[Airbus Amber]

Decoding Neural Signatures in an Emergency Driving Situation using OT

Human Focus Technology at CRT

Catalina Obando
Pierre Benjamin and XRV
June 21 2021

AIRBUS

Propose agenda

1. Context human monitoring
2. Emergency Braking use case
3. Detect emergency situation: DeepNet technique
4. Predict pilot's performance: Spatio-temporal models (KL decomposition)

Human monitoring

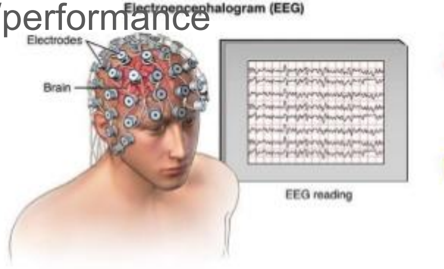
Monitoring human actions/behaviors by means of different type of sensors: eye-tracking, video, neurophysiological data.

To :

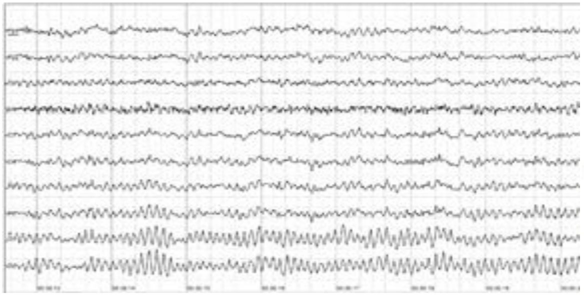
- Improve monitoring for cockpit design, cockpit certifications, air traffic management, other applications …

- Provide objective measures of various Human Factors

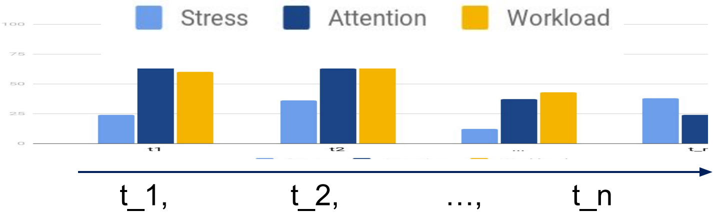
- Develop robust statistical methods to **quantify** and **predict** mental activity/performance



Formalization of the problem



$X_t \in \mathbb{R}^{C \times T}$: Temporal process of neurophysiological state



Y_t : Temporal process of mental states/performance

Given the neurophysiological information, can we predict the psychological state or performance?

$$P(Y_{T+1}, \ldots, Y_{T+p} = y_{T+1}, \ldots, y_{T+p} | Y_0, X_0, \ldots, X_T)$$

Objective

Study methods in a simple experiment setup to decode meaningful information from brain activity

1. Public available EEG data
2. Airbus-like context
3. Notion of mental state

Emergency Braking use case

24. Emergency braking during simulated driving (002-2016)

Participants	18
Signals	59 EEG, 2 EOG, 1 EMG, 7 others
Data	VPae, VPbba, VPgab, VPgag, VPgam, VPja, VPbad, VPdx, VPgac, VPgah, VPih, VPsaj, VPbax, VPgaa, VPgae, VPgal, VPii, VPsal
License	Creative Commons Attribution Non-Commercial No Derivatives license (CC BY-NC-ND 4.0)
Licensor	Neurotechnology Group, Technische Universität Berlin, Germany
Description	TXT
Publication	DOI
Contact	Stefan Haufe

Haufe, Stefan, et al. "EEG potentials predict upcoming emergency brakings during simulated driving." *Journal of neural engineering* 8.5 (2011): 056001.

Experimental setup

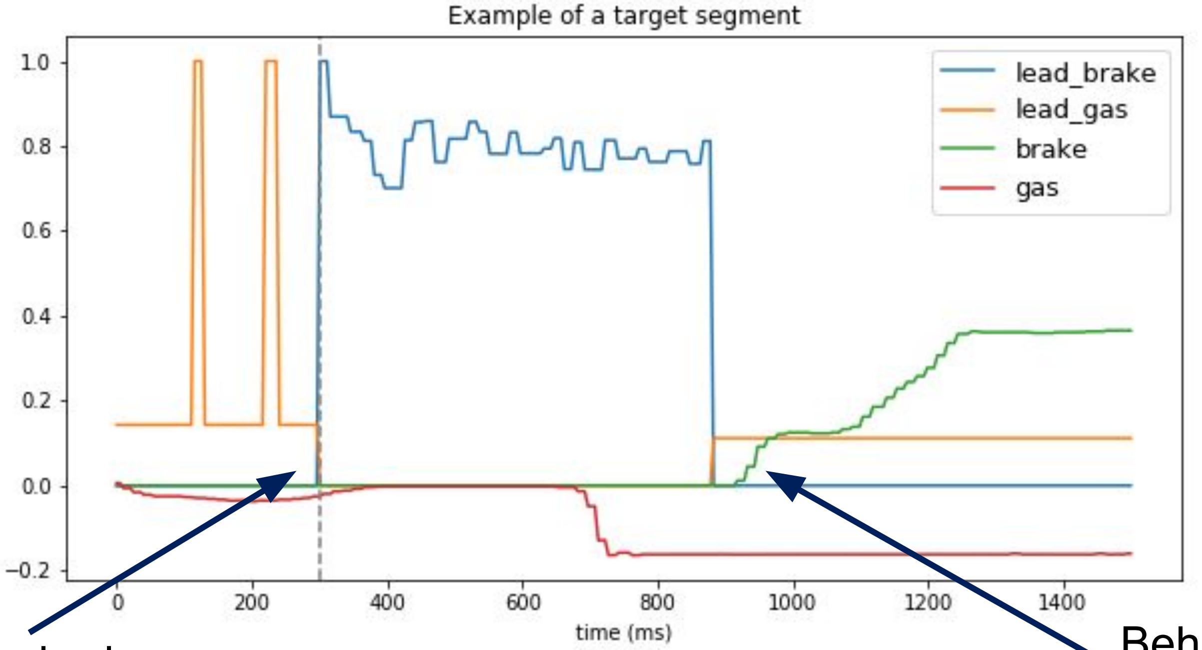
Figure 1. Snapshot of the experimental setup.

Task: drive a virtual racing car using the steering wheel and gas/brake pedals, following a computer-controlled lead vehicle

- Number of subjects: 18
- Event: While the participants were within the desired maximal distance of **20 m**, the lead vehicle occasionally (20–40 s inter-stimulus-interval, randomized) decelerated abruptly to between 60 and 80 km h−1 (randomized).
- Event distribution: 225 ± 17 critical (emergency braking) situations were artificially induced
- Duration: Three blocks (45 min each) of driving were conducted with rest periods of 10–15 min in between

AIRBUS

Typical event: behavioral variables



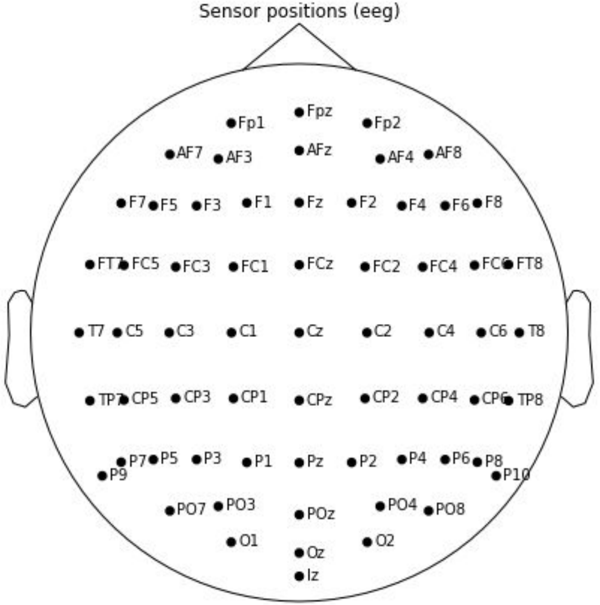
Stimulus:
Lead vehicle brakes

Behavioral response:
Pilot brakes

Can we decode from the EEG data the reaction to the stimulus before the behavioral response?

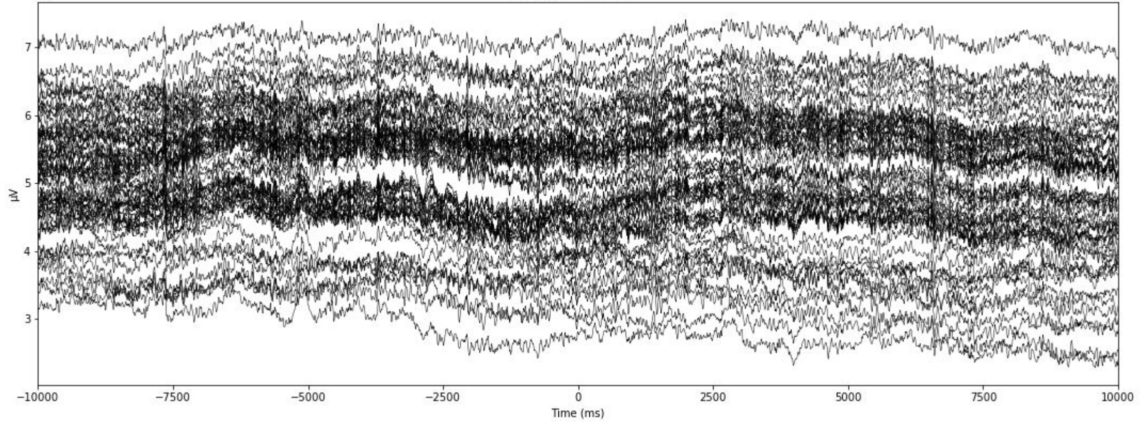
AIRBUS

EEG data:

