9th Graz Brain-Computer Interface Conference
Join Forces - Increase Performance
GRAZ BCI

BIOMEDICAL ENGINEERING GROUP
UNIVERSITY OF VALLADOLID

MEDUSA

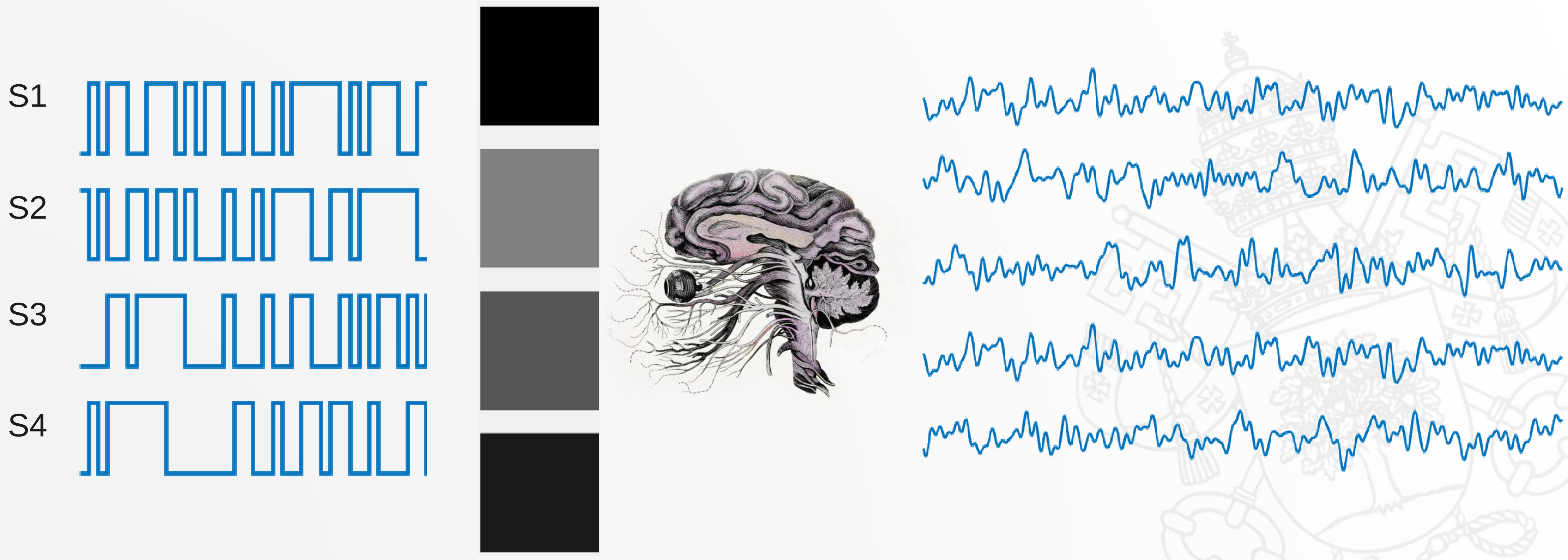
Bitwise reconstruction of visual stimulation patterns from EEG using deep learning for c-VEP decoding

