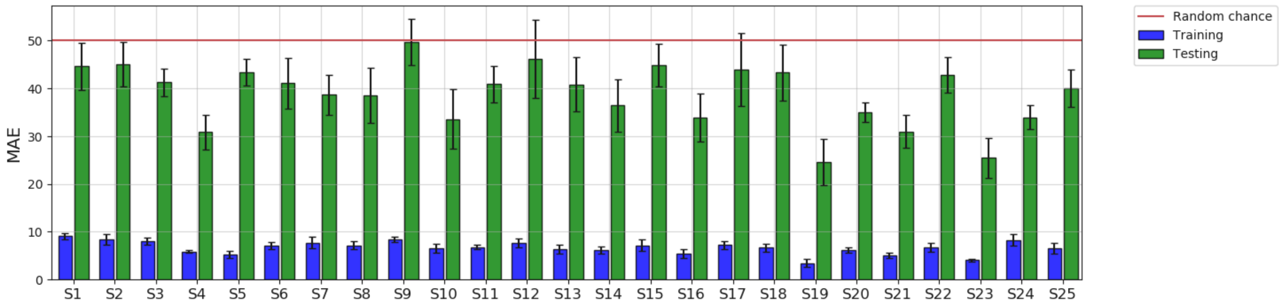
T2



T3



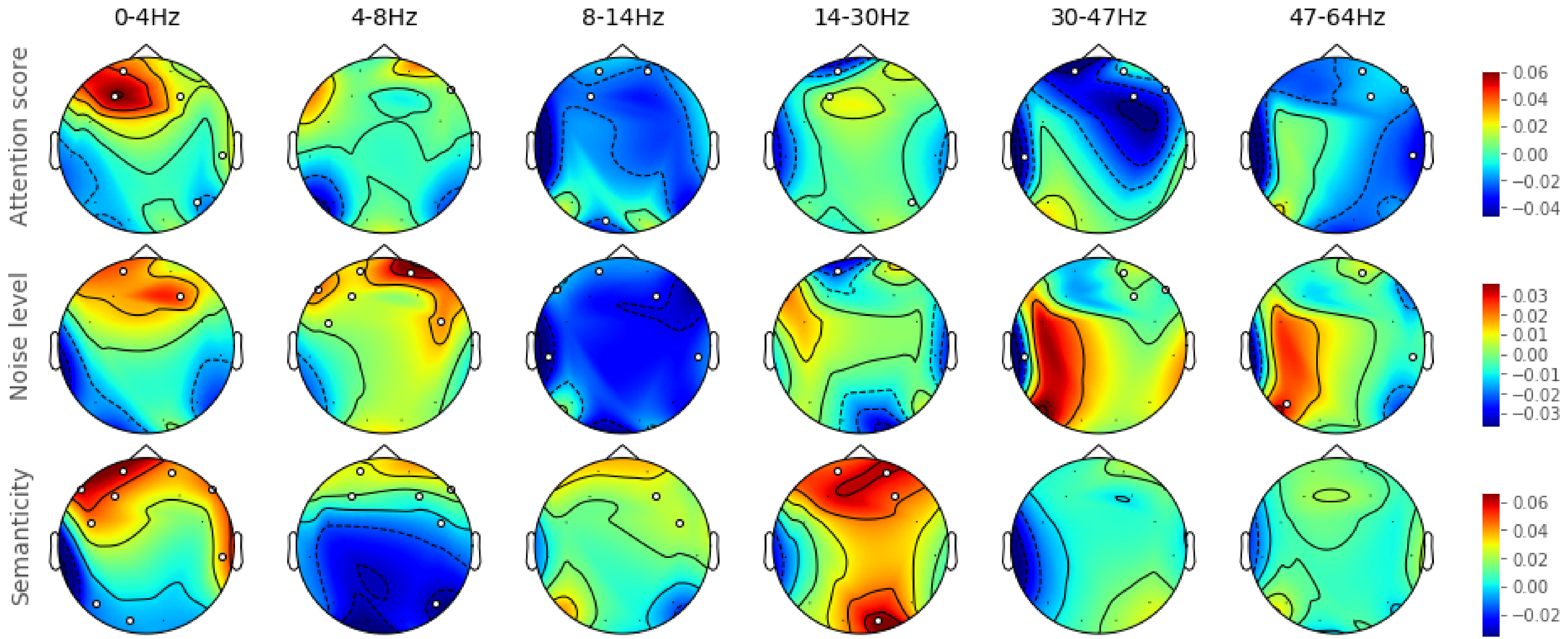
T1



For attention score and noise level, Spearman's rank correlation

Analysis of EEG: Correlation analysis

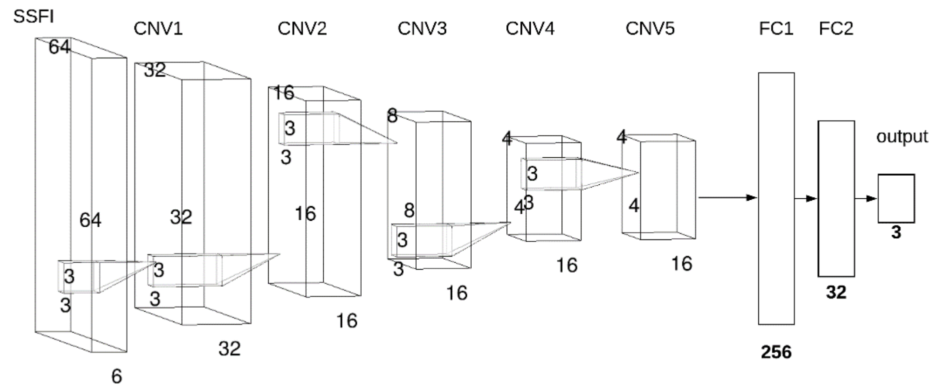
Correlation of each channel with given activity **average** across all the participants