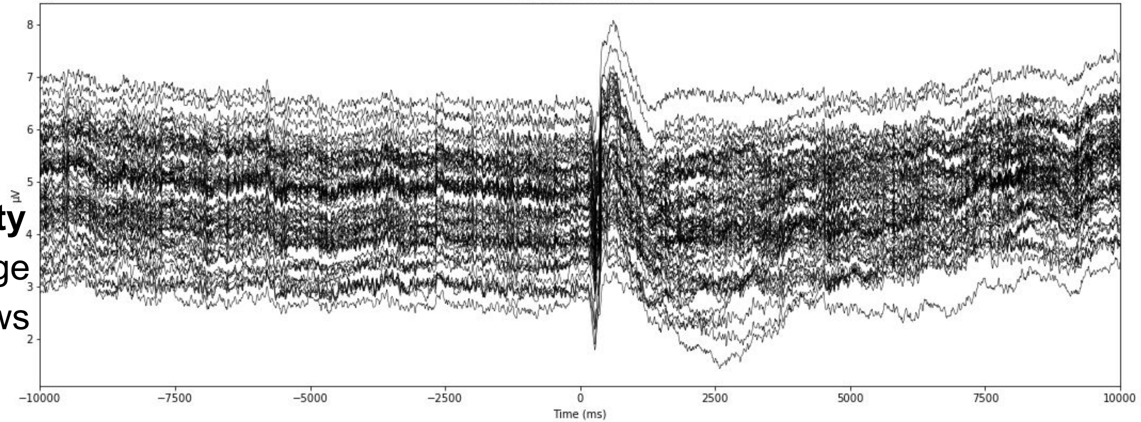


EEG is the recording of **electrical activity** along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain

Driving situation

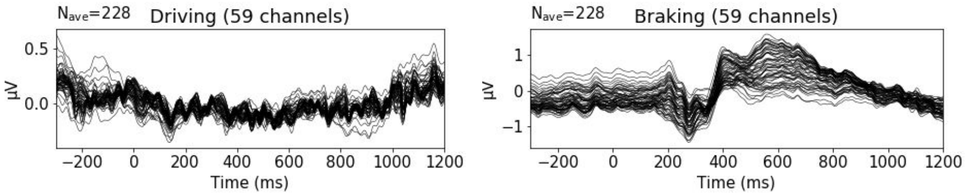


Emergency braking situation

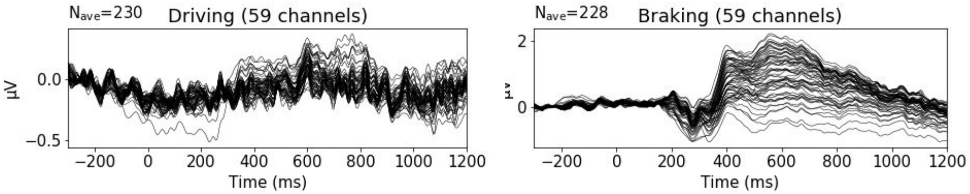


Data Preprocessing - example for one subject

1. Split data into segments: **non-target segments** and **target segments** center around a braking event

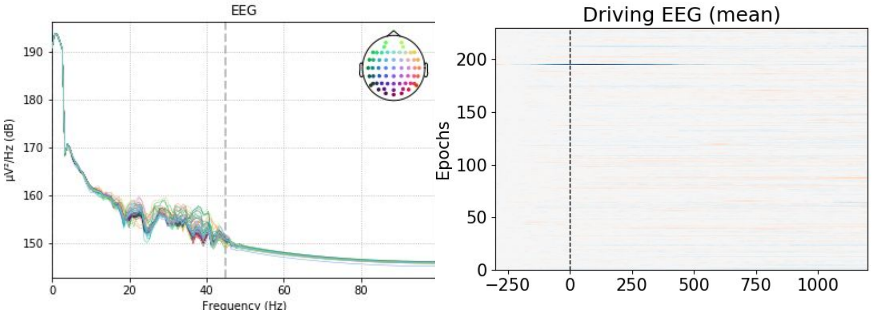


2. Baseline correction: subtract mean over first 100ms

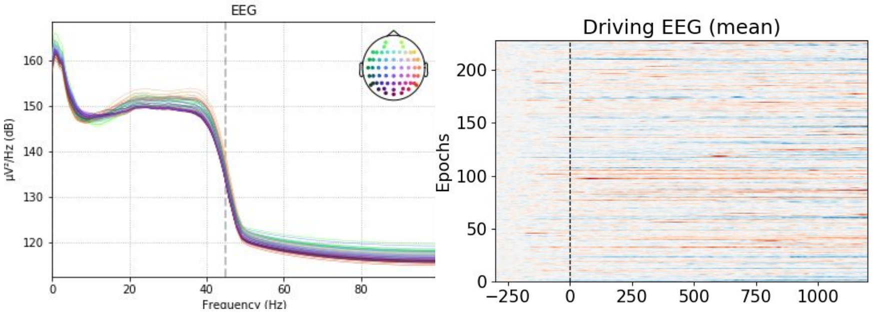


3. Remove segments that have abnormal high or lower potential

Abnormal target segments



Channel average over all target segments



Approach

We want a predictive model that can capture different mental states from EEG data

Classical ML approach:
- Tailor EEG features by an engineered process
- Drawback: feature extractions requires a lot of domain knowledge and it can be context dependent, therefore we would like a method that is more easily generalised

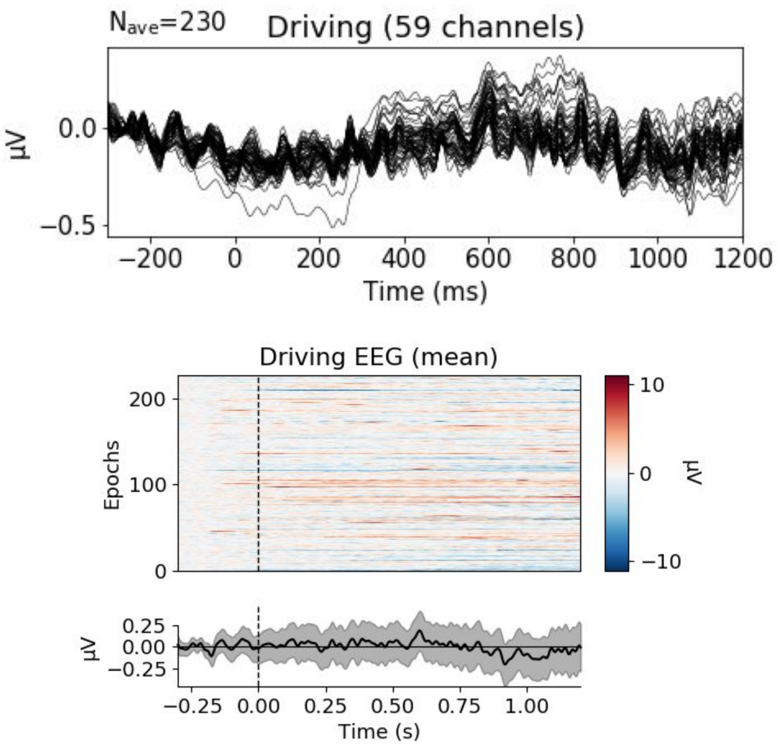
Proposed approach has two main avenues:
1. Neural Network architecture
2. K.L. decomposition

Detecting emergency situations

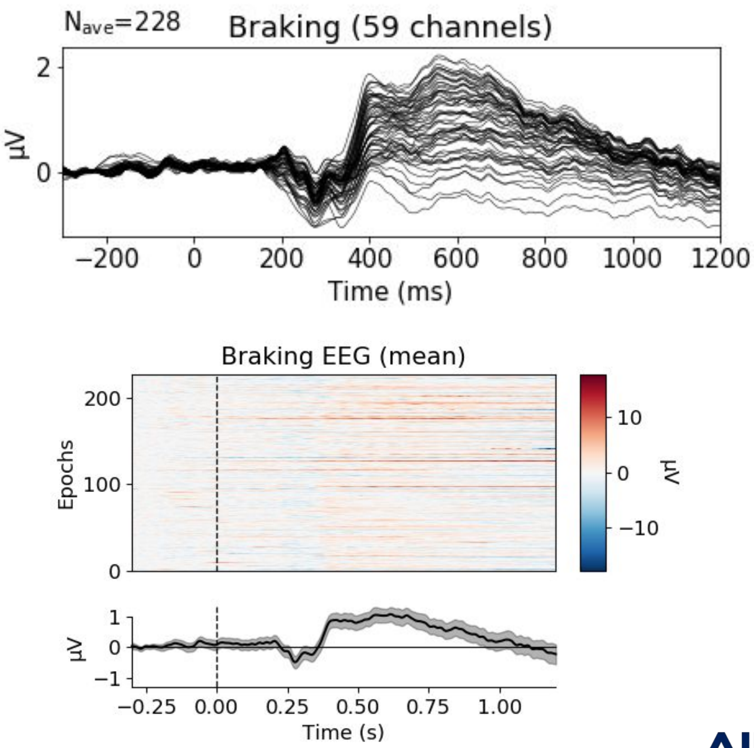
Normal driving vs. braking event

Driving vs Braking

Non-Target segments



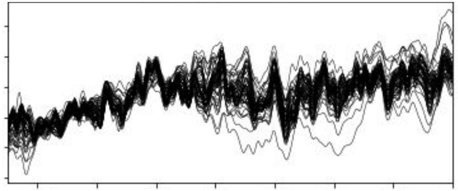
Target segments



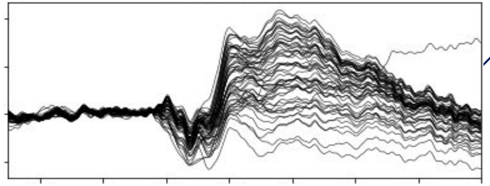
Chambon, Stanislas, et al. "A deep learning architecture for temporal sleep stage classification using multivariate and multimodal time series." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 26.4 (2018): 758-769.

