école normale supérieure paris-saclay

Detecting Sleep Apnea from raw physiological signals by Dreem

Challenge Data Report

Représentations Parcimonieuses

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Outline

Introduction

- **Problem:** Sleep Apnea is a common breathing-related sleep disorder that affects both sexes, yet, it is under-diagnosed, with a significant number of cases being undetected. To diagnose it, PSG recordings of raw physiological signals must be manually analyzed by trained experts.
- **Solution:** Develop automated methods to detect Sleep Apnea. This would make the diagnosis more efficient and could help to detect the undetected cases.

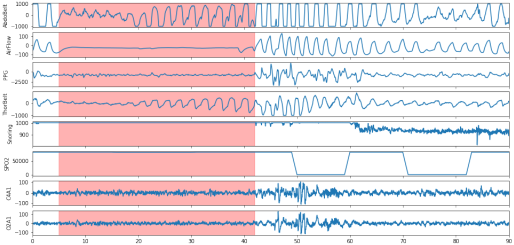

Figure: Example of an apnea event

Motivation

dreem

Samples of 44 nights recorded with a Polysomnography including the raw physiological signals:

- Abdominal belt
- Airflow
- Cardiac activity
- Thoracic Belt
- Snoring indicator
- O2 saturation of the blood
- Two EEG derivations

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Related Work (1)

- Deep Learning based methods : U-Net, DOSED, DeepSleepNet, TinySleepNet, ...

DOSED: A deep learning approach to detect multiple sleep micro-events in EEG signal

S. Chambon[a,b,c,*,1], V. Thorey[b,1], P.J. Arnal[b], E. Mignot[a], A. Gramfort[c,d,e,*]

DeepSleepNet: a Model for Automatic Sleep Stage Scoring based on Raw Single-Channel EEG

Akara Supratak, Hao Dong, Chao Wu, and Yike Guo*

Related Work (2)

- Machine Learning based models

Automatic detection of sleep apnea events based on inter-band energy ratio obtained from multi-band EEG signal

Suvasish Saha [1], Arnab Bhattacharjee [1], Shaikh Anowarul Fattah [1]

An Intelligent Sleep Apnea Classification System Based on EEG Signals

V. Vimala [1] · K. Ramar [2] · M. Ettappan [3]

Apnea Detection Based on Respiratory Signal Classification

Laiali Almazaydeh, Khaled Elleithy, Miad Faezipour and Ahmad Abushakra
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Data Exploration And Exposed Challenges

- **Idea** : Have a better understanding of the database by looking at what characterizes an apnea event.

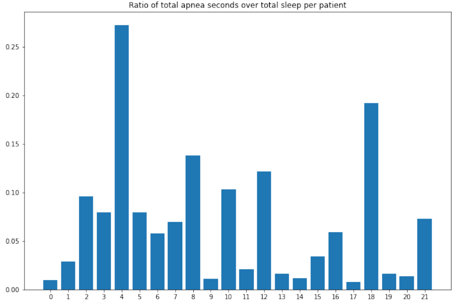


Figure: Ratio of total apnea seconds over total sleep time for each patient in the training set.

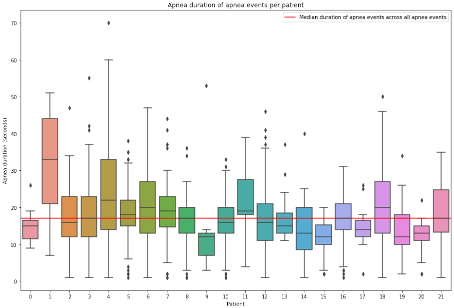


Figure: Duration of apnea events per patient

Data Exploration And Exposed Challenges

Subject-dependent data $\longrightarrow$ Highly complex problem.

We should not try to recognize some general patterns shared by all patients going through apnea episodes but to try to catch a difference in the behavior of the input signals when doing an apnea.

Feature Extraction (1)

- **Idea** : Compare statistical features of normal sleep and apnea events.