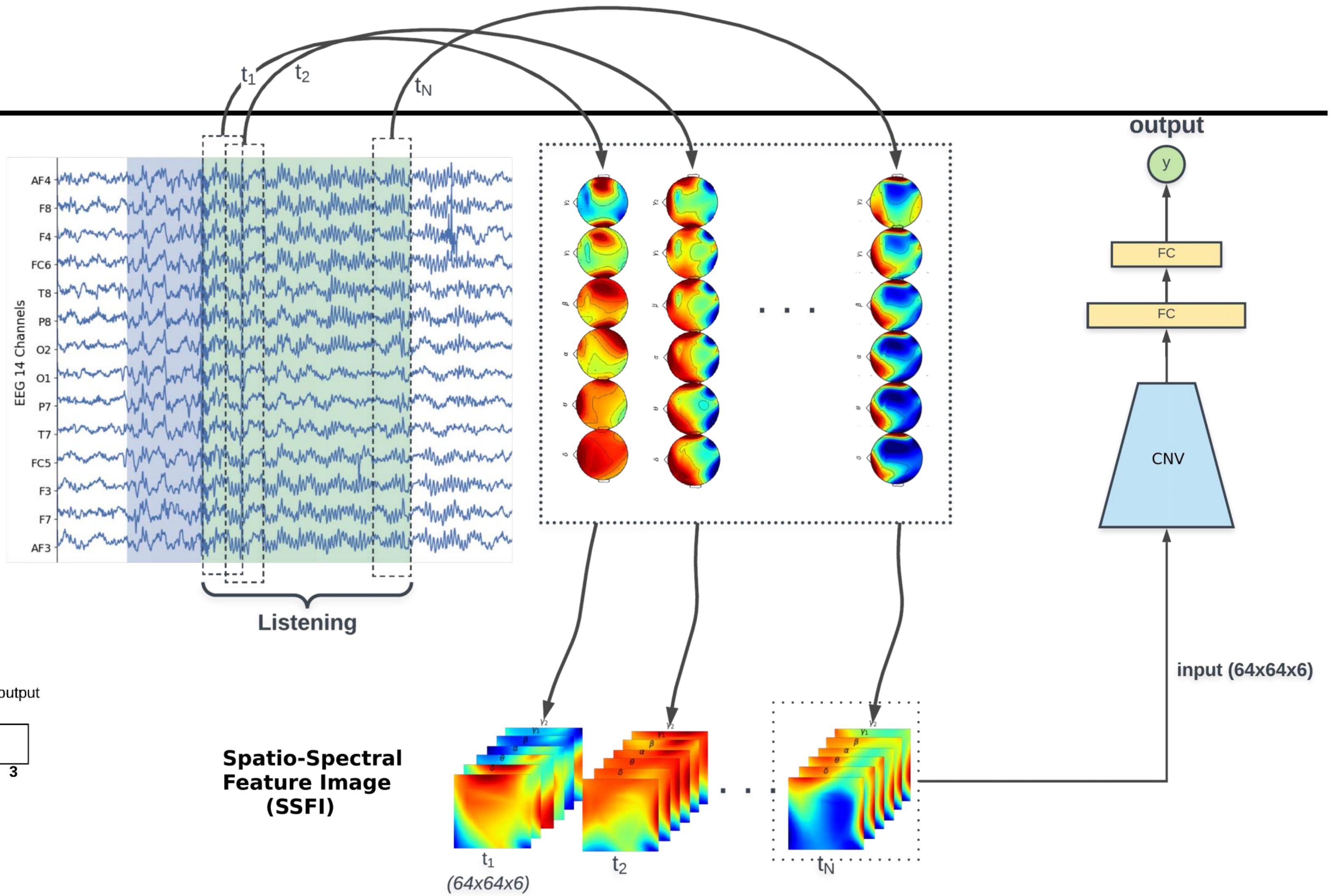


Sensors with significant correlation (*$p<0.05$*) are highlighted.

Applying Deeplearning: CNN

- Converting EEG Signal into images – Spatio-Spectral-Feature-Image
- Using CNN for LWR Task