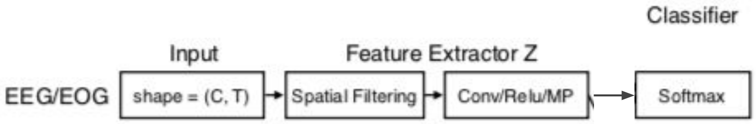
Network architecture + input data

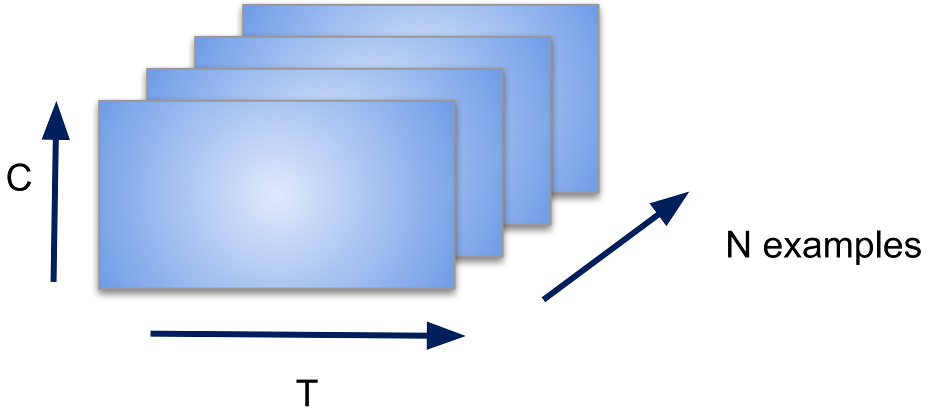
Target segments



Non-Target segment







Input data

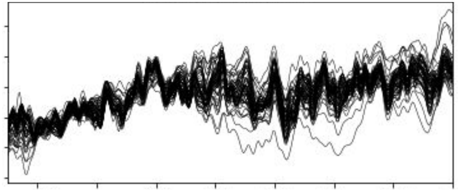
Target segments are those in which the braking response was given no earlier than 300 ms and no later than 1200 ms after the lead vehicle's braking onset
Non-target segments are those in which any braking response is at least 5000ms away

AIRBUS

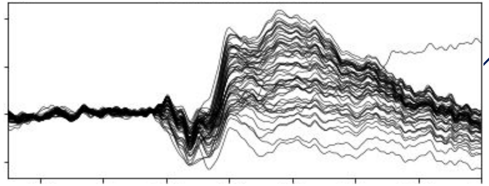
Chambon, Stanislas, et al. "A deep learning architecture for temporal sleep stage classification using multivariate and multimodal time series." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 26.4 (2018): 758-769.

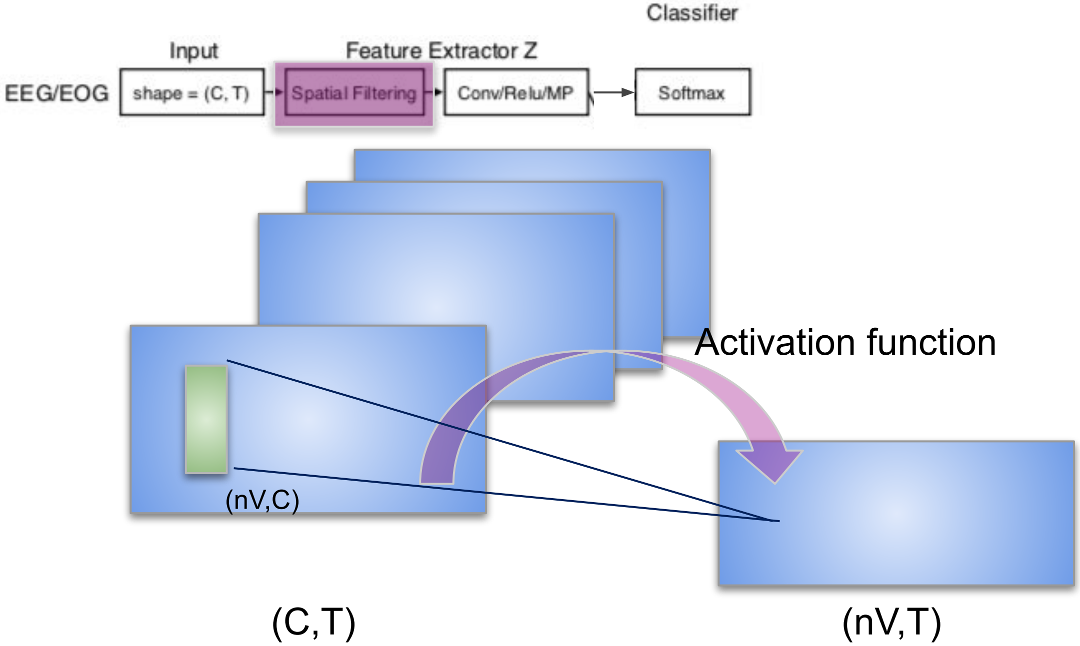
Network architecture + input data

Target segments



Non-Target segment





Where

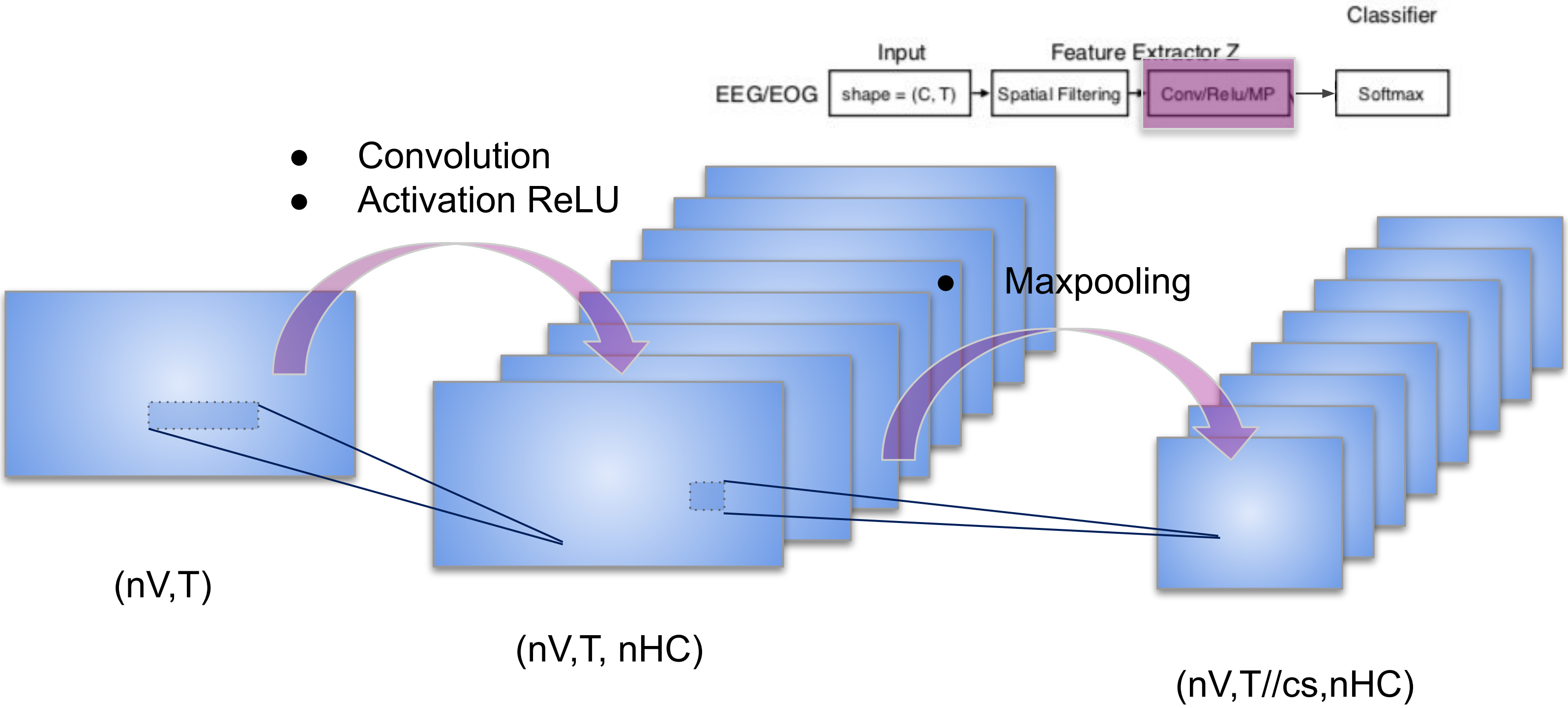
C: number of EEG channels

T: time duration

nV: number of virtual channels

Chambon, Stanislas, et al. "A deep learning architecture for temporal sleep stage classification using multivariate and multimodal time series." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 26.4 (2018): 758-769.

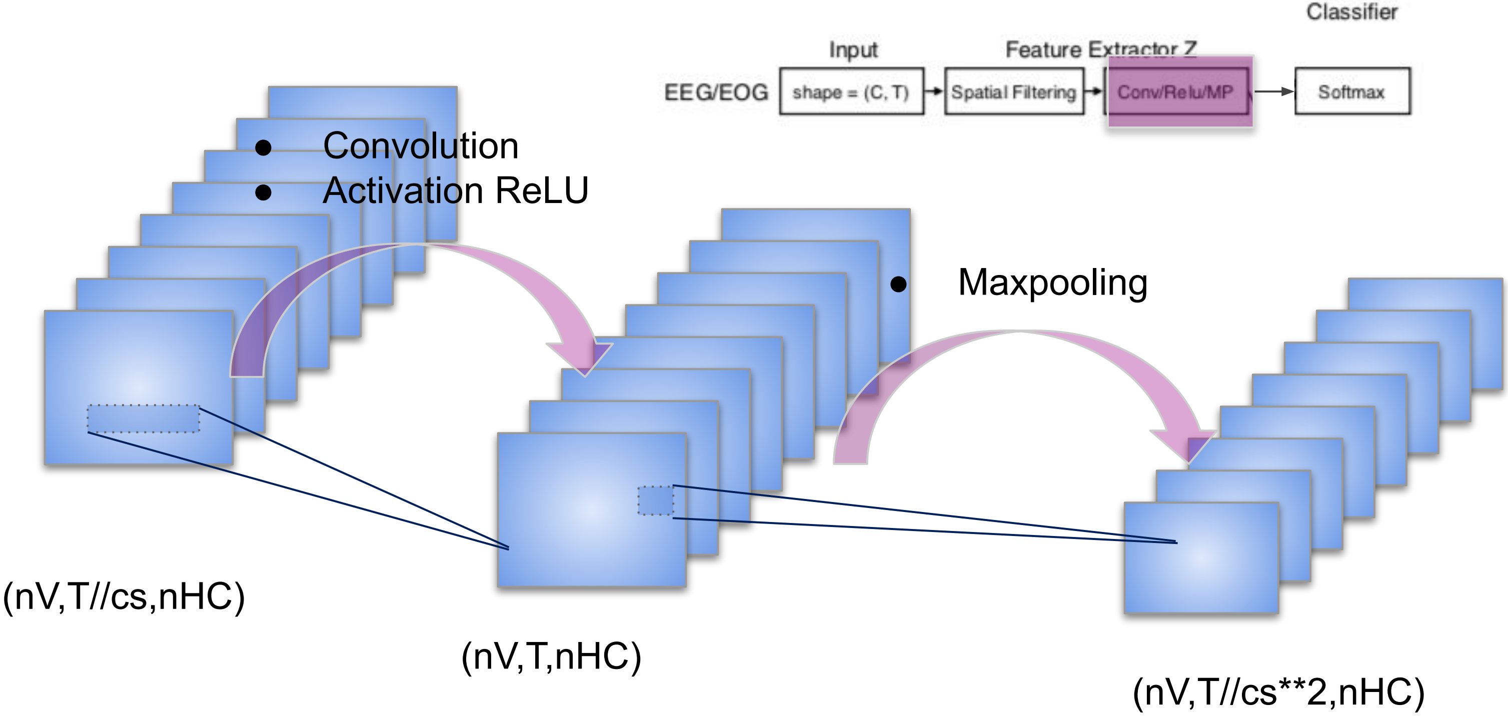
Network architecture + input data



Where :
nHC are the number of hidden channels
cs is the convolution size

Chambon, Stanislas, et al. "A deep learning architecture for temporal sleep stage classification using multivariate and multimodal time series." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 26.4 (2018): 758-769.