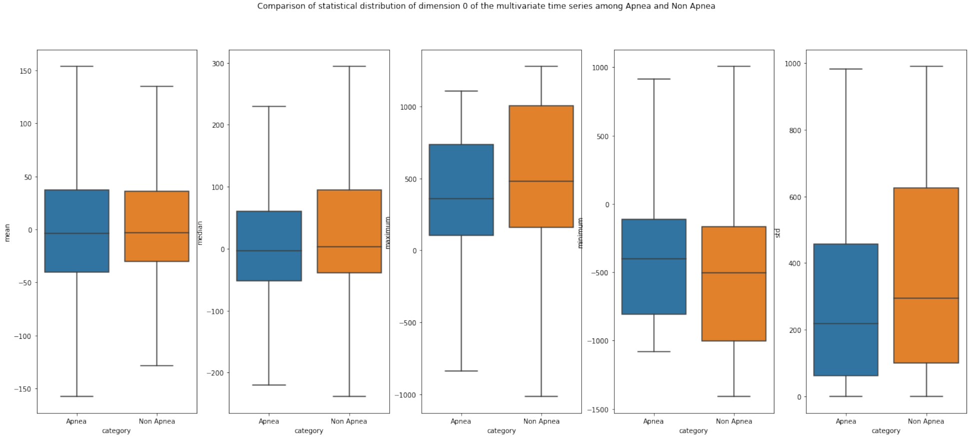


Figure: Comparison of Abdominal Belt Statistics

Feature Extraction (2)

- **Idea** : Compare statistical features of normal sleep and apnea events.

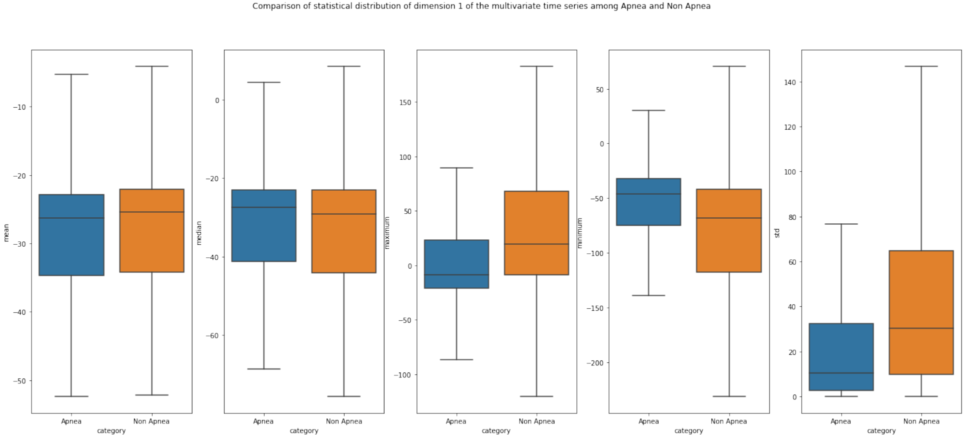


Figure: Comparison of Airflow Statistics

Feature Extraction (3)

- **Idea** : Compare statistical features of normal sleep and apnea events.

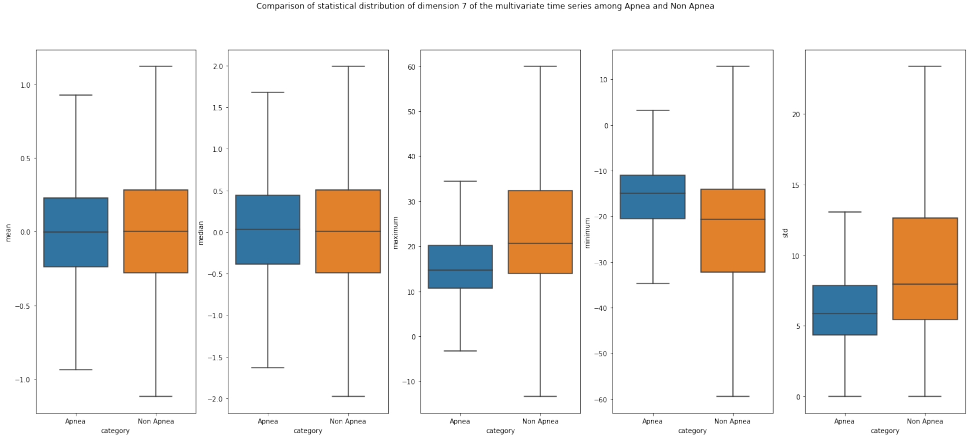


Figure: Comparison of O2-A1 EEG derivation statistics école normale supérieure paris–saclay

Signal- Denoising (1)

- **Idea** : Denoise the raw signals as to get rid of the captor's unavoidable noise.
- **Solution** : Use SSA to keep the signal's components that do not correspond to background noise.