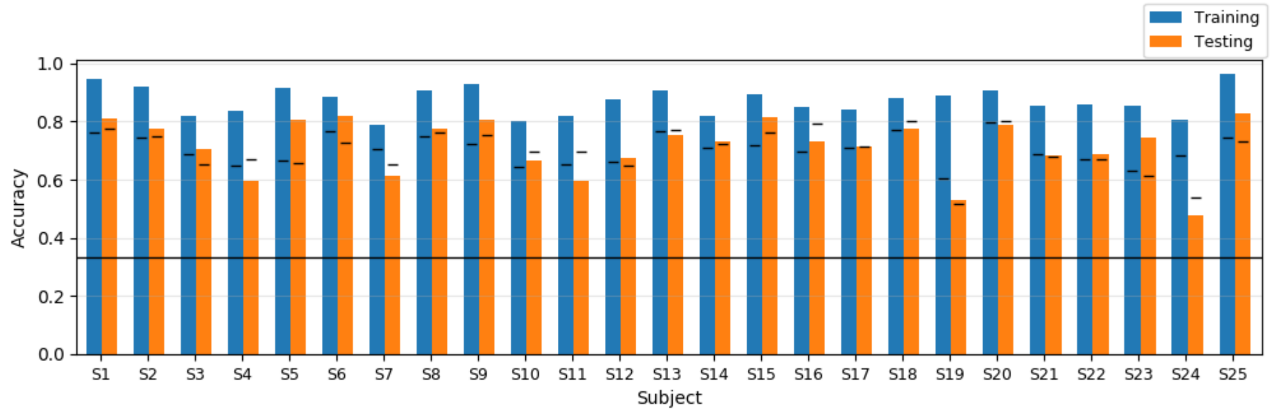


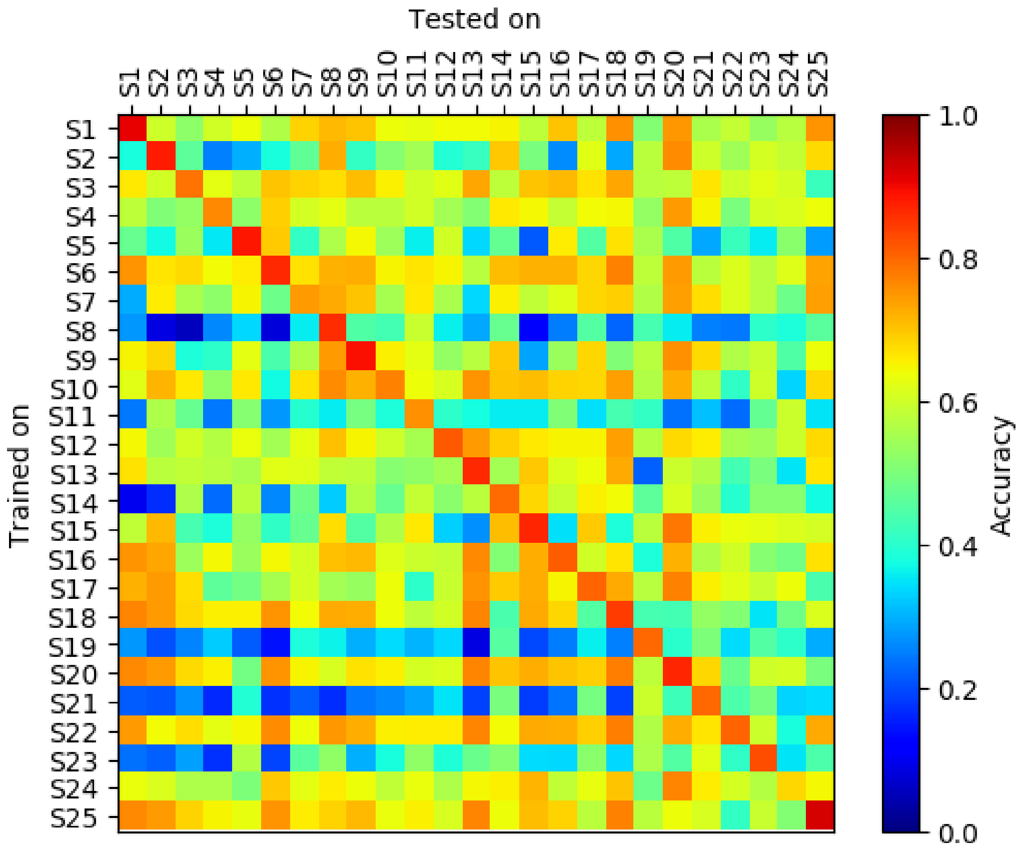


For Task 1: LWR classification using CNN

Inter-Subject Dependency analysis

- **For Task 1: LWR classification using CNN**
- Individual Subjects
- Inter-subject Dependency Analysis





**Article is under review*

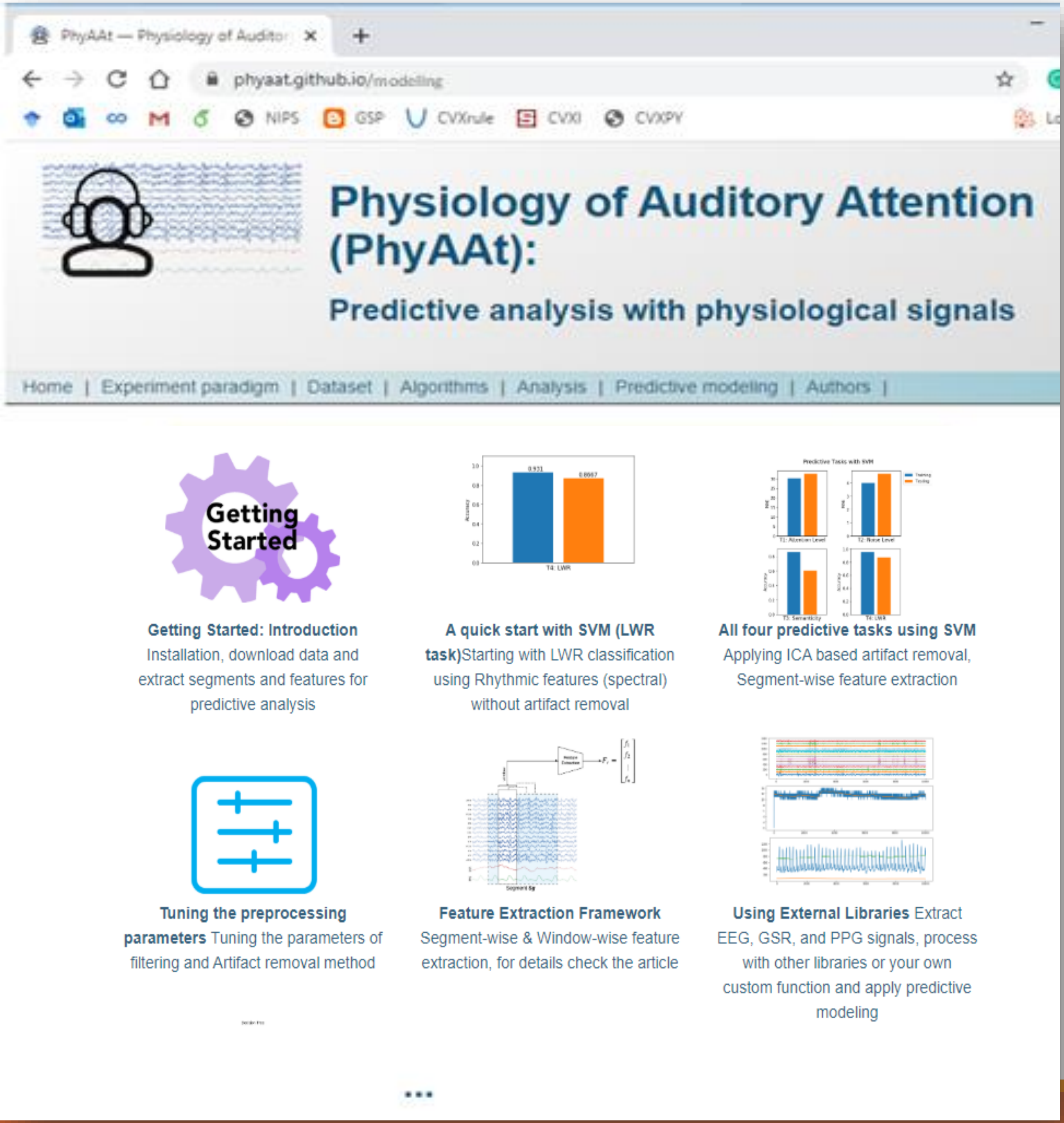
Conclusions

- The experiment and collected data is unique of its kind
- Brain activity from collected data shows consistency with literature
- Proposed artifact removal algorithm gives control to tune the parameters and perform better than state-of-the-art algorithms
- Collected data can be used to analyse and understand the auditory mechanism of brain
- All the resources (data, helper code, library and reproducible results) are* shared on project homepage: *https:PhyAAt.github.io*
- All the source code and algorithms are* distributed with python library: phyaat, which can be installed using pip

-

\- *pip install phyaat*

https://PhtAAt.github.io



For paying *Attention**

**At least Auditory one*

Any
Questions ?