Network architecture + input data

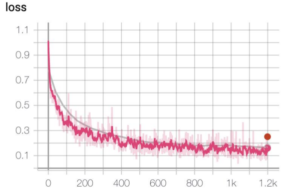


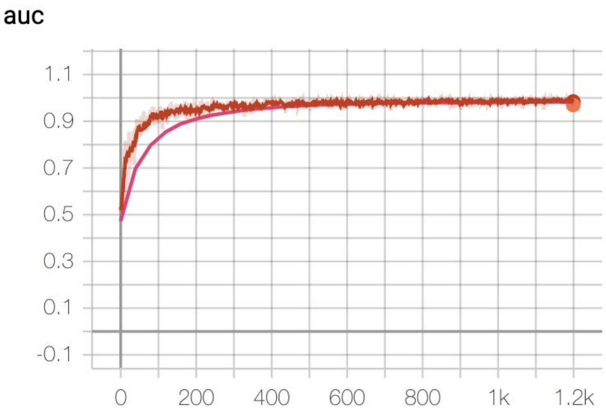
Where
nHC: number of hidden channels
cs: convolution size

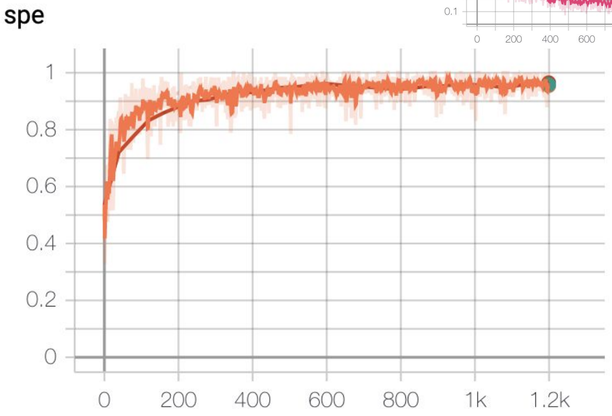
AIRBUS

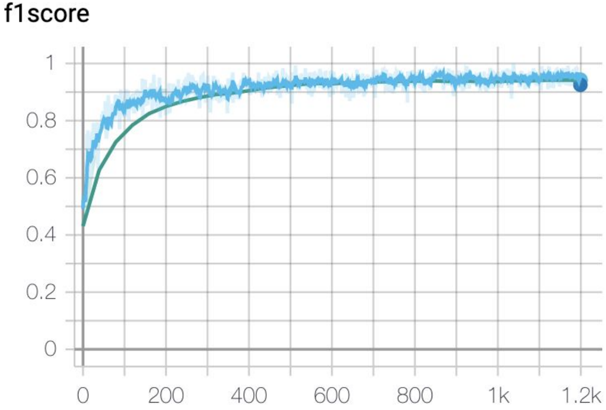
Results DreemNet

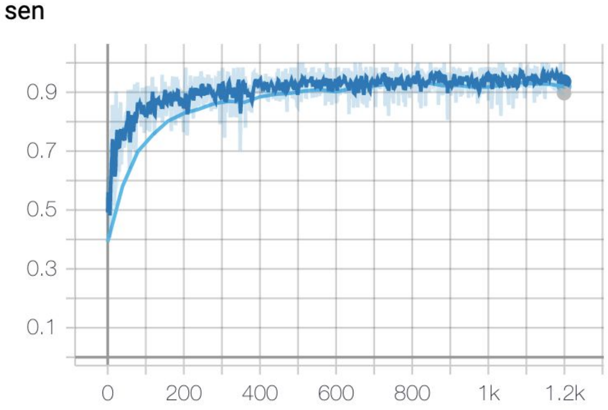
Spectral Filter	No
Balanced	Yes
VCs	59
convsize	2^4(80ms)
nhidden	2^3
poolsize	2^3
Window size	1500ms
Spatial filter #param	3481
Convolution #param	1168
Total #param	7010