1. Compute the signal x trajectory matrix X with a window of size N_w:

$$X = \begin{pmatrix} x[0] & \dots & x[N - N_w - 1] \\ x[1] & \dots & x[N - N_w] \\ \vdots & \ddots & \vdots \\ x[N_w - 1] & \dots & x[N - 1] \end{pmatrix}$$

Signal- Denoising (2)

2. Compute the trajectory matrix X Singular Value Decomposition:

$$X = \sum_{k=1}^{N_w} \lambda_k u_k v_k^t$$

3. Analyze the singular value distribution and remove the lowest ones, since they correspond to noise.

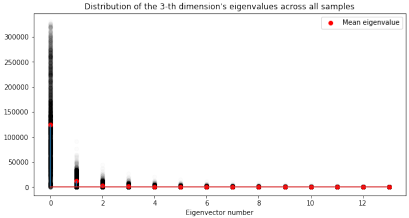


Figure: Mean singular values for the Thoracic Belt signal on the training dataset

Signal- Denoising (3)

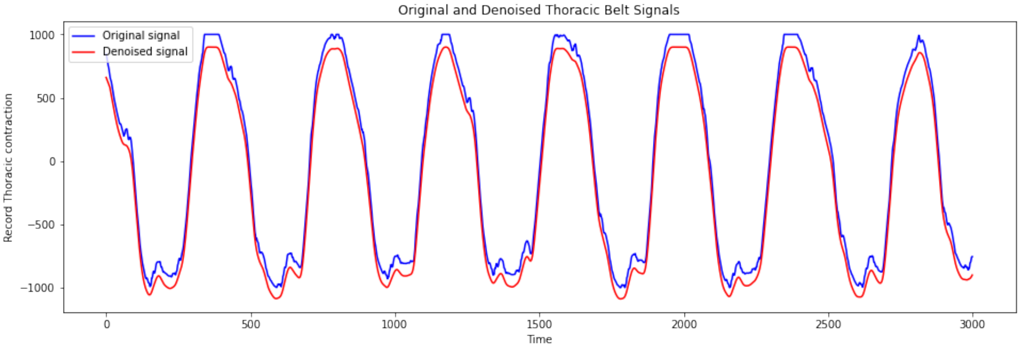


Figure: Comparison of original signal and denoised signal with SSA

EEG Analysis (1)

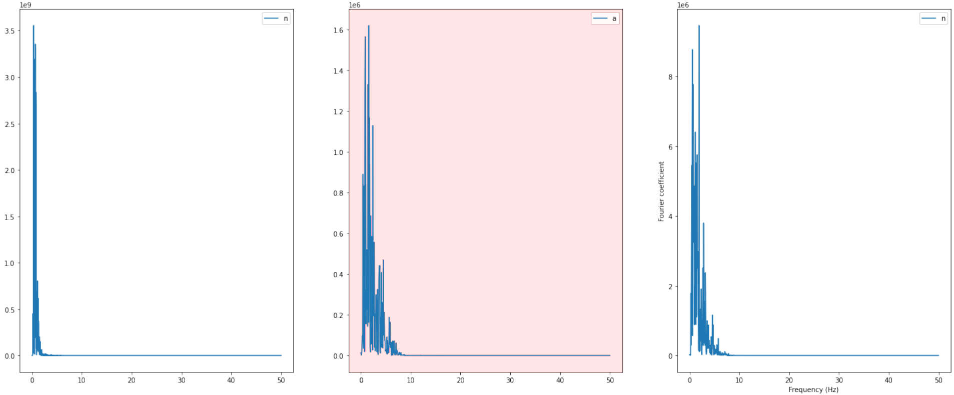


Figure: Spectrogram computed on windows of 5 seconds for three successive periods of non apnea(white background), apnea (pink) and non apnea (white)

EEG Analysis (2)

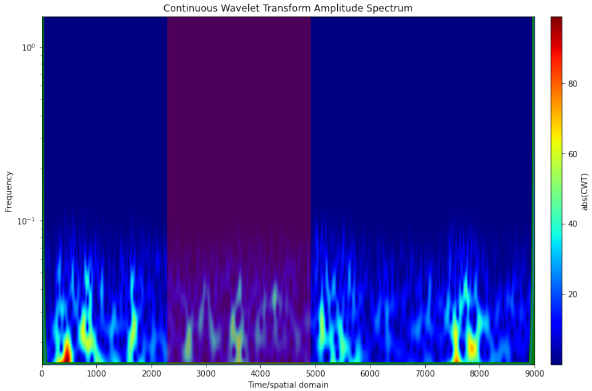


Figure: Mel spectrogram for three successive periods of non apnea (white background), apnea (pink) and non apnea (white)