Eduardo Santamaría-Vázquez

eduardo.Santamaria.vazquez@uva.es
www.gib.tel.uva.es
www.medusabci.com

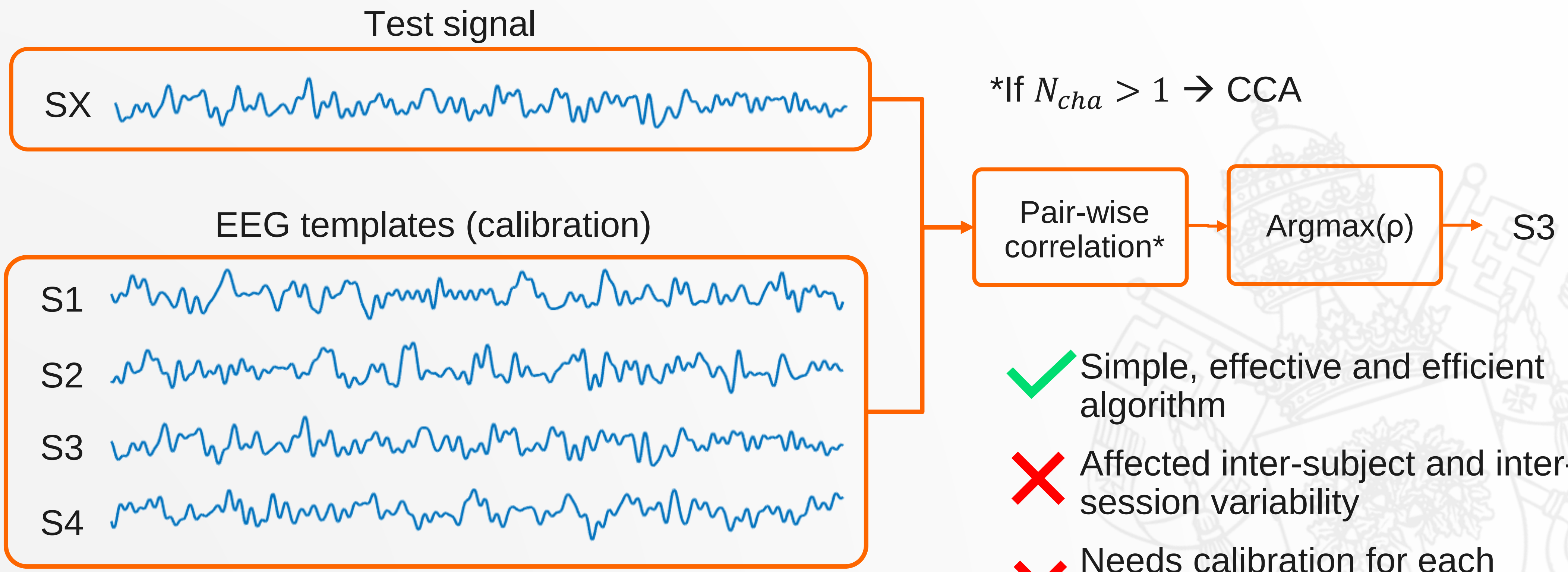
Introduction

- **Visual stimulation patterns in c-VEP-based BCIs**



Introduction

- **Classical (reference) method: correlation with EEG templates**



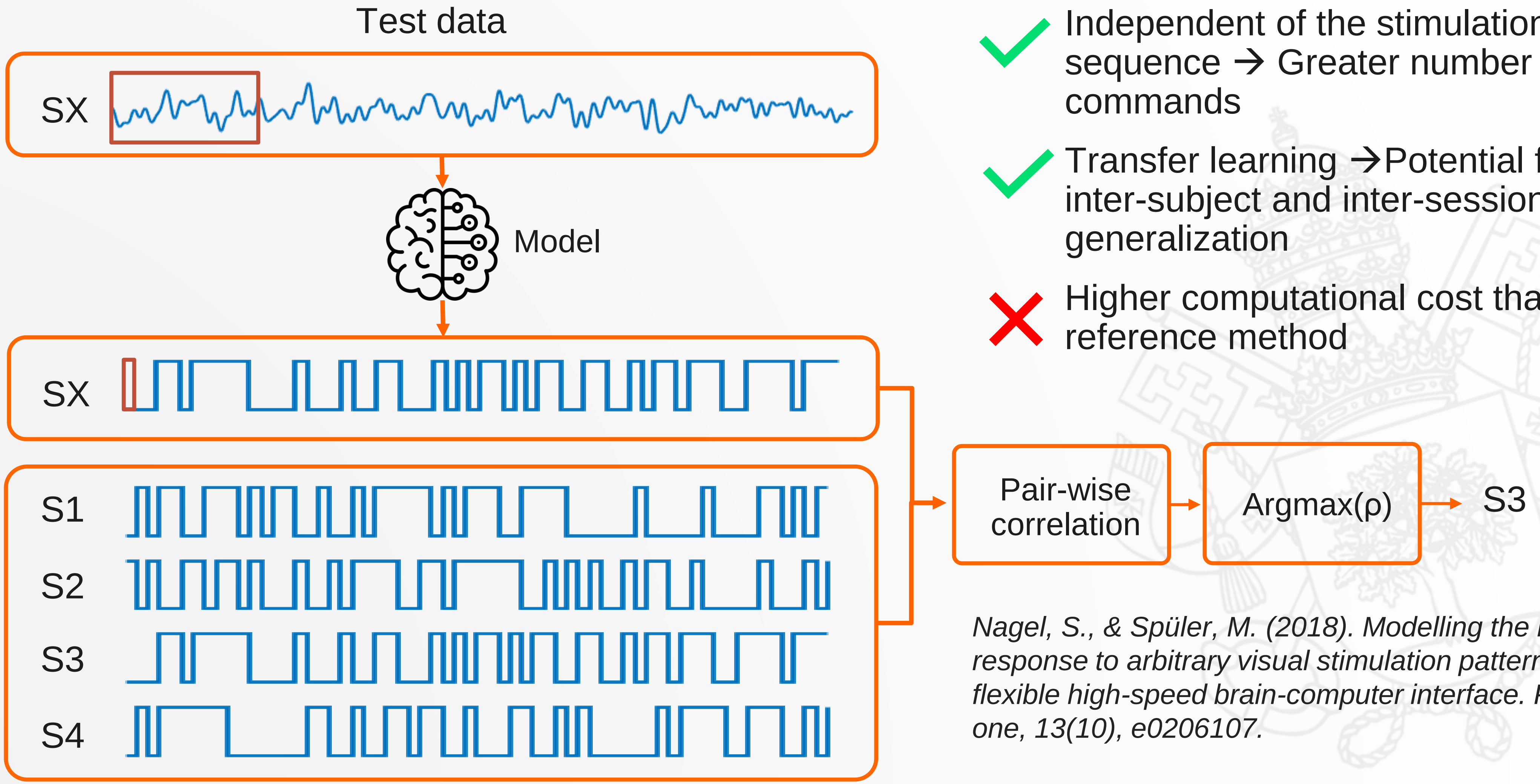
✔ Simple, effective and efficient algorithm