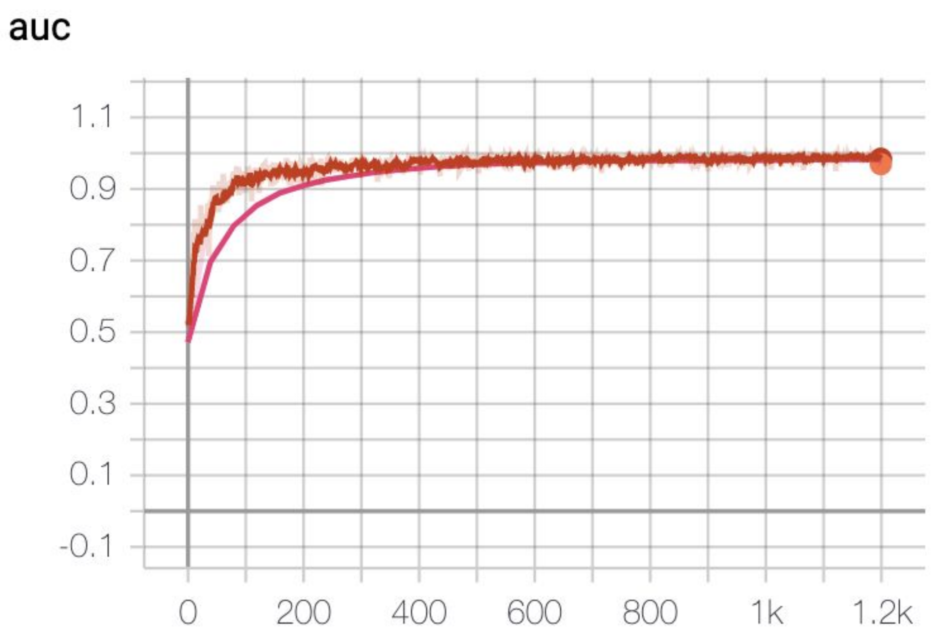




AIRBUS

Results DreemNet

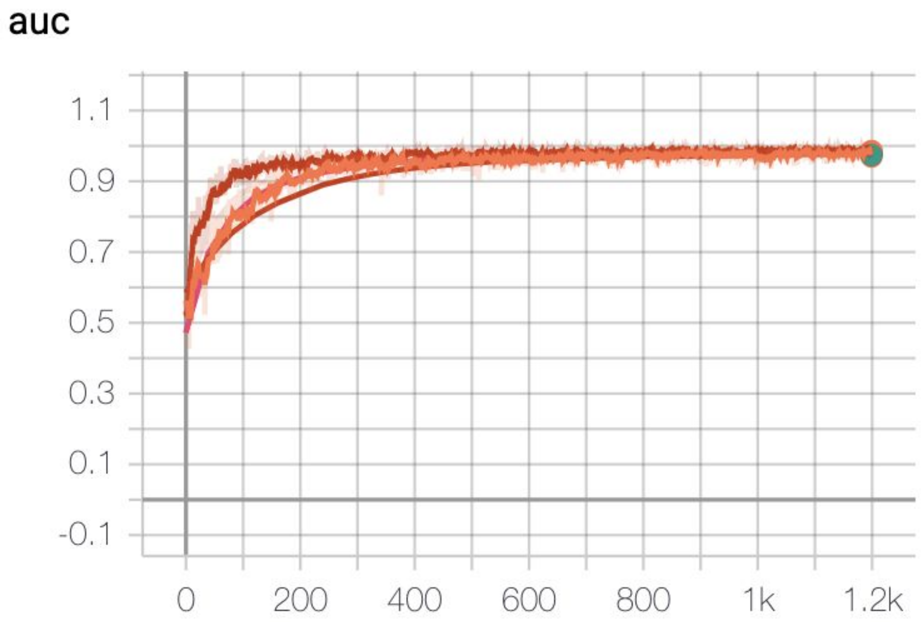
7010 param | 59 virtual channels



Results DreemNet

7010 param | 59 virtual channels

2159 param | 10 virtual channels



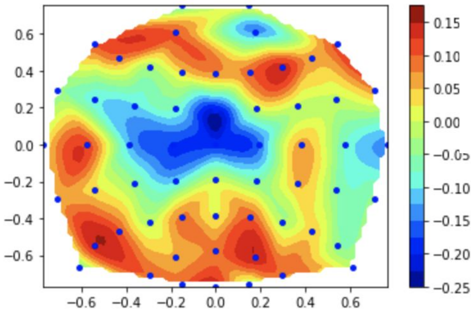
AIRBUS

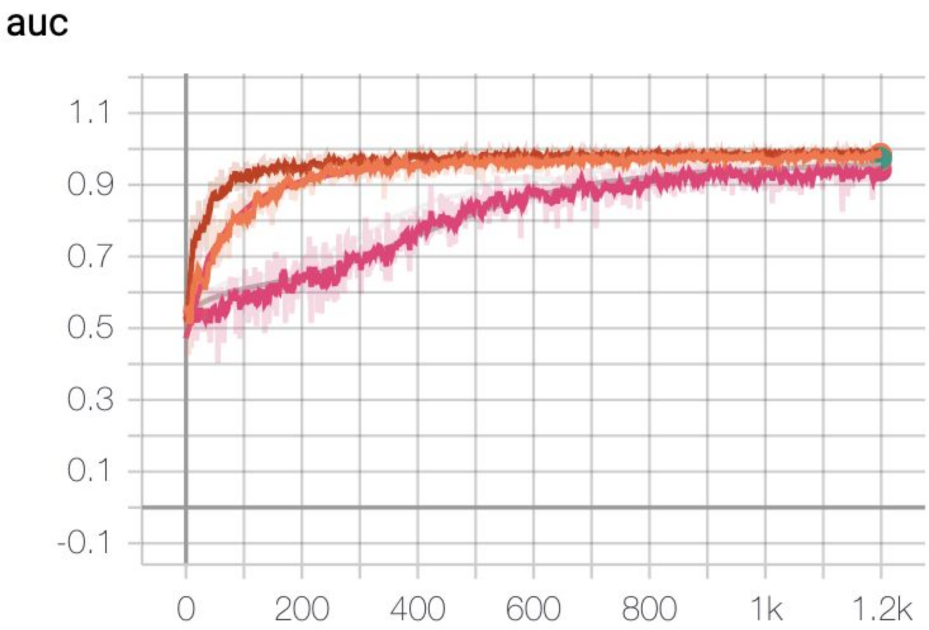
Results DreemNet

7010 param | 59 virtual channels

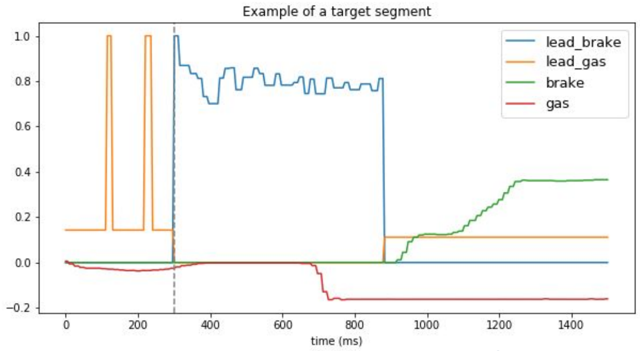
2159 param | 10 virtual channels

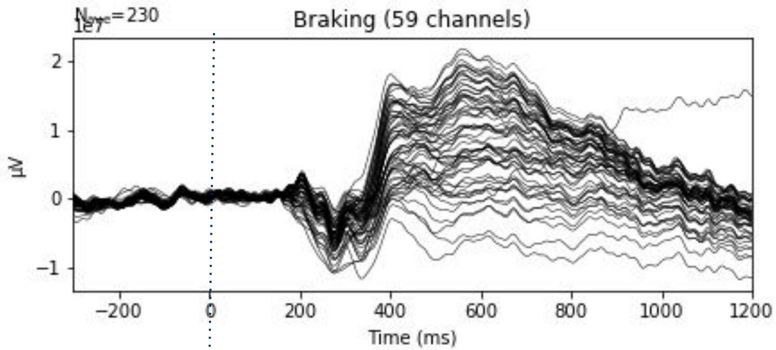
1268 param | 1 virtual channels





Varying window size





1200ms after stimulus

1000ms after stimulus

800 ms after stimulus

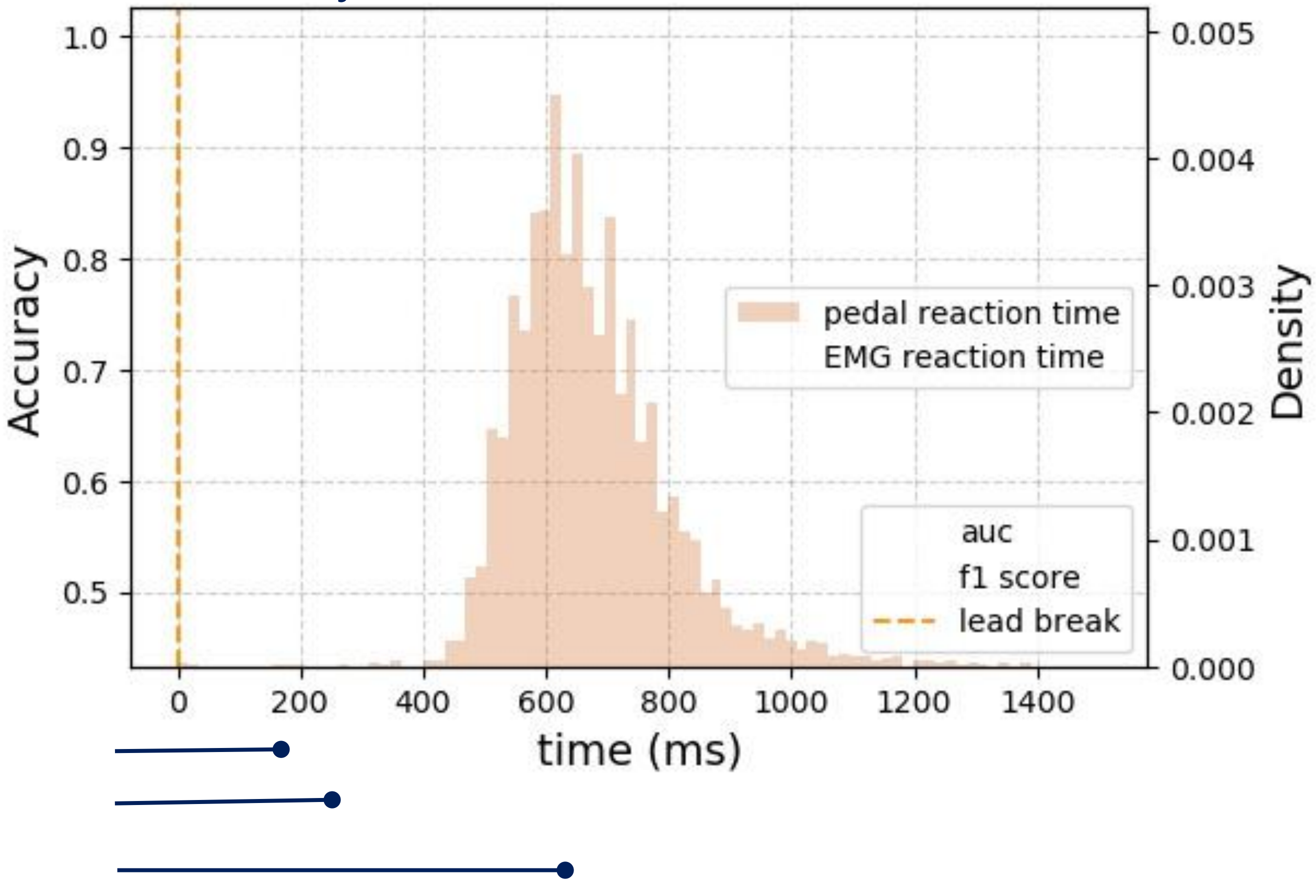
.
.
.