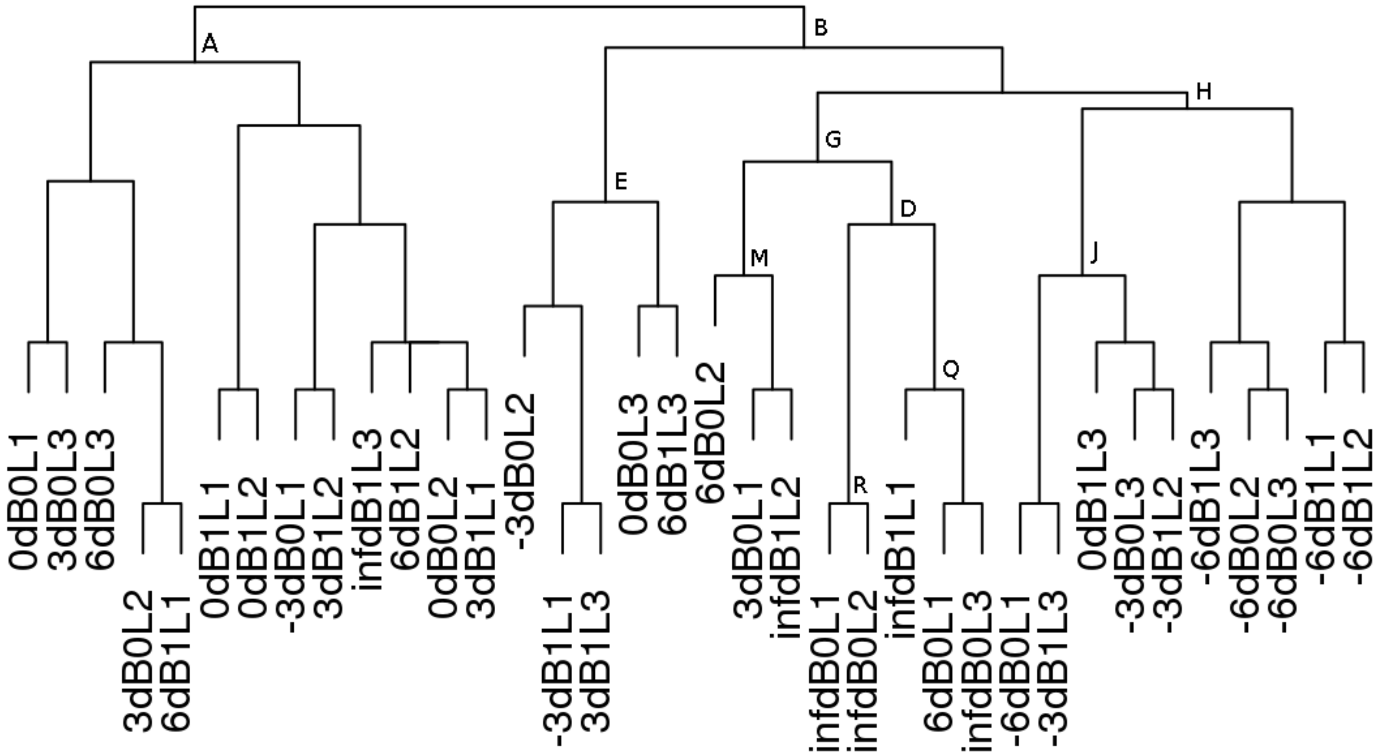
https://PhyAAt.github.io

Extra Slides

ANOVA – Attention score

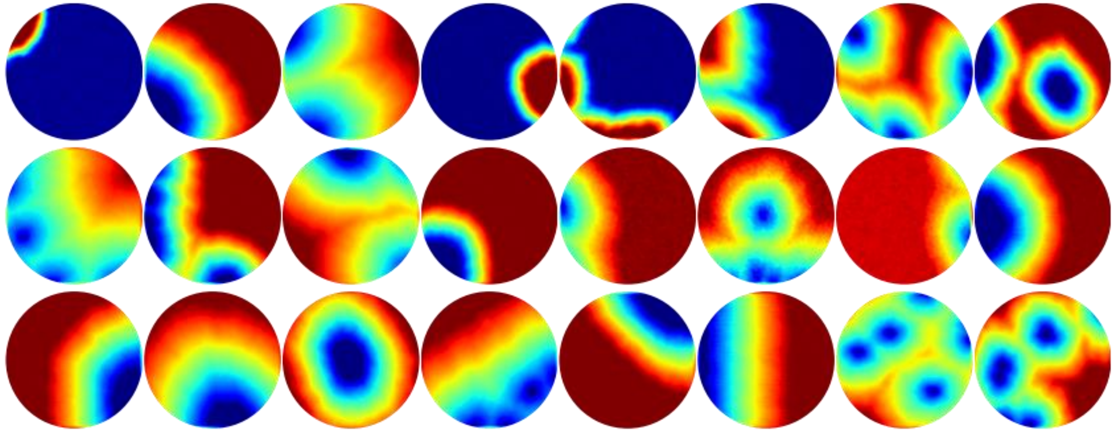
Variable(s)	*F*-ratio	$p - value$	$\eta^2_{partial}$
Noise level (SNR)	$F(5, 120) = 238.500$	$\approx 10^{-16}$	0.909
Length of stimulus	$F(2, 48) = 95.9220$	$\approx 10^{-16}$	0.800
Semanticity of stimulus	$F(1, 24) = 115.611$	$\approx 10^{-10}$	0.828
Noise*Length*Semanticity	$F(35, 840) = 72.771$	$\approx 10^{-16}$	0.752