✘ Affected inter-subject and inter-session variability

✘ Needs calibration for each stimulation sequence → limited number of commands

Introduction

- **Bit-wise reconstruction approaches:**

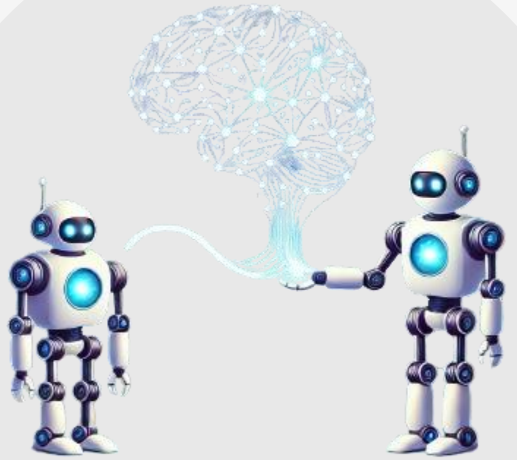


- ✓ Independent of the stimulation sequence → Greater number of commands
- ✓ Transfer learning →Potential for inter-subject and inter-session generalization
- ✗ Higher computational cost than the reference method

Nagel, S., & Spüler, M. (2018). Modelling the brain response to arbitrary visual stimulation patterns for a flexible high-speed brain-computer interface. PloS one, 13(10), e0206107.

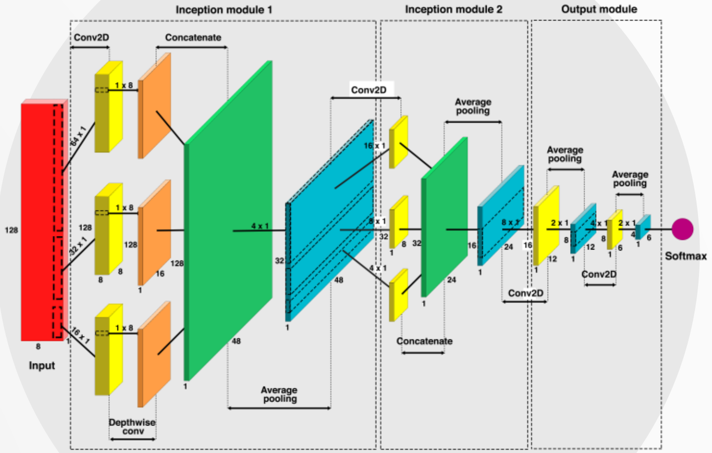
Introduction

Transfer learning



- Robustness to inter-subject and inter-session variability
- Zero calibration

Model design



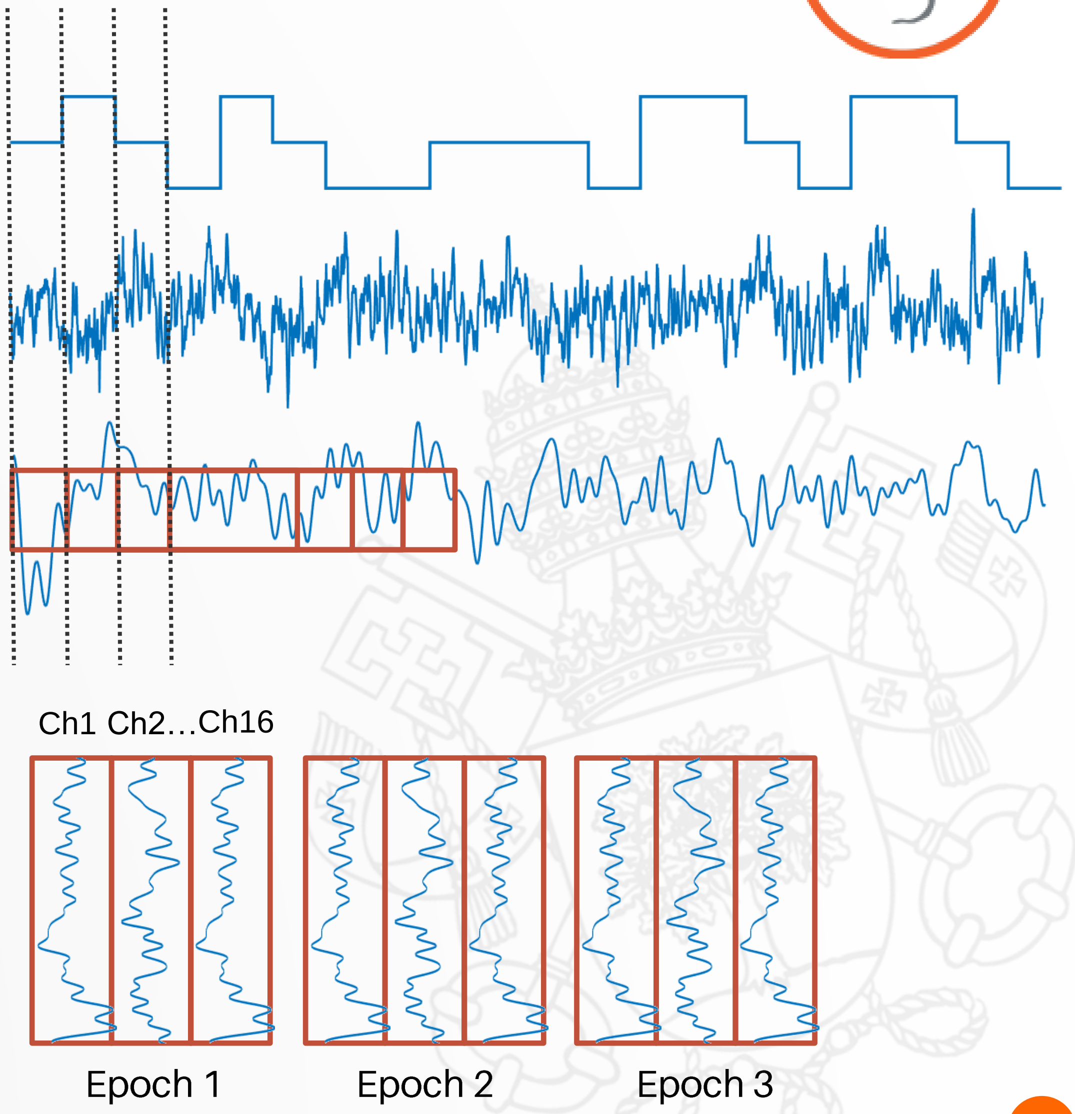
- Architectures and hyperparameteres
- Multiclass classification for non-binary stimulation