EEG Analysis (3)

TABLE I. THE FREQUENCY BANDS OF EEG SIGNALS

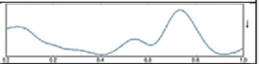
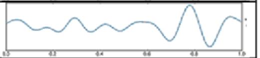
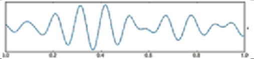
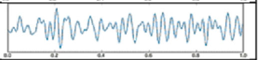
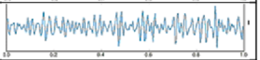
Waves	Frequency bands (Hz)	Behaviour Trait	Signal Waveform
Delta	0.3 – 4	Deep sleep	
Theta	4 – 8	Deep Meditation	
Alpha	8 – 13	Eyes closed, awake	
Beta	13 – 30	Eyes opened, thinking	
Gamma	30 and above	Unifying consciousness	

Figure: EEG frequency changes during sleep

EEG Analysis (4)

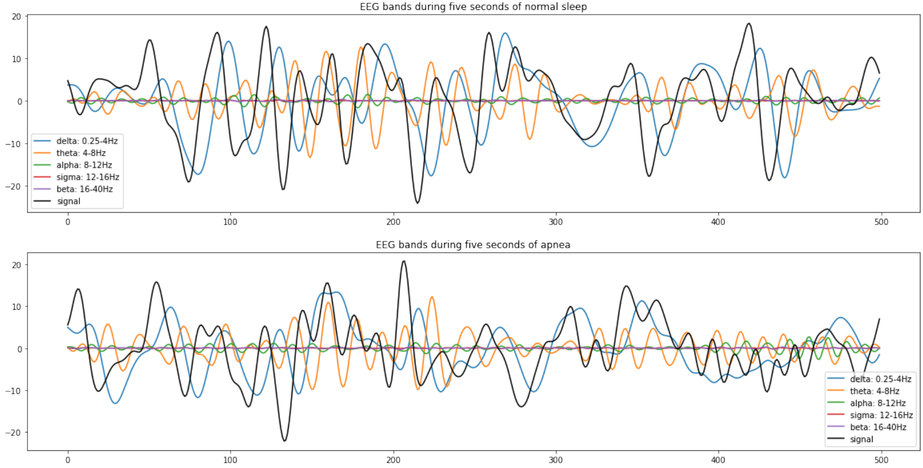


Figure: Comparison of EEG-bands between normal sleep and the middle of an apnea event

EEG Analysis (5)

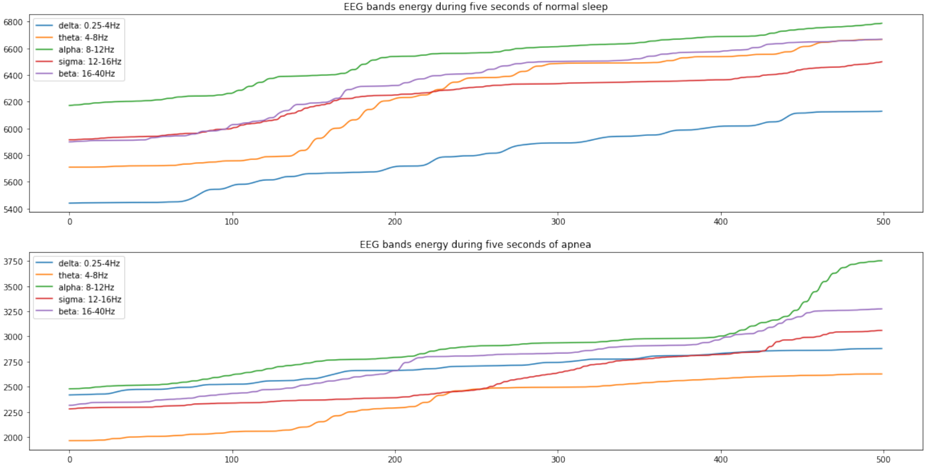


Figure: Comparison of EEG-bands energy between normal sleep and the middle of an apnea event

EEG Analysis (6)