200 ms after stimulus

stimulus = lead car brake

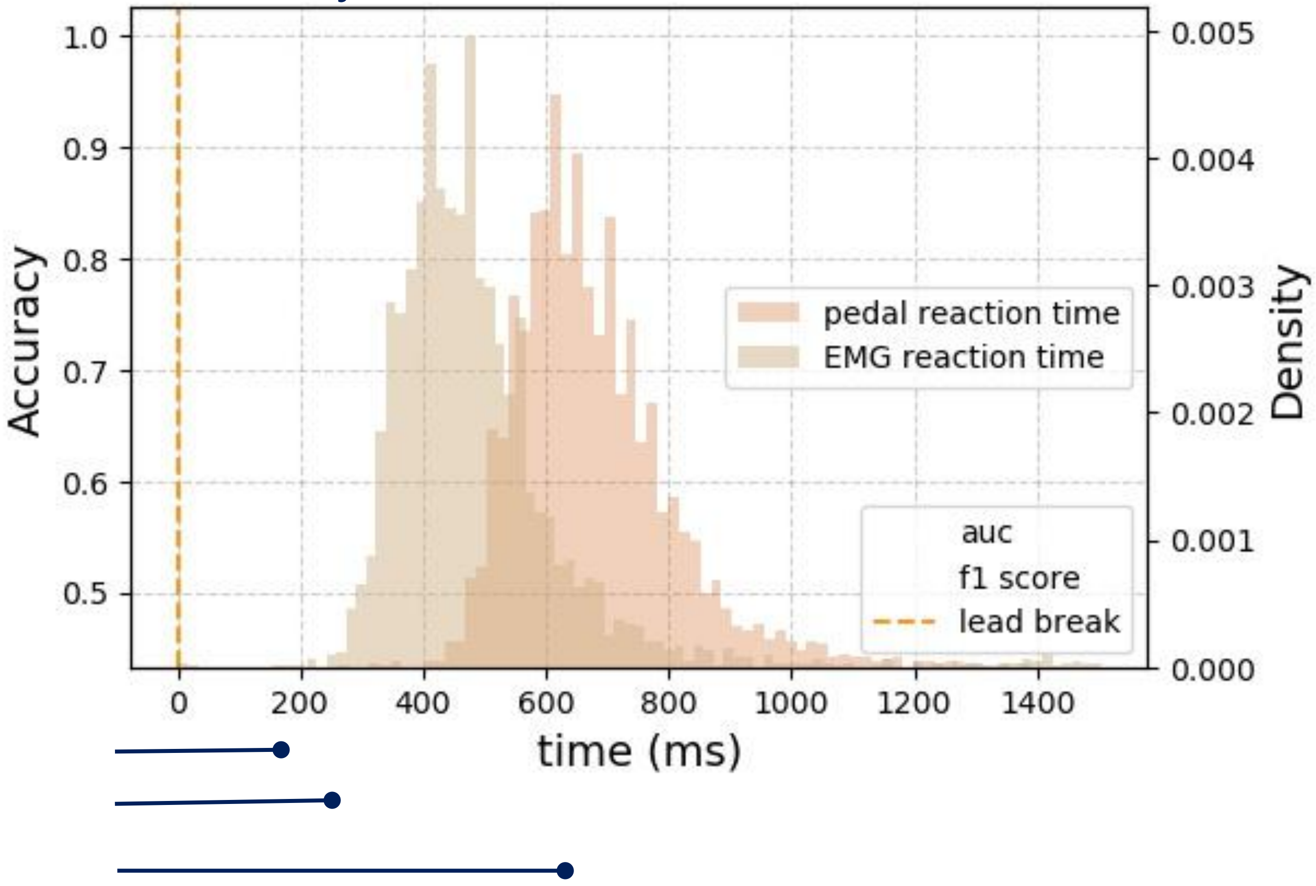
AIRBUS

Results time window study



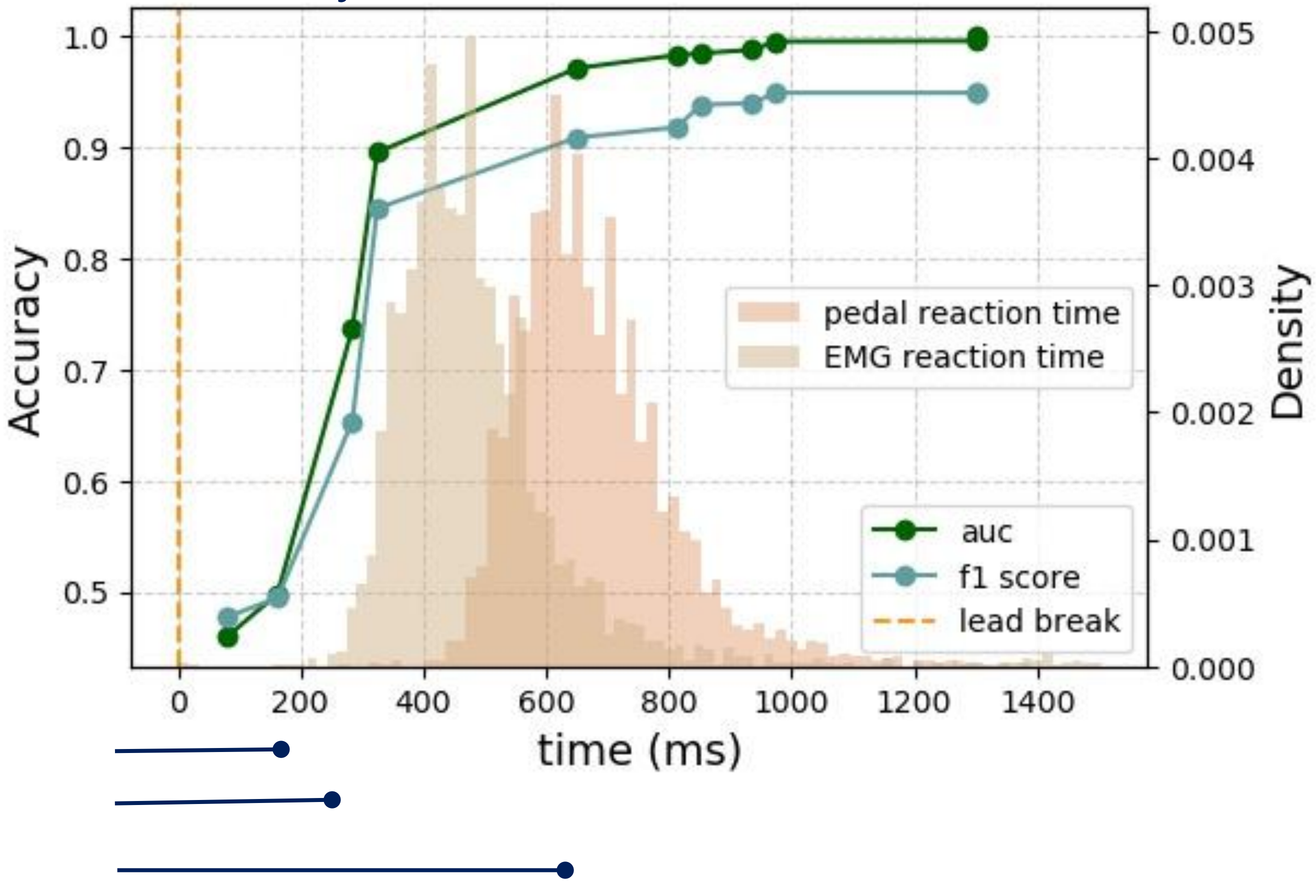
AIRBUS

Results time window study



AIRBUS

Results time window study



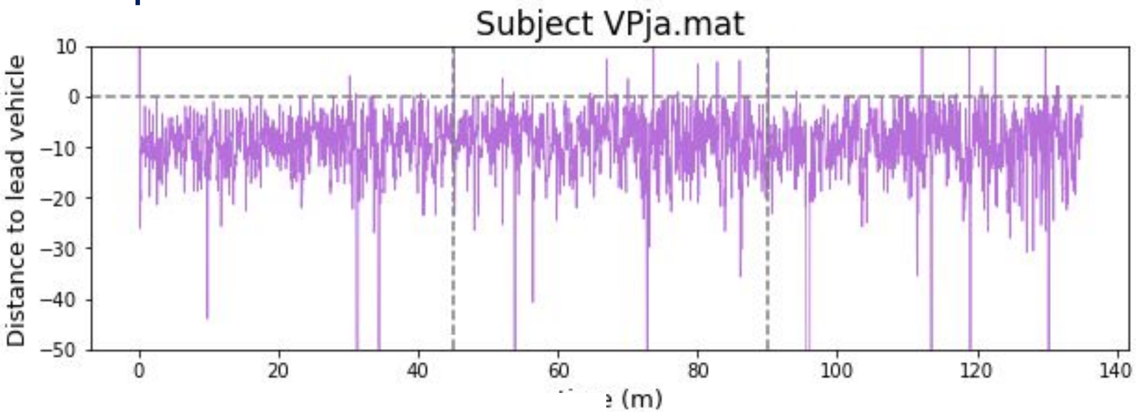
Summary

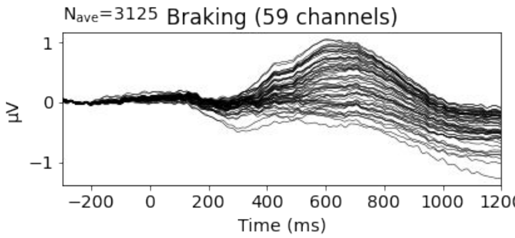
- The proposed NN architecture works well at classifying the two raw mental states: normal driving and emergency situation
- The number of electrodes can be reduce to one virtual channel while preserving model accuracy
- The proposed system is able to detect an emergency situation prior to the pilot’s behavioural response (50% faster than the pedal reaction)

