ALMA MATER STUDIORUM
UNIVERSITÀ DEGLI STUDI DI BOLOGNA

Brain-Computer interfacing using deep neural networks: an introduction

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Outline

- **Neural decoding**
- Electroencephalography (EEG)
- EEG decoding via convolutional neural networks

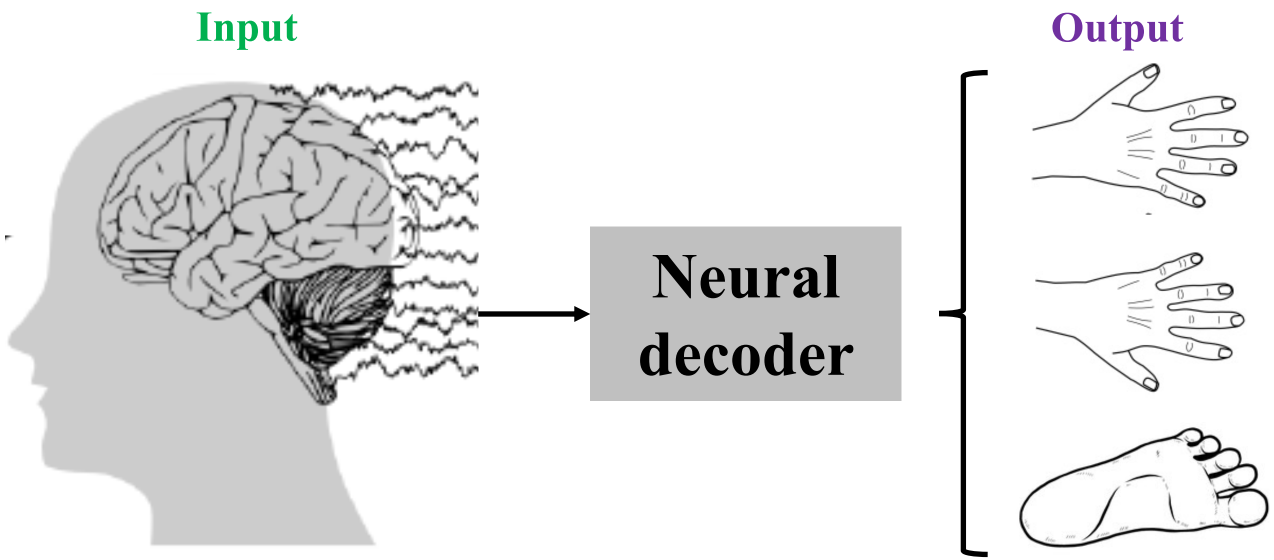
Neural decoding

Neural time series

- Brain activity recorded from:
  - ➢ different sites on the scalp (e.g., electroencephalogram, EEG)
  - ➢ different neurons from the cortex (e.g., neurons' spiking rate)

…representation of the neural activity = decoder input

…subjects' internal state or behaviour associated to the input = decoder output



Neural decoding

Neural time series

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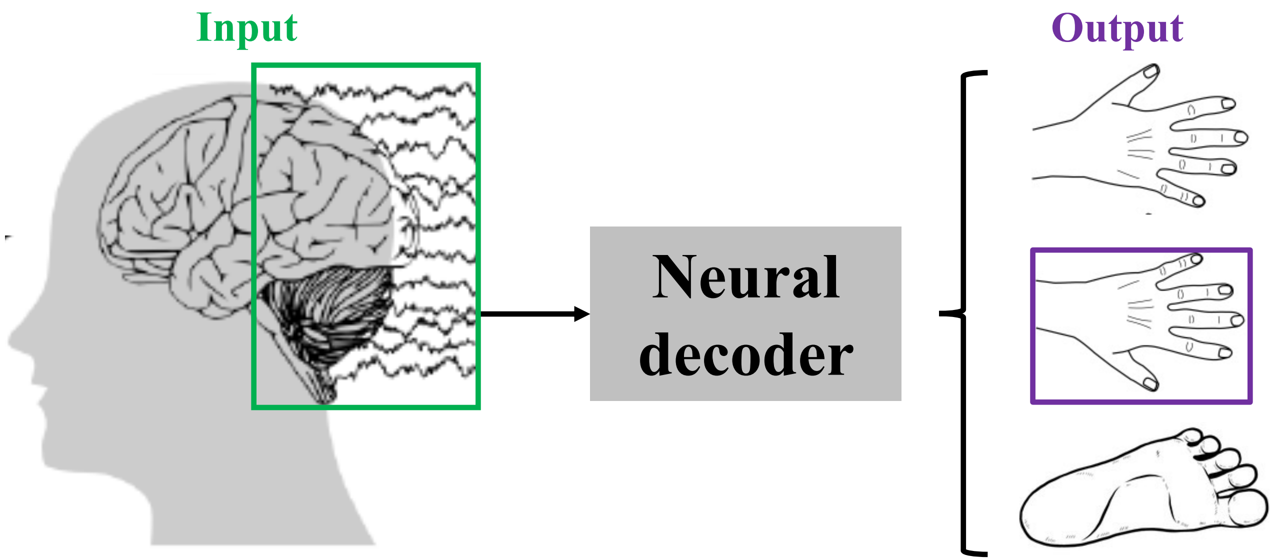