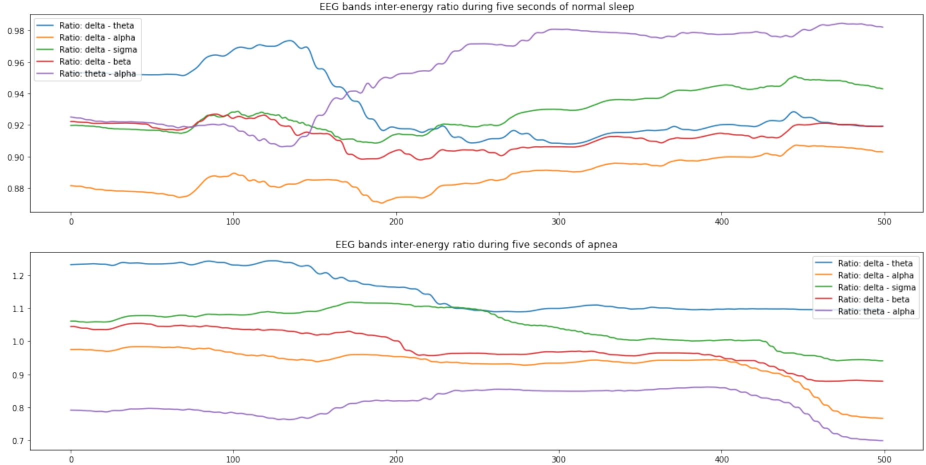


Figure: Comparison of EEG-bands inter-energy ratios between normal sleep and the middle of an apnea event

Models

- **Idea** : The relationship between these features and the output is far from simple
  $\longrightarrow$ Use CNNs to capture the meaningful features of the eight signals
- **Idea** : Create an unique classifier on the EEG bands known behaviour (inductive bias)
- Final Model : **Ensemble** model

$$p^{final} = \lambda p^{CNN} + (1 - \lambda) p^{graphs\ on\ EEG}$$

Models- CNN (1)

U-Time: A Fully Convolutional Network for Time Series Segmentation Applied to Sleep Staging

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Models- CNN (2)

3x1 Linear Layer ReLU (channels=8, padding=1)
Max Pooling layer
3x1 Convolution Layer ReLU (channels=8, padding=1)
Max Pooling layer
3x1 Convolution Layer ReLU (channels=16, padding=1)
Max Pooling layer
3x1 Convolution Layer ReLU (channels=32, padding=1)
Max Pooling layer
3x1 Convolution Layer ReLU (channels=64, padding=1)
Max Pooling layer
3x1 Convolution Layer ReLU (channels=128, padding=1)
Max Pooling layer
3x1 Convolution Layer ReLU (channels=64, padding=1)
3x1 Convolution Layer ReLU (channels=32, padding=1)
Max Pooling layer
3x1 Convolution Layer ReLU (channels=16, padding=1)
1x1 Convolution Layer ReLU (channels=2, padding=0)

Table 1: CNN architecture 5-16-32-64-128-64-32-16

Models- CNN (3)

- **Choice of the loss function**

1. Use the Cross Entropy Loss for the binary classification task

$$\mathcal{L}_{CE}(y, p^{pred}) := -(y \log(p^{pred}) + (1-y)\log(1-p^{pred}))$$

2. The classes are highly imbalanced, so we should penalize the errors made on the rare class (here apnea)

$$\mathcal{L}_{CE}^{weighted}(y, p^{pred}) := -(\alpha_1 y \log(p^{pred}) + \alpha_2 (1-y)\log(1-p^{pred}))$$

where $\alpha_1 = \frac{|negative\ samples|}{|positive\ samples|}$

Models- CNN (4)

3. **Problem :** F1 score is non differentiable
   $\longrightarrow$ **Solution :** Differentiable version F1 score Example :
   - y = 1, p = 0.3 $\longrightarrow$ True Positive = 0.3, False Negative = 0.7
   - y = 0, p = 0.6 $\longrightarrow$ True Negative = 0.4, False Positive = 0.6
4. Better suited to maximize the final objective

Models- Graphs (1)

- **Idea :** Recover only the EEG signals from a sample and use an independent classifier on them to bring some interpretability to the output
- We now have a multivariate set instead of a multimodal one.
- Use graph signals!

