LUNDS UNIVERSITET
FRTN70 PROJECT IN SYSTEMS, CONTROL AND LEARNING

PREDICTING A SUBJECT'S CARD WITH THE MUSE-S HEADBAND

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Overview of the project

- Make an application that can predict the card a subject is thinking about;
- the input - EEG data from Muse-S;
- the output - the card prediction.
- Riemannian Geometry and Machine Learning (ML) to make predictions

Motivation

MUSE-S EEG HEADBAND

Simple device for BCI that is able to catch the P300 needed for our project. The big advantage of the Muse S is that it is using the LSL protocol (which is commonly used for BCI devices) and that it has some community support, which makes it easy to use and ideal for prototyping.

DEVELOPMENT IN PYTHON

First option programing language for ML related projects as it has a broad range of libraries for them. It has a huge community support and tailor made libraries useful for EGG processing and recording. We used Pycharm as our preferred IDE and Anaconda as our package management.

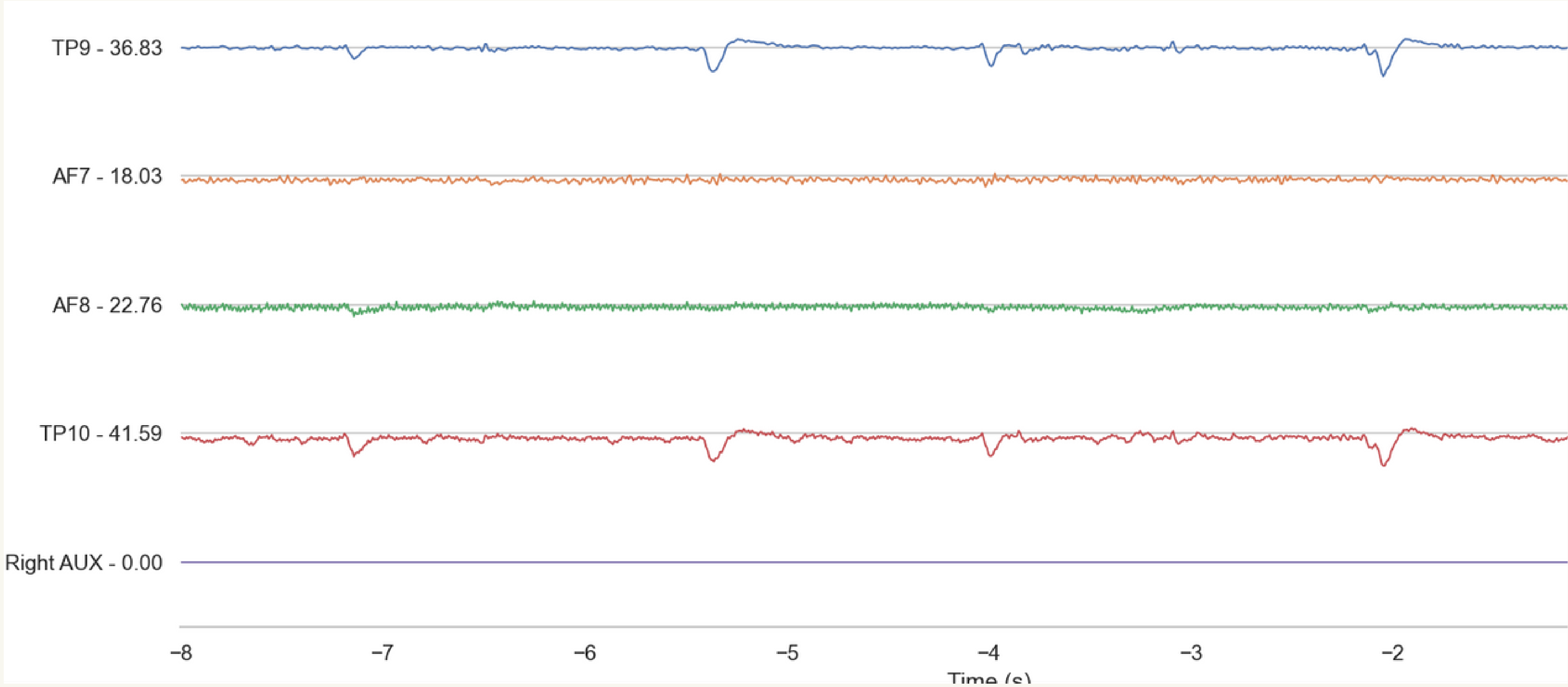
Machine Learning with Scikit-Learn

MACHINE LEARNING APPROACH

- represent an epoch of data as a covaraince matrix + Riemannian distance to compute means of labels + projection to a euclidean tangent space + classifier
- a simple classifier
- spatial filter + classifier