Hierarchical clustering

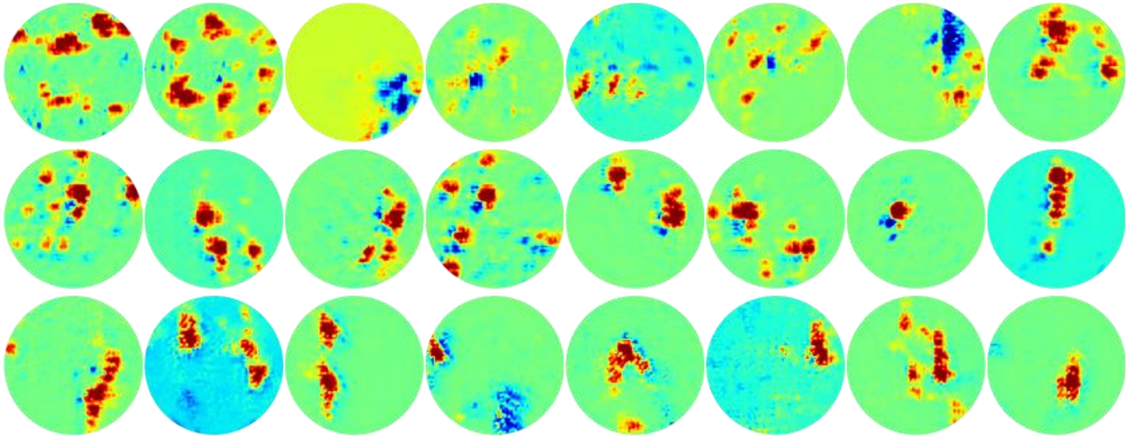


CNN – Feature maps

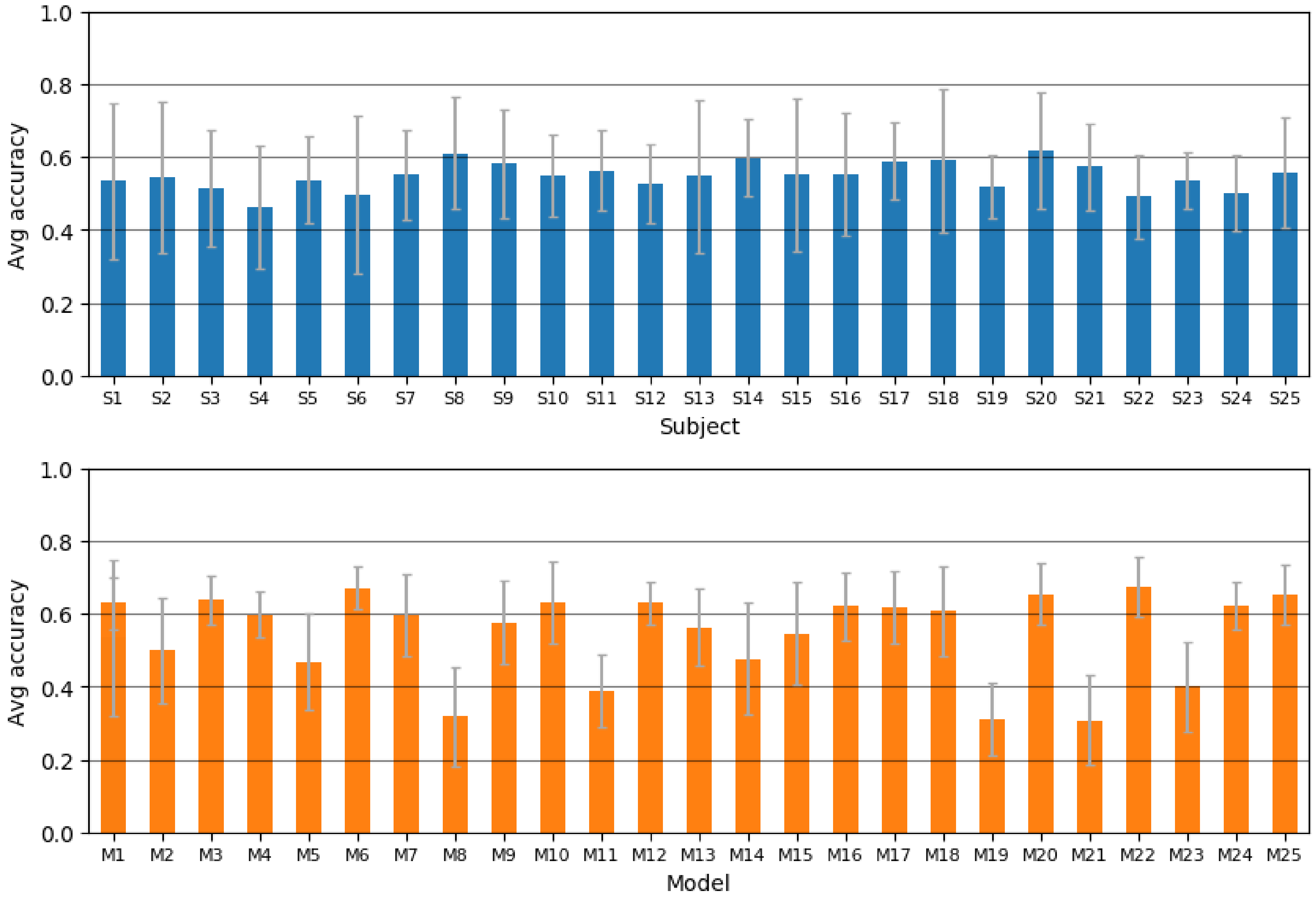
Conv1