Usability

- Early stopping
- Asynchronous control

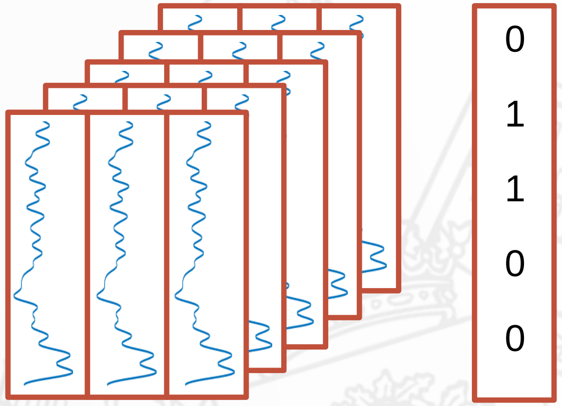
Signal processing

- **Preprocessing:**
  - Band pass filter between 1 and *SPR/2* Hz, where *SPR* is the stimulus presentation rate. Typically, 30 or 60 Hz for monitor rates of 60 and 120 Hz, respectively
  - Notch filter between 49 and 51 Hz to eliminate power line component
  - Common average reference
- **Feature extraction:**
  - Epoch extraction from 0 to *W* ms relative to stimulus onset. Some papers use short windows (*W* = 250 ms), but we've found that larger windows work better.
  - Z-score normalization from -250 to 0 ms relative to stimulus onset
  - Feature arrays: *S* samples x *C* channels



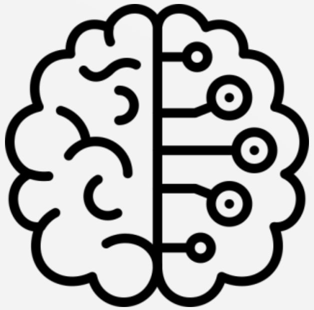
Signal processing

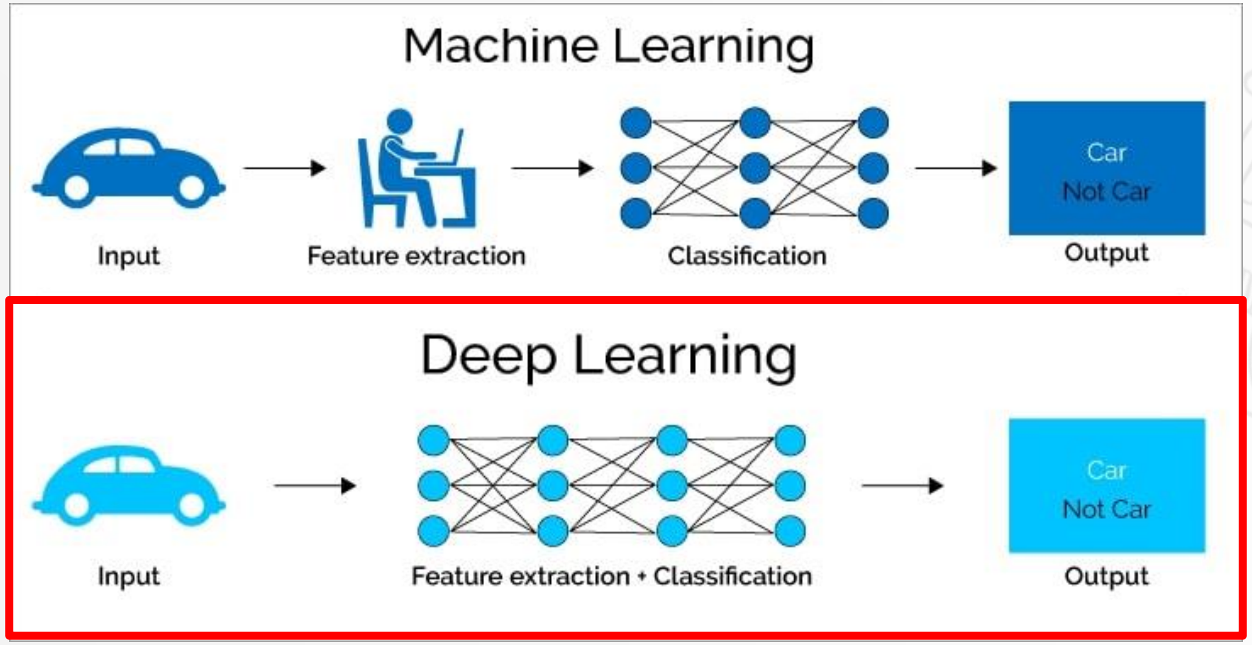
- **Training dataset:**
  - Each epoch is labeled with the corresponding stimulus type.
  - Dataset: *N stimulus x S samples x C channels*
    - *N stimulus = N trials x N sequence length x N stimulation cycles*
  - Labels array: *N stim x 1*
  - The number of classes is defined by the different stimulus types.