P300 PARADIGM

As the user is supposed to pick a card, P300 paradigm is more suitable. The P300 is a pattern (detectable after approximatively 300 ms) triggered by an event-related potential (ERP) that in our case would be when a person recognizes the card show in the GUI app.



Project Stages

GUI APP

The cards were displayed using a GUI app.
First phase: Ace of hearts; Second phase: the user can pick any card.

DATA RECORDING AND PROCESSING

The EEG data was collected from six subjects.

OFFLINE CLASSIFICATION

We tested a few classifiers in order to find the one with the best performances.:

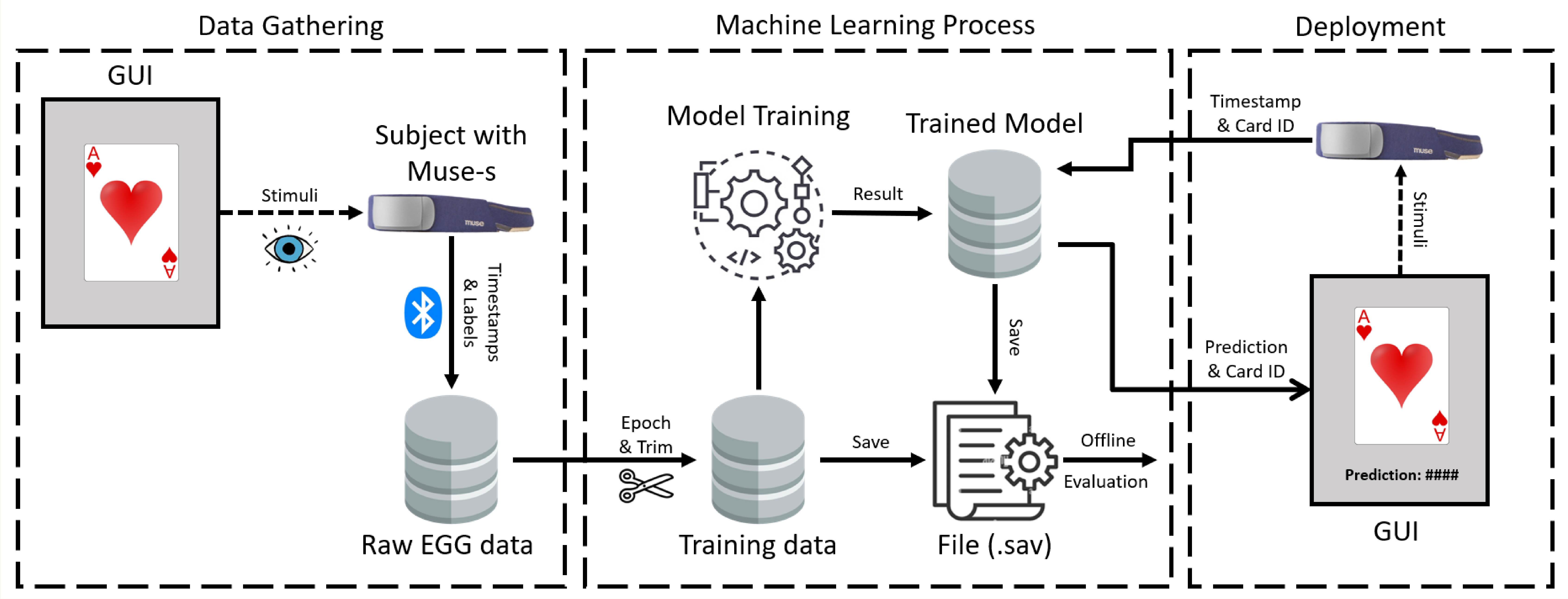
- BNCI2014009 from MOABB
- 4-card dataset

REAL TIME CLASSIFICATIONS

We used the classifier that had the best performances in offline.