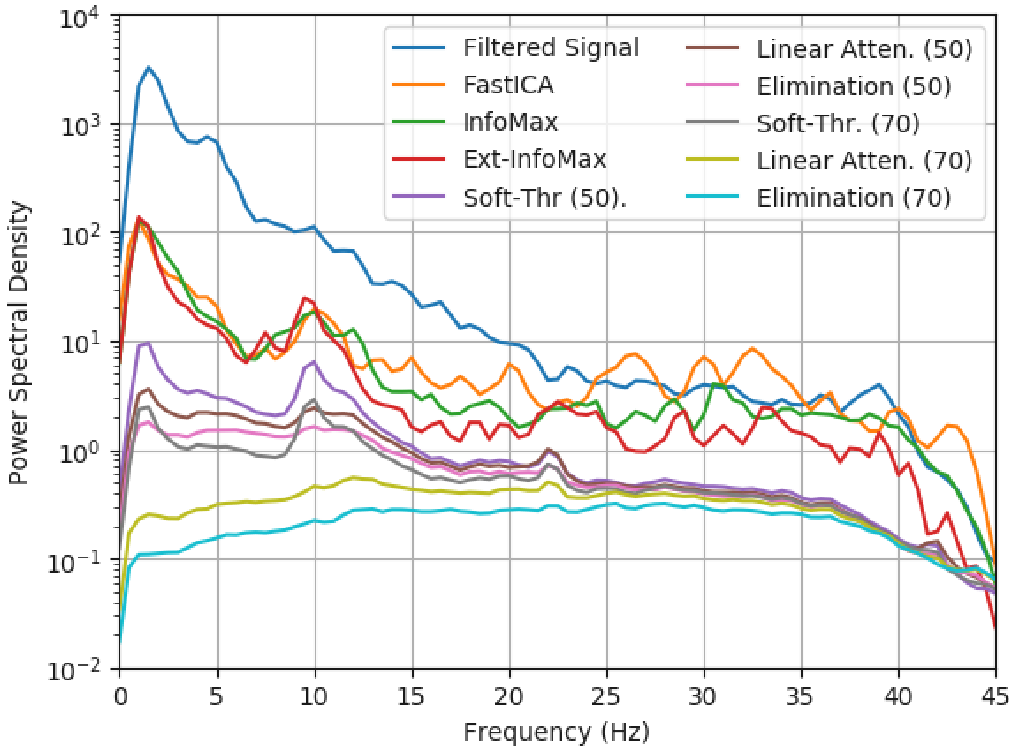
Conv5

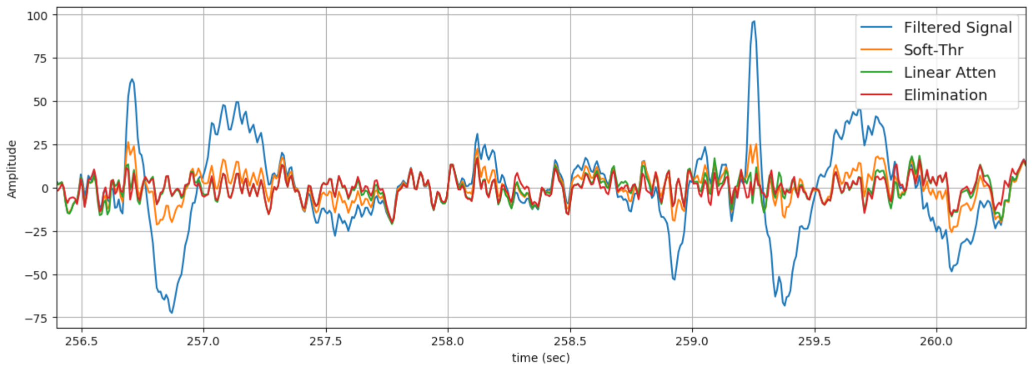


ISD Analysis

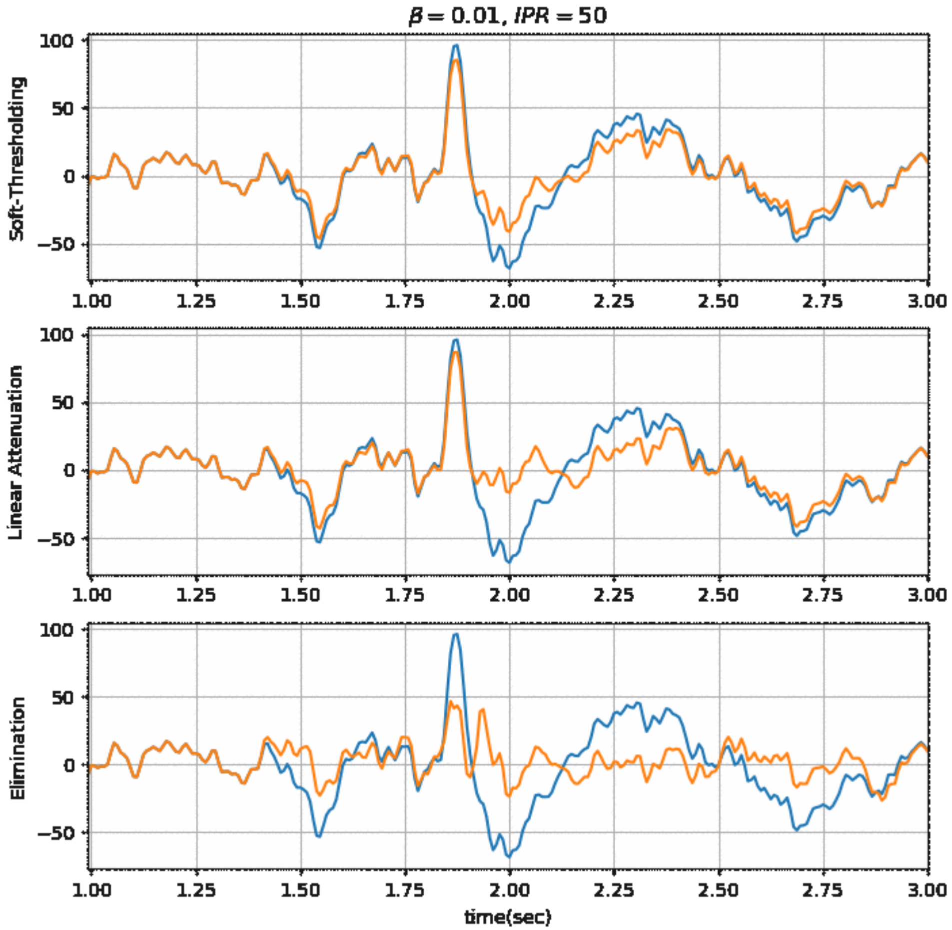