Signal processing

- **Model characteristics:**
  - Non-linearity: modelling the visual system + EEG measurement requires non-linear models
  - Complexity: high-level features may be more robust to EEG variability
  - Supervised learning



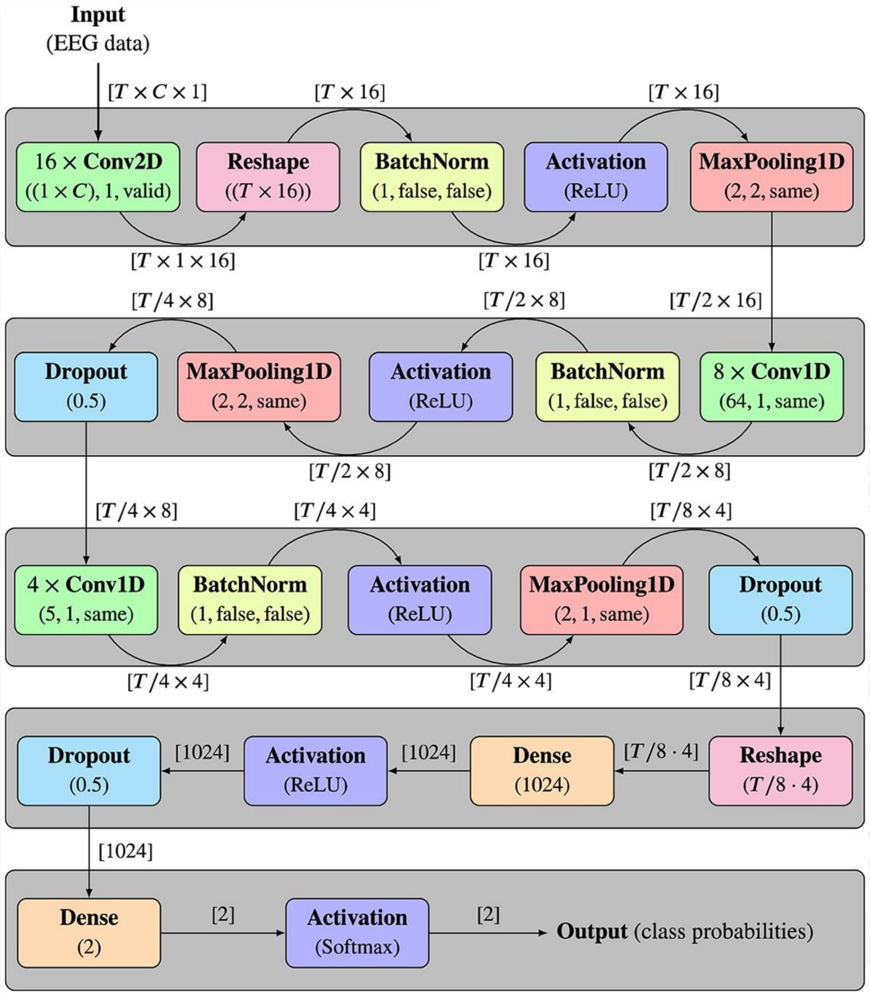


Linear regression
Ridge regression
Linear discriminant analysis
Support vector machine

Multilayer perceptron
Convolutional neural networks
Recurrent neural networks
Transformers

Signal processing

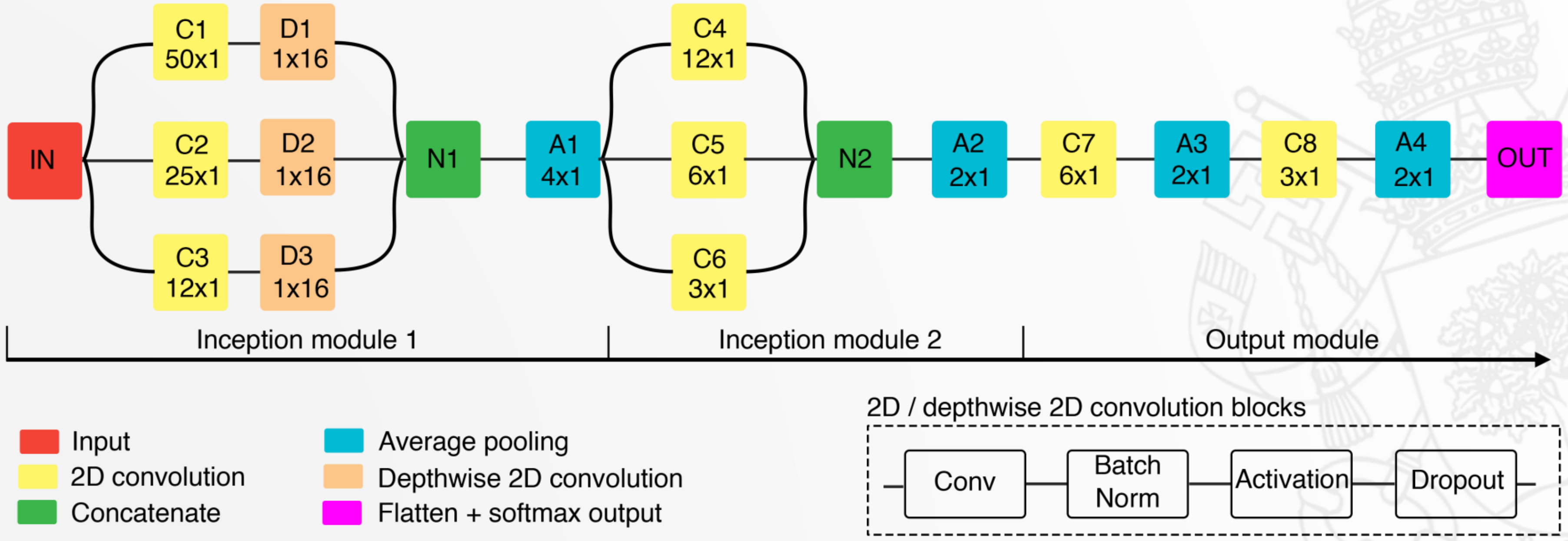
- **EEG2Code CNN – from Nagel and Spüller. (2018):**
  - Efficient and simple convolutional neural network designed as subject-specific model
  - Five layers with convolutions, batch normalization, ReLU activation and MaxPooling
  - Includes a dense layer at the end before the classification layer
  - Dropout regularization to avoid overfitting
  - Input windows of 250ms