Experiment

Flowchart



Data Gathering
Machine Learning Process
Deployment
GUI
Subject with Muse-s
Stimuli
Timestamps & Labels
Raw EGG data
Model Training
Trained Model
Result
Save
Epoch & Trim
Training data
Save
File (.sav)
Offline Evaluation
Timestamp & Card ID
Stimuli
Prediction & Card ID
Prediction: ####
GUI

Datasets

BNCI2014009 dataset

- P300 evoked potentials recorded in three different sessions from ten healthy subjects with experience in recording EEG data.
- Four subjects (for analysis)
- Focus on one out of 36 different characters
- 256 Hz with a low-pass, high-pass filter (with cutoff frequencies 0.1 Hz and 20 Hz)

4-card dataset

- The data recorded from Muse-s when running the first part of our experiment
- P300 evoked potentials recorded in a session for two different subjects

Results

BNCI2014009 dataset (offline classification)

Accuracy of the models for four subjects from the BNCI2014009 dataset

Model	Filter	Feature	Classifier	Subject 1	Subject 2	Subject 3	Subject 4
1	None	stacked channels	LR	0.90	0.95	0.82	0.94
2	Xdawn	stacked channels	KNN	0.80	0.87	0.71	0.89
3	Xdawn	stacked channels	LR	0.87	0.93	0.77	0.92
4	Xdawn	ERP covariances	LR	**0.93**	**0.96**	**0.86**	**0.95**
5	CSP	stacked channels	LDA	0.57	0.61	0.57	0.58
6	None	ERP covariances	MDM	**0.93**	**0.96**	0.74	0.83

Imbalanced dataset: 288 ’target’ labels + 1440 ’non-target’ labels

Naive classifier: 83%

BNCI2014009 dataset (offline classification)

Confusion matric of model (4) for BNCI2014009

		Confusion matrix	
		Target	Non-target
BNCI2014009	Target	95	193
	Non-target	41	1399

Precision: 0.32

Recall: 0.69

4-card dataset (offline classification)