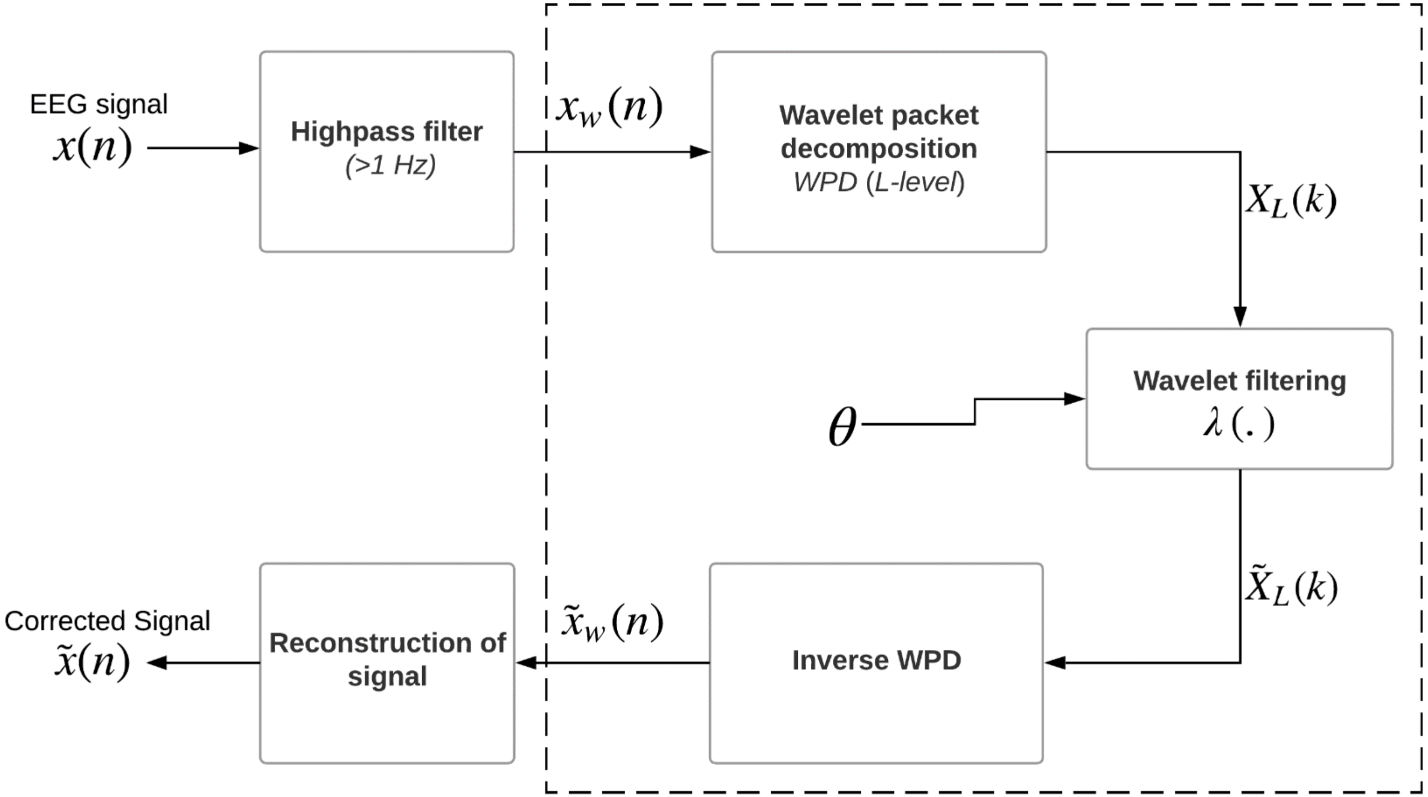
Artifact removal algorithm





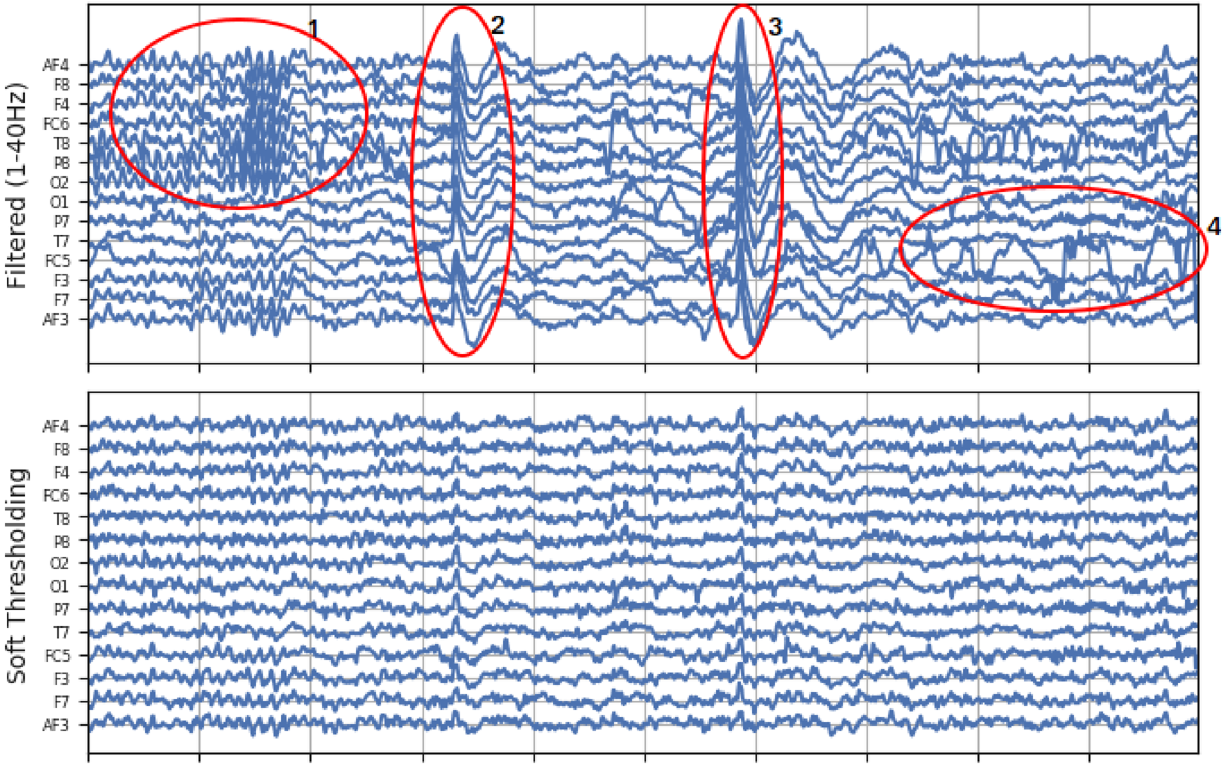
Artifact Removal Algorithm: Tunable, based on WPD