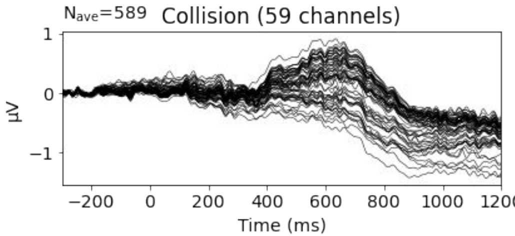
Predicting pilot performance

Collision event vs normal braking

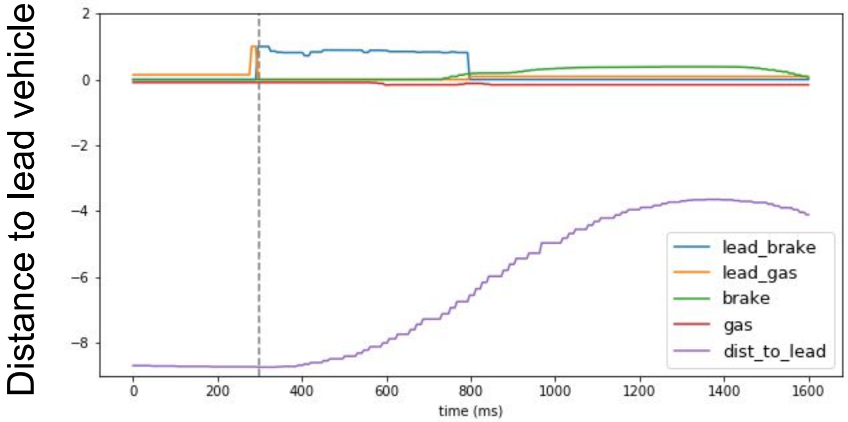
Pilot’s performance



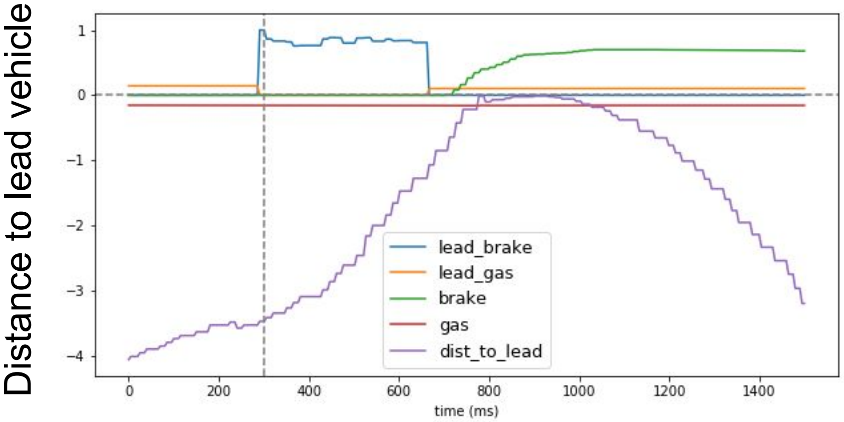




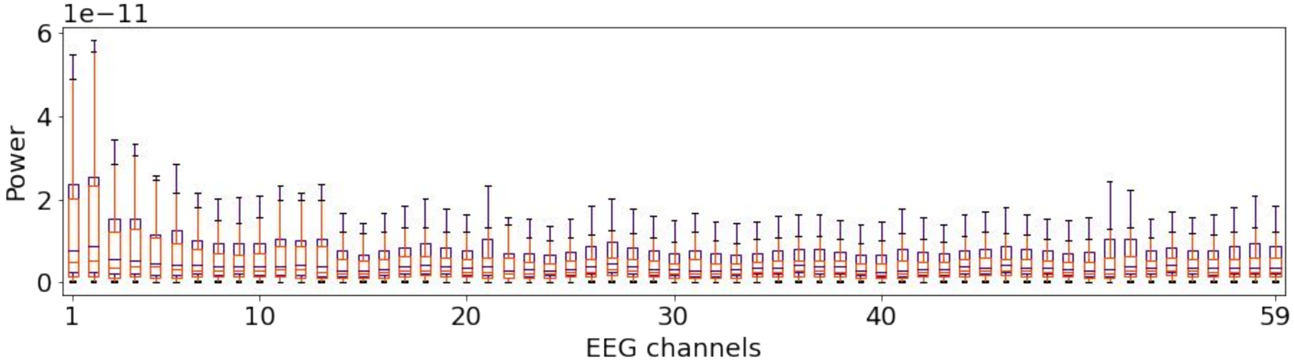
Normal braking

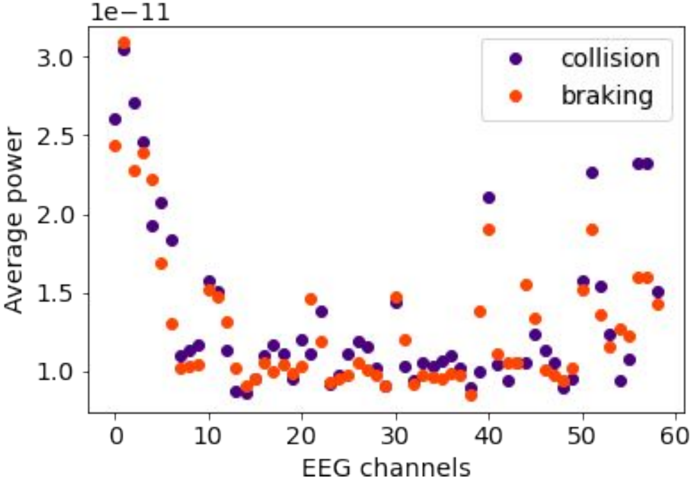


Collision



Do Collision and Braking segments carry different information?



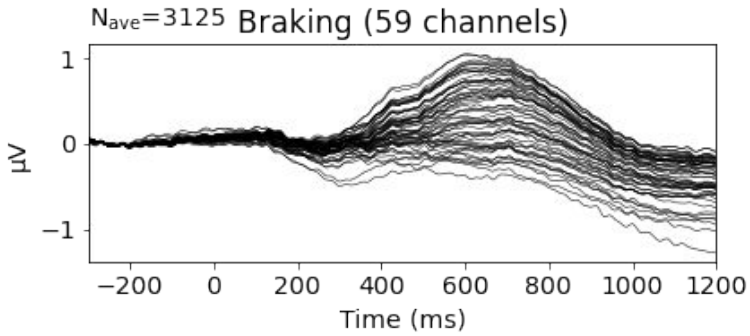


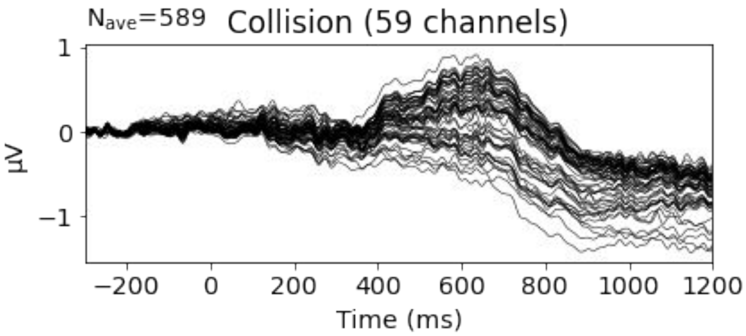
- Kolmogorov-Smirnov statistical test shows that the null hypothesis can be rejected for all channels. H0: Power collision and braking distributions come from the same distribution

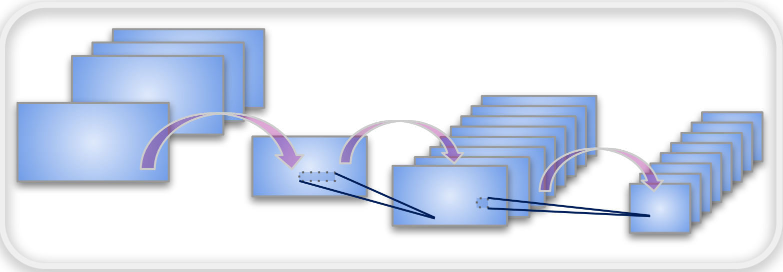
- Collision and Braking segments are characterized by its power

- Average power will be use to validate the model

Normal Braking vs Collision







- Results around 0.65 accuracy
- A lot of overfitting - Not enough data for too many parameters

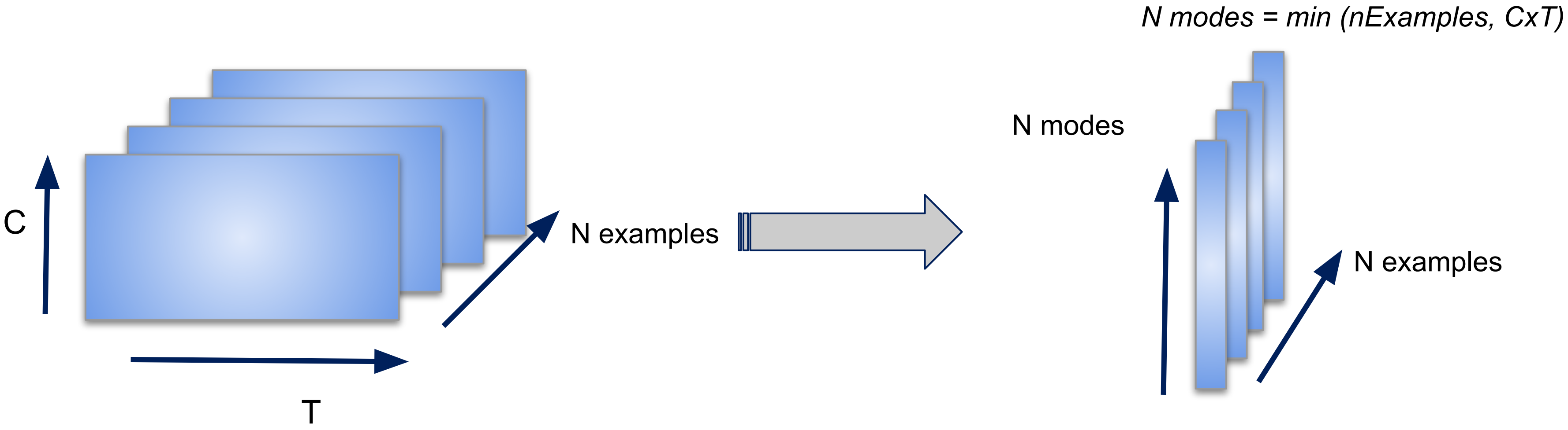
[Airbus Amber]

Dimensionality reduction: Karhunen-Loeve decomposition

Spatio-temporal models

AIRBUS

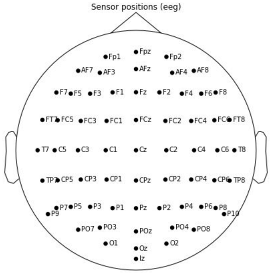
Dimension reduction by KL decomposition



$$Y(x, y, z, t, \omega) = \sum_{i=1}^{\infty} \sqrt{\lambda_i} * \phi_i(x, y, z, t) * \xi_i(\omega)$$

Deterministic part

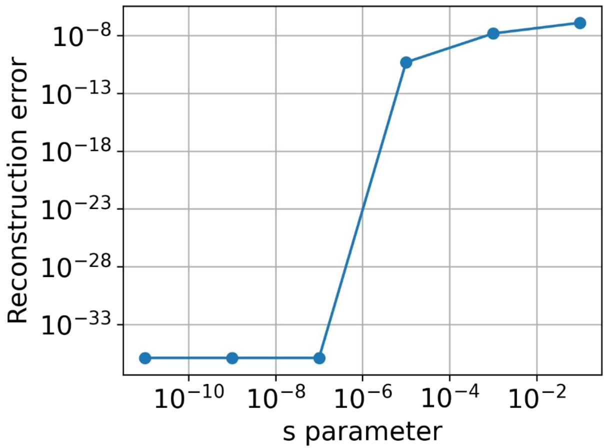
stochastic part

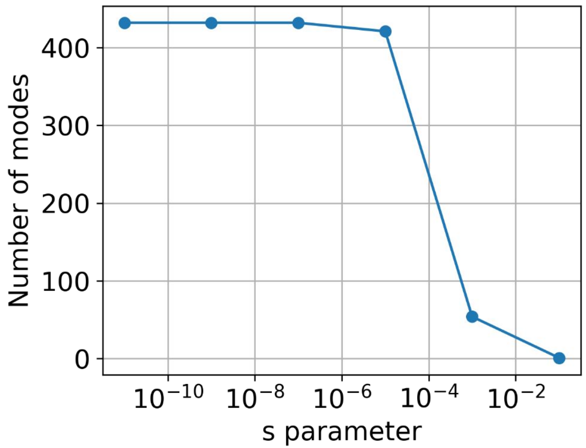


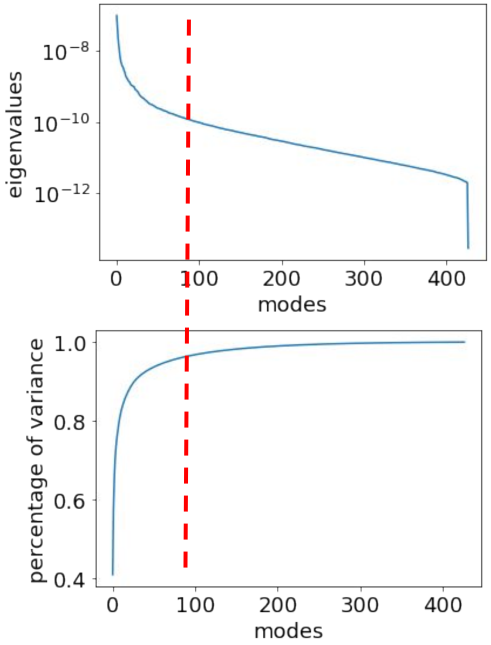
Truncation or not?