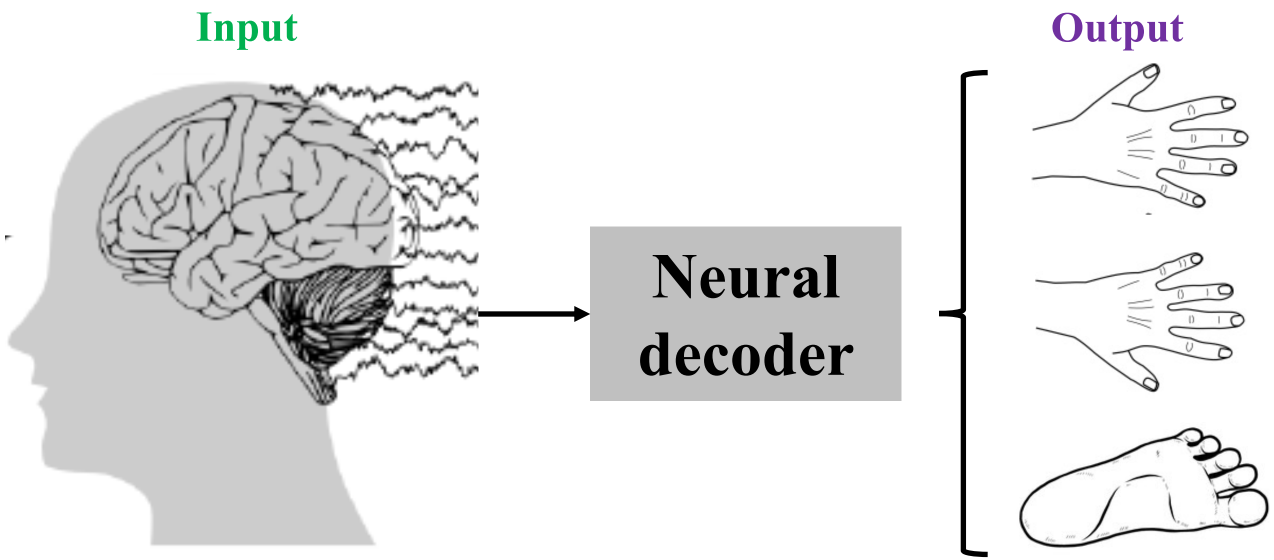
…representation of the neural activity = decoder input