Nagel, S., & Spüller, M. (2018). Modelling the brain response to arbitrary visual stimulation patterns for a flexible high-speed brain-computer interface. PloS one, 13(10), e0206107.

Signal processing

- **EEG-Inception – from Santamaría-Vázquez *et al.* (2023):**
  - Multiscale EEG analysis through Inception modules: 250ms, 125ms, and 72.5ms
  - Efficient integration of different techniques for EEG analysis: depthwise convolutions, dropout, batch normalization and average pooling
  - The last layer has p output neurons: 2, 3, 5, 7 or 11 classes



Santamaría-Vázquez, E., Martínez-Cagigal, V., & Hornero, R. (2023, June). Bit-wise reconstruction of non-binary visual stimulation patterns from EEG using deep learning: a promising alternative for user-friendly high-speed c-VEP-based BCIs. In *International Work-Conference on Artificial Neural Networks* (pp. 603-614). Cham: Springer Nature Switzerland.

Signal processing

- **Classical training approach:**
  - Training with trials from the test subject
  - Subject-specific models
- **Zero-calibration training approach:**
  - Training with trials from other subjects
  - Subject-agnostic models
  - Require complex models and large datasets → High computational cost

Signal processing

- **Fine-tuning training approach:**
  - Mixes previous approaches

Initialization → Fine-tuning → Evaluation

Initialization

- Initialize the model with trials from other subjects
- Subject-agnostic model
- Complex models to extract high-level features

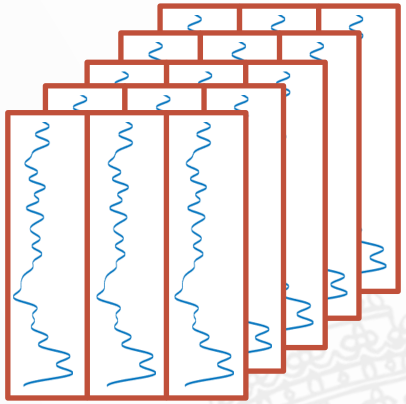
Fine-tuning

- Fine-tuning with trials from the test subject
- Subject-specific model
- Recommended technique: 2 step fine-tuning.
- Techniques to avoid overfitting are required

Evaluation

- The sequence for each trial is reconstructed and correlated with the posible sequences
- The command corresponding to the higher correlation is selected

Signal processing

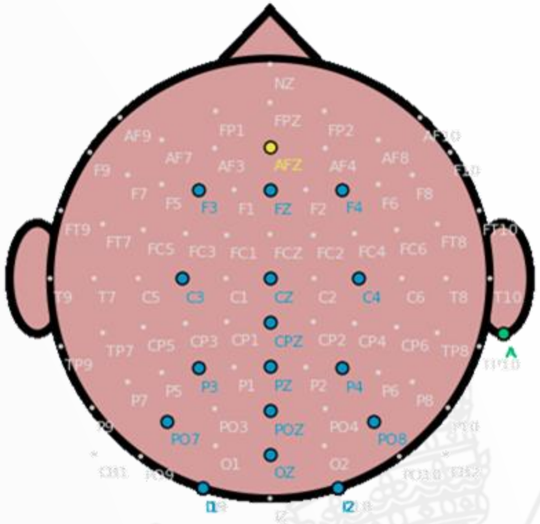


- **Testing dataset:**
  - Feature array (1 trial): *N* stim x *S* simples x *C* channels
    - *N = N sequence length x N stimulation cycles*