Accuracy of the models for the 4-card dataset

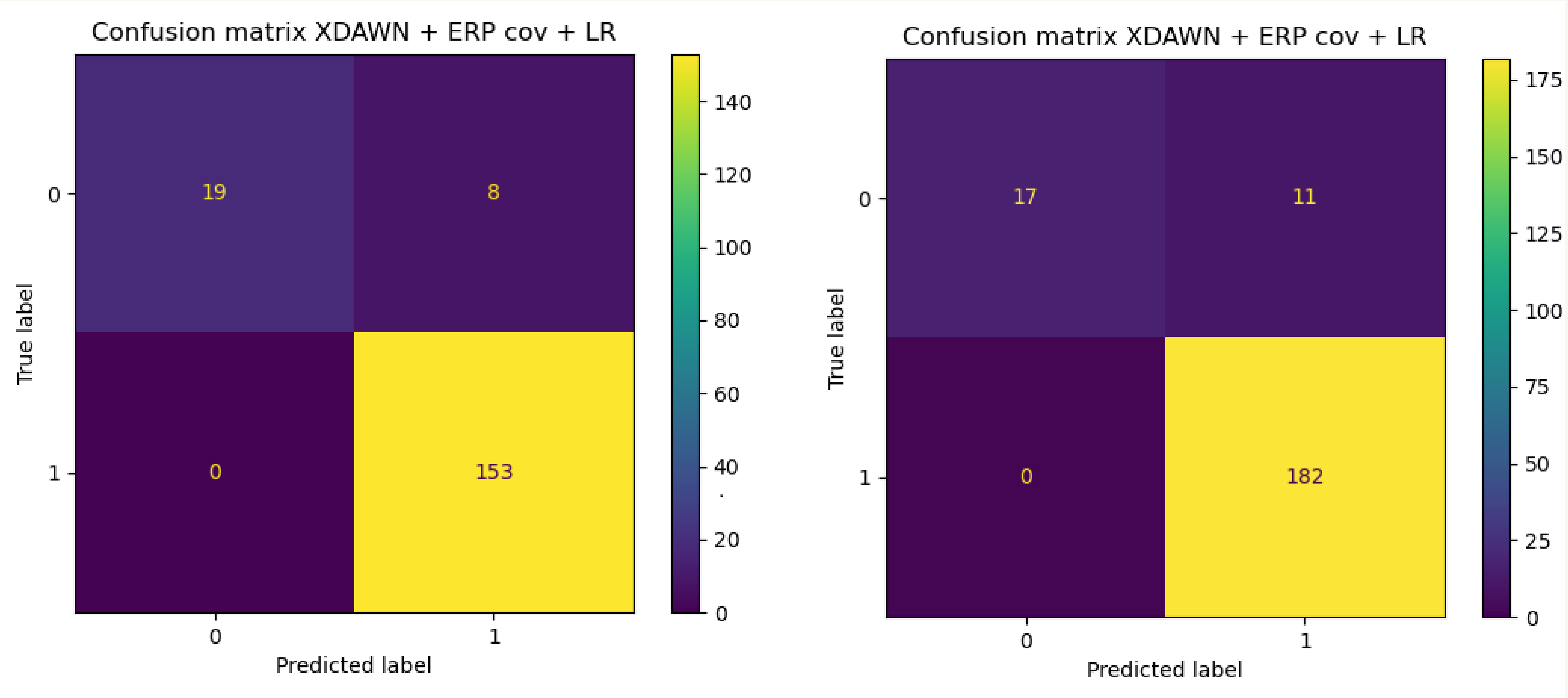
Model	Filter	Feature	Classifier	Subject 1	Subject 2
1	None	stacked channels	LR	0.90	0.76
2	Xdawn	stacked channels	KNN	0.90	**0.82**
3	Xdawn	stacked channels	LR	**0.91**	0.77
4	Xdawn	ERP covariances	LR	**0.91**	**0.82**
6	None	ERP covaraince	MDM	0.79	0.71
7	Xdawn	stacked channels	LDA	**0.91**	0.80
8	None	ERP covaraince	LR	0.90	**0.82**
9	None	PSD	LR	0.84	**0.82**

Imbalanced dataset: 52 ’target’ labels + 308 ’non-target’ labels; 44 ’target’ labels + 256 ’non-target’ labels

Naive classifier: 85%

4-card dataset (offline classification)

Confusion matrix for Subject 1 (left) and Subject 2 (right)



Precision: 0.7 (Subject 1), 0.6 (Subject 2)

Recall: 1 (Subject 1), 1 (Subject 2)

Real-time classification

Real-time target predictions over total appearances

Card	Subject 1	Subject 2	Subject 3	Subject 4
A	1/85	0/40	1/85	1/85
3	0/76	**3/41**	0/76	0/69
K	**15/71**	0/38	0/71	0/79
9	0/69	1/31	**2/68**	**1/67**
Total	16/300	4/150	3/300	2/300

Precision: 0.21 (Subject 1), 0.07 (Subject 2), 0.02 (Subject 3), 0.01 (Subject 4))

Recall: 0.93 (Subject 1), 0.75 (Subject 2), 0.66 (Subject 3), 0.5 (Subject 4)

Cross-session experiment

Real-time cross-session predictions for Subject 1

Prediction	A	3	K	9	Total
Target	2	**10**	0	0	12
Non-target	83	**68**	73	64	288

Precision: 0.14

Recall: 0.83

Conclusion

Achieved Goals

- Developed a BCI system to predict the card a subject is focusing on in real-time with the signals recorded by a Muse-S headband
- Tested different models with the BNCI2014009 dataset from MOABB
- Tested several models with our own dataset
- Tested the best model in real-time.

Future Improvements

- Switching the card a subject is asked to focus on at every run
- Adding more cards
- Performing more real-time experiments
- More classification methods
- A preprocessing step before filtering (a low-pass, high-pass filter)
- Transfer Learning techniques to make the data more robust to noise, movements, etc.


Thank you!
...Questions?