Reconstruction error : L2 norm

Variation of eigen values







S: The threshold used to select the most significant eigenmodes

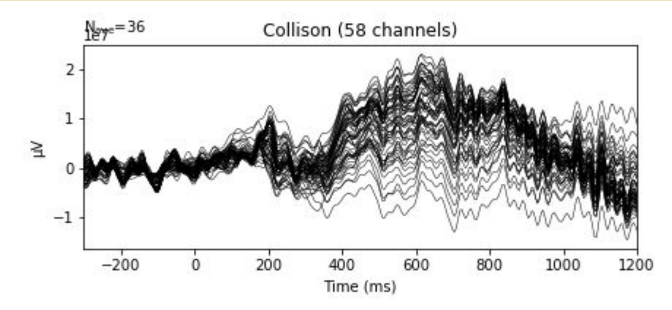
Truncation index chosen in function eigen values variation

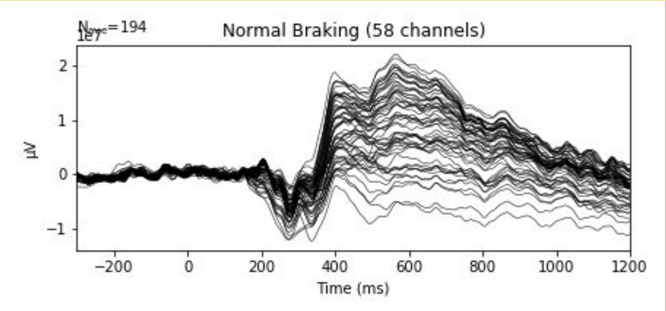
AIRBUS

Methodology

$$Y(x, y, z, t, \omega) = \sum_{i=1}^{\infty} \sqrt{\lambda_i} * \phi_i(x, y, z, t) * \xi_i(\omega)$$

measured EEG





Distribution estimation & validation

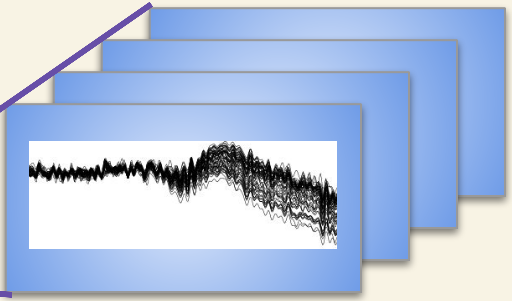
$\phi_c \sim \mathcal{L}_c$

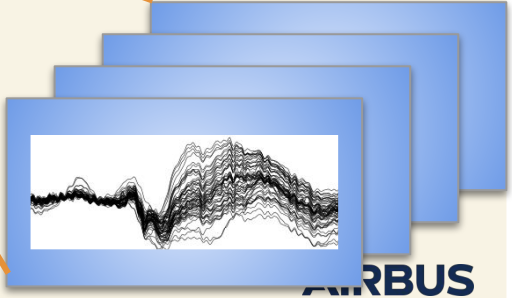
Sample modes

$\phi_b \sim \mathcal{L}_b$

size(dim, #examples)

synthetic EEG

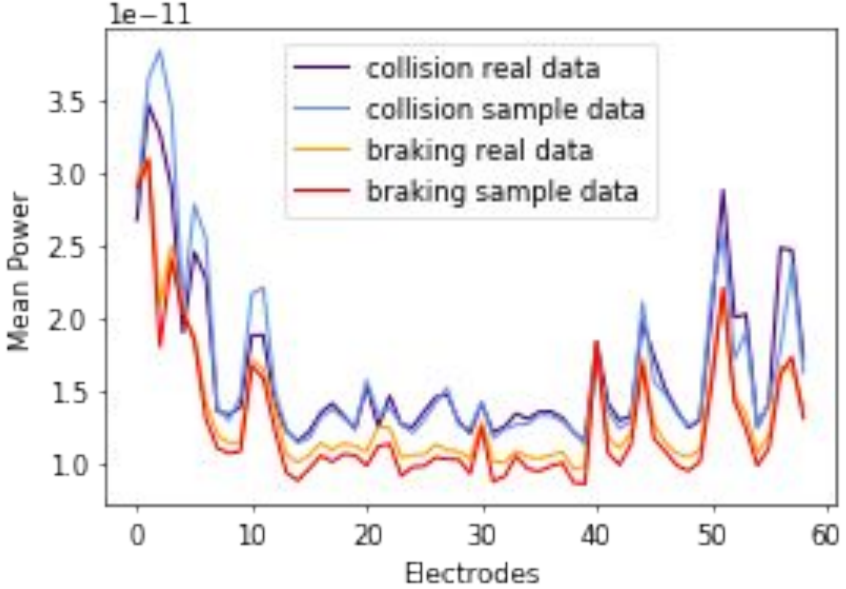


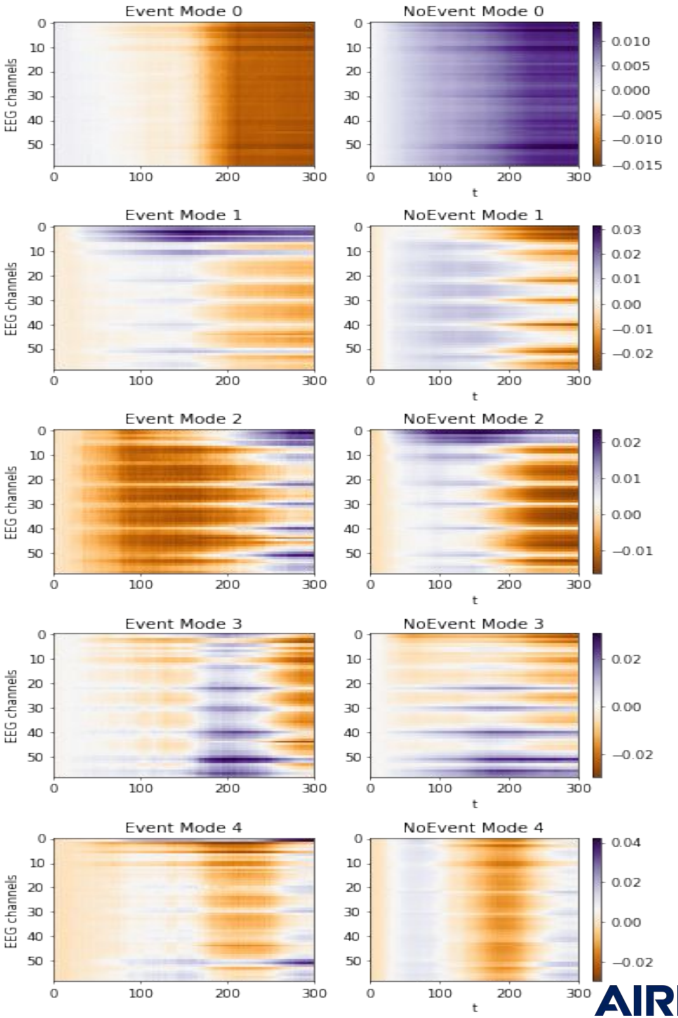


AIRBUS

Validation over signal power

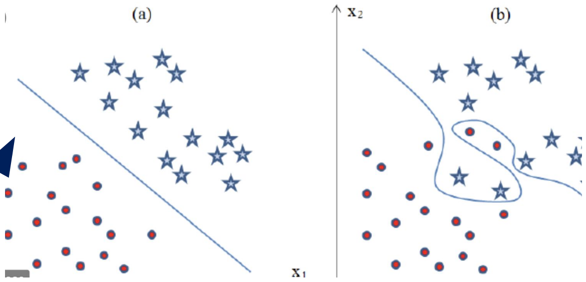
KL decomposition: ot.KarhunenLoeveSVDAlgorithm
Copula: ot.EmpiricalBernsteinCopula
Marginals: ot.HistogramFactory()
Build distribution: ot.ComposedDistribution

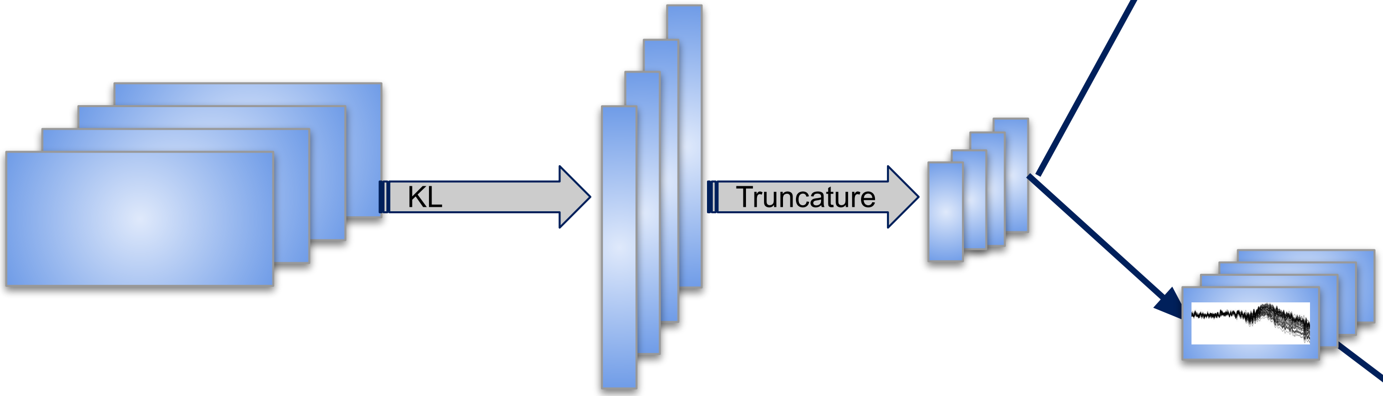


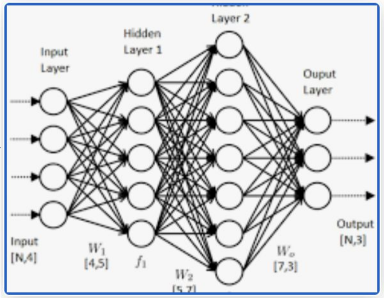


AIRBUS

Process for classification







- Random Forest Classifier over the modes yield 0.8 accuracy
- Next : DeepNet learn with synthetic data

AIRBUS

Conclusions

- The KL decomposition allow us to separate the space and also to sample new data in a meaningful way

- The projection of unseen process on the eigenmodes basis yields a good classification of pilot’s performance.

Next:

- Improve KL compression: extracting information by frequency bands

- Avoid overfitting by augmenting EEG data feed intos NN architecture

[Airbus Amber]

Thank you for your attention