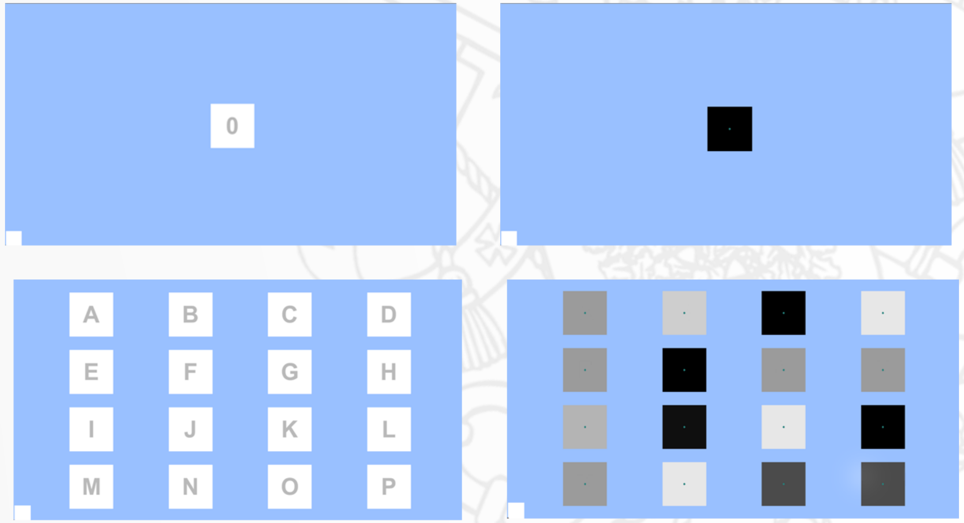
- **Command decoding**
  - Predict labels of the test dataset keeping the corresponding order
  - Calculate correlation with all the posible stimulation sequences
  - Select the command corresponding to the highest correlation.

Subjects & signals

- **Database –** from [Martínez-Cagigal *et al.* (2023)]
    - 15 healthy users (1 discarded due to different sample rate)
    - *g.USBamp* with 16 active channels
    - Sampling rate of 256 Hz
    - Monitor refresh rate of 120 Hz
    - 16 commands (A, B, …, P)



- **Paradigm and evaluation procedure**
    - Circular shifting paradigm
    - For each m-sequence $p \in \{2, 3, 5, 7, 11\}$
        1. Calibration: 6 runs x 5 trials x 10 cycles
        2. Test: 2 runs × 16 trials × 10 cycles



Martínez-Cagigal, V., Santamaría-Vázquez, E., Pérez-Velasco, S., Marcos-Martínez, D., Moreno-Calderón, S., & Hornero, R. (2023). Non-binary m-sequences for more comfortable brain-computer interfaces based on c-VEPs. Expert Systems with Applications (Accepted).

Results classical approach, non-binary sequences

- **Accuracy with EEG-Inception with classical training approach:**

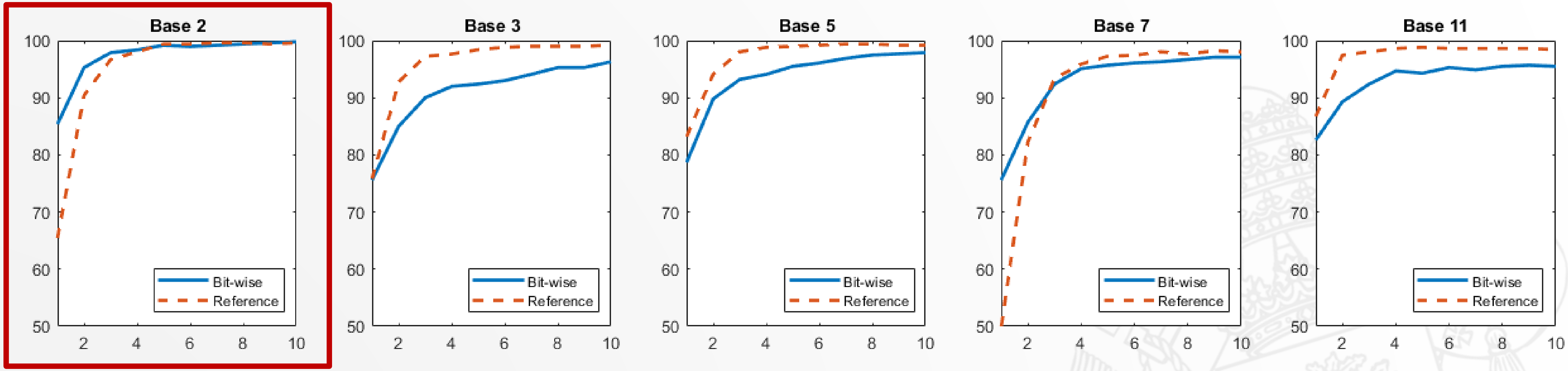
Base	Number of cycles										Mean
	1	2	3	4	5	6	7	8	9	10	
2	85.4	95.3	97.9	98.4	99.2	99.0	99.2	99.4	99.6	99.8	**97.3**
3	75.6	85.0	90.0	92.0	92.4	93.0	94.1	95.3	95.3	96.3	**90.9**
5	78.7	89.8	93.2	94.1	95.5	96.1	96.9	97.5	97.7	97.9	**93.7**
7	75.6	85.7	92.4	95.1	95.7	96.1	96.3	96.7	97.1	97.1	**92.8**
11	82.6	89.3	92.4	94.7	94.3	95.3	94.9	95.5	95.7	95.5	**93.0**

- The model is able to classify stimuli encoded with different shades of gray with acceptable accuracy

Santamaría-Vázquez, E., Martínez-Cagigal, V., & Hornero, R. (2023, June). Bit-wise reconstruction of non-binary visual stimulation patterns from EEG using deep learning: a promising alternative for user-friendly high-speed c-VEP-based BCIs. In *International Work-Conference on Artificial Neural Networks* (pp. 603-614). Cham: Springer Nature Switzerland.