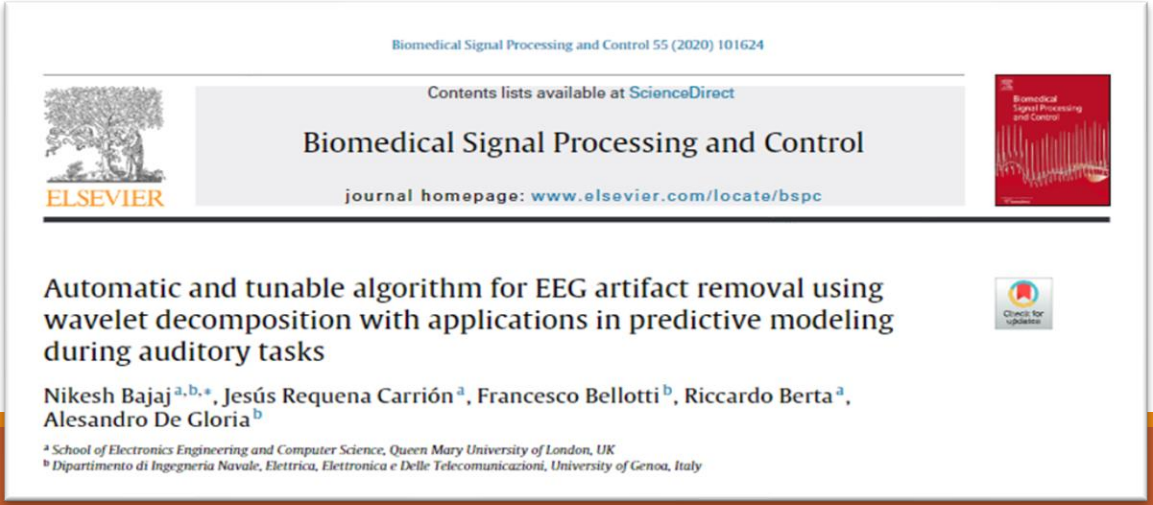




Artifacts in EEG

- EEG signal is contaminated by artifacts
- Proposed an **automatic and tunable artifact removal algorithm**, based on wavelet packet decomposition [1]
- Perform better, compared to state-of-the-art and gives control over suppression





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Automatic and tunable algorithm for EEG artifact removal using wavelet decomposition with applications in predictive modeling during auditory tasks

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Conclusions

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*in progress

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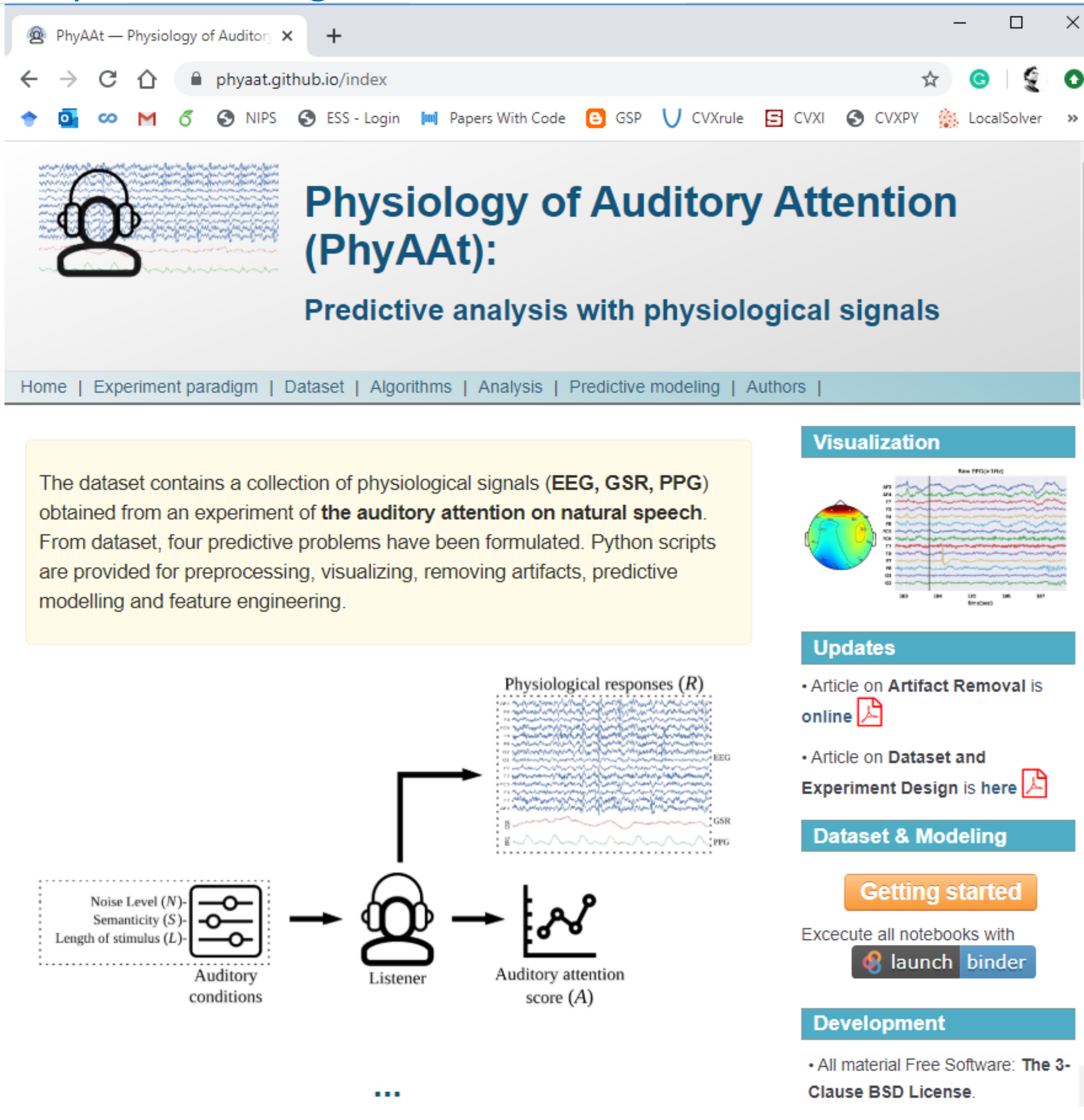

Formulation of predictive tasks

T1: Attention score prediction

$$A' = f_A(R)$$

T2: Noise level prediction

$$N' = f_N(R)$$

T3: Semanticity prediction

$$S' = f_S(R)$$

T4: Subtask prediction - LWR

$$T' = f_T(R)$$

Feature extraction: $R \rightarrow F_r$