…subjects' internal state or behaviour associated to the input = decoder output

Neural activity decoding

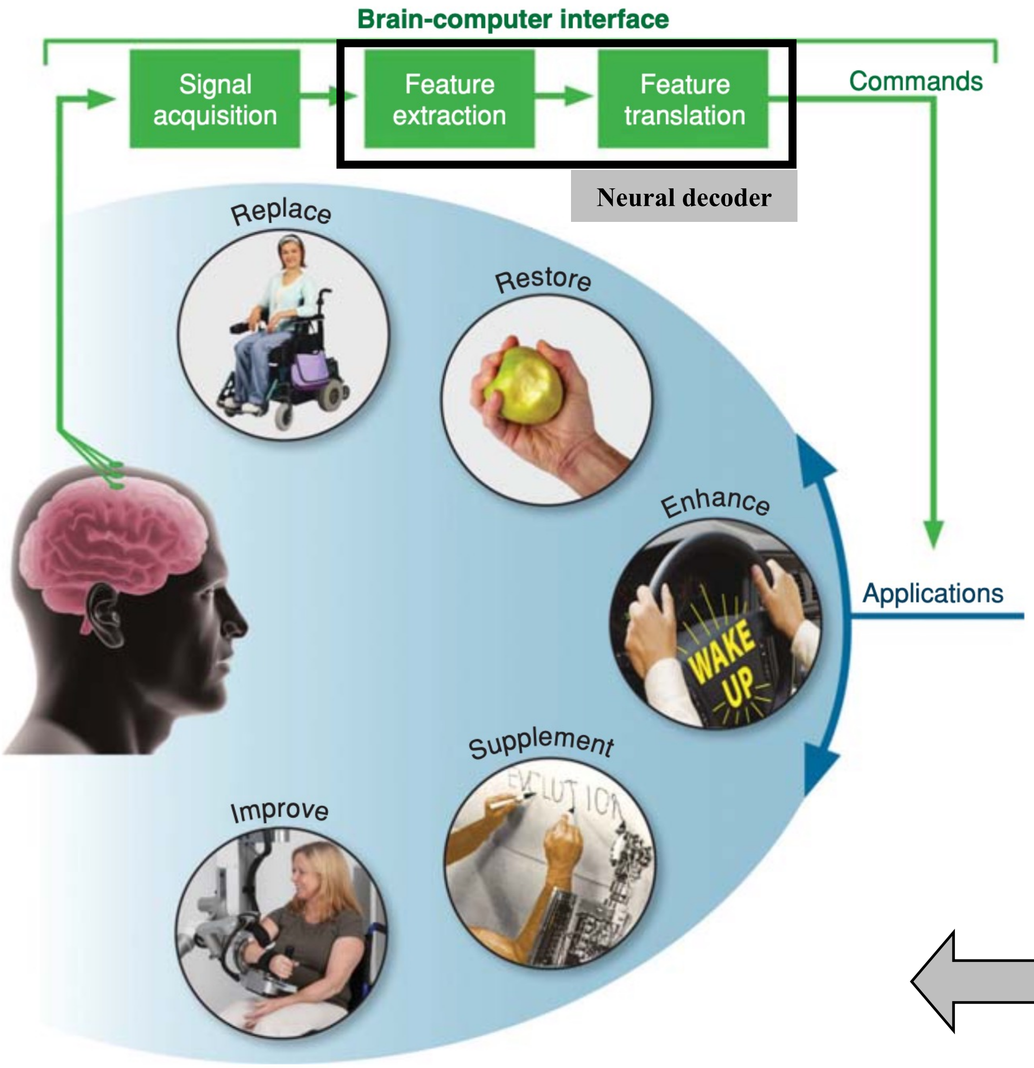
Find the relationship that maps the correct output to input multivariate neural activity

Neural decoding

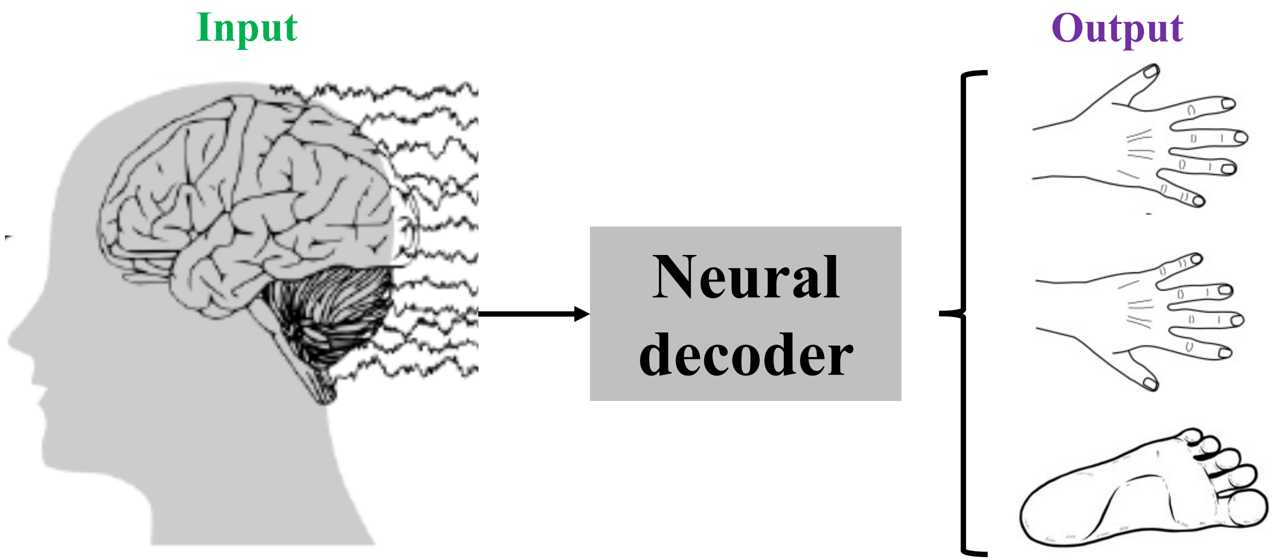


Why do we need neural decoding?

Neural decoding