Results classical approach, non-binary sequences

- **Comparison with reference method:**



- The binary case was the only scenario where bir-wise reconstruction yields higher accuracy than the reference method:
  - More training examples per class?
  - Hyperparameter optimization?

Santamaría-Vázquez, E., Martínez-Cagigal, V., & Hornero, R. (2023, June). Bit-wise reconstruction of non-binary visual stimulation patterns from EEG using deep learning: a promising alternative for user-friendly high-speed c-VEP-based BCIs. In *International Work-Conference on Artificial Neural Networks* (pp. 603-614). Cham: Springer Nature Switzerland.

Results zero calibration, binary sequence

- **Accuracy per subject for EEG-Inception with zero calibration**

Subj	Number of cycles									
	1	2	3	4	5	6	7	8	9	10
1	56,2	81,2	93,8	93,8	96,9	96,9	100	100	93,8	96,9
2	53,1	71,9	84,4	81,2	93,8	96,9	96,9	100	100	100
3	75	78,1	81,2	93,8	96,9	100	96,9	100	100	100
4	81,2	90,6	93,8	90,6	96,9	100	100	100	100	100
5	18,8	31,2	34,4	46,9	53,1	59,4	62,5	65,6	75	71,9
6	53,1	68,8	78,1	84,4	81,2	84,4	87,5	87,5	93,8	90,6
7	75	87,5	90,6	96,9	96,9	96,9	93,8	93,8	96,9	100
8	56,2	62,5	78,1	87,5	90,6	96,9	96,9	100	100	100
9	84,4	96,9	100	100	100	100	100	100	100	100
10	50	62,5	81,2	84,4	84,4	84,4	84,4	81,2	87,5	87,5
11	12,5	15,6	15,6	21,9	15,6	12,5	18,8	18,8	18,8	18,8
12	15,6	6,2	6,2	9,4	6,2	3,1	6,2	3,1	3,1	6,2
13	59,4	81,2	93,8	96,9	96,9	100	100	100	100	100
14	28,1	37,5	50	56,2	62,5	65,6	81,2	84,4	90,6	87,5
15	40,6	56,2	71,9	87,5	96,9	96,9	96,9	96,9	100	100
M	**50,6**	**61,9**	**70,2**	**75,4**	**77,9**	**79,6**	**81,5**	**82,1**	**84**	**84**
M2	**56,2**	**69,7**	**79,3**	**84,6**	**88,2**	**90,6**	**92,1**	**93,0**	**95,2**	**95,0**

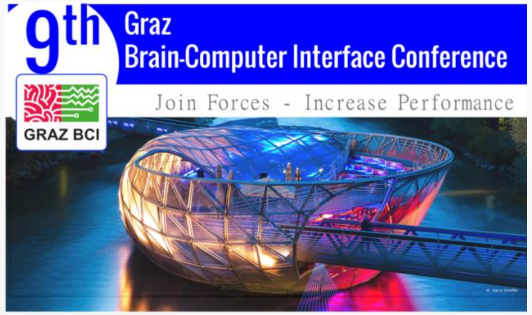
Results fine-tuning, binary sequence

- **Accuracy results per subject for EEG-Inception using fine-tuning with 5 trials (25s)**

Subj	Number of cycles									
	1	2	3	4	5	6	7	8	9	10
1	81,2	96,9	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
2	90,6	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
3	93,8	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
4	93,8	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
5	43,8	75,0	90,6	93,8	93,8	96,9	100,0	100,0	100,0	100,0
6	87,5	96,9	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
7	96,9	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
8	84,4	93,8	96,9	100,0	100,0	100,0	100,0	100,0	100,0	100,0
9	87,5	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
10	93,8	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
11	37,5	40,6	53,1	68,8	78,1	84,4	84,4	87,5	90,6	87,5
12	21,9	46,9	59,4	59,4	68,8	75,0	87,5	93,8	96,9	96,9
13	78,1	93,8	96,9	96,9	100,0	100,0	100,0	100,0	100,0	100,0
14	34,4	56,2	62,5	71,9	78,1	84,4	90,6	93,8	100,0	100,0
15	87,5	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
M	**72,4**	**84,9**	**89,2**	**91,6**	**93,8**	**95,4**	**97,1**	**98,1**	**99,0**	**98,8**

Conclusions

- **Modelling VEPs requires complex non-linear models → deep learning**
  - The complexity of the model is limited by the size of the database
- **Bitwise reconstruction models do not improve the reference method for $p > 2$ in our experiments**
  - Not enough complexity? → new architectures
  - More observations needed to train the model? → get more data
- **Bitwise reconstruction models allow zero calibration approaches**
  - High accuracy for the majority of subjects
  - Certain subjects exhibit specific brain activity that differs from the majority of the population
  - More data should help to train more robust models



BIOMEDICAL ENGINEERING GROUP
UNIVERSITY OF VALLADOLID

MEDUSA

Bitwise reconstruction of visual stimulation patterns from EEG using deep learning for c-VEP decoding

Eduardo Santamaría-Vázquez

eduardo.Santamaria.vazquez@uva.es
www.gib.tel.uva.es
www.medusabci.com