Models- Graphs (2)

- **Smoothness on a graph signal** x:

$$S(x) = x^T L x = \frac{1}{2} \sum_{(i,j)\in\mathcal{E}} W_{i,j}(x_i - x_j)^2$$

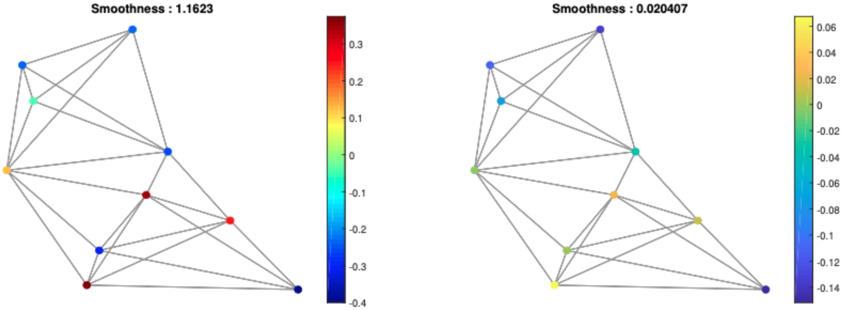

Figure: Smoothness evaluation on two graphs signals: The smoothness decreases on smoother graphs

Models- Graphs (3)

- **How do we learn the graph signal Laplacian?**
- Use correlation between signals:

$$W_{i,j} = \begin{cases} (corr)(x_i, x_j) & \text{if } \mathrm{corr}(x_i, x_j) > \lambda \\ 0 & \text{else} \end{cases}$$

Models- Graphs (4)

- **How do we learn the graph signal Laplacian?**

$$\min_{Y,L} ||X - Y||_F^2 + \alpha \mathrm{tr}(Y^T L Y) + \beta ||L||_F^2$$

$$\text{s.t} \begin{cases} \mathrm{tr}(L) = D \\ L_{i,j} = Lj, i \leq 0, i \neq j \\ L\mathbf{1}_D = \mathbf{0}_D \end{cases}$$

- Y is a smooth approximation of the signals X
- The constraints impose L to be a graph laplacian
- Solution by alternating minimization in two convex optimization problems: one for Y with a form closed solution, one for L with quadratic programming.

Results - CNN

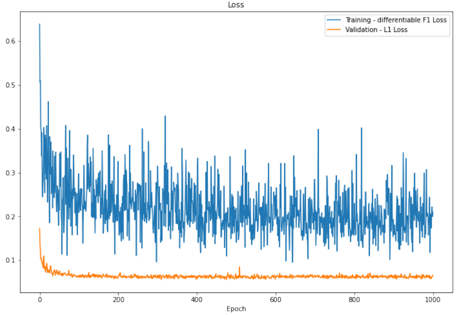

Figure: Evolution of the training and validation differentiable F1 loss.

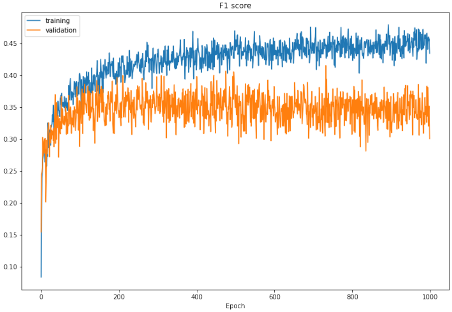

Figure: Evolution of the training and validation F1 score

Training set	Validation set	Testing set
0.444	0.415	0.282

Table: F1 score of our model

Results - Graphs

- Not satisfying results
- Why ? Introduced features not really discriminating both classes :

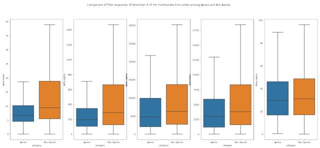

Figure: EEG 1 - Distribution of the 5 most important inter band energy features.

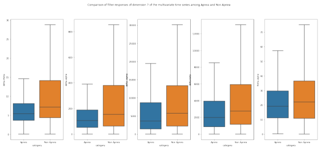

Figure: EEG 2 - Distribution of the 5 most important inter band energy features.

Figure: On this dataset, inter band energy features from EEG signals seem not to be discriminating both classes

Further investigation

- Find deeper expertise on the **EEG** signals provided
- **Post processing** to have continuous blocks of positive classes with certain size
- Transition Probabilities between states : Hidden Markov Model (**HMM**)?
- Models adapted to **time series** : LSTM, RNN, Attention, ...

Conclusion

- **Noisy** data
- **Multi-modal** time series
- Classification task **subject-dependent**
- Neural Networks : lack of **interpretability**

Thank You

for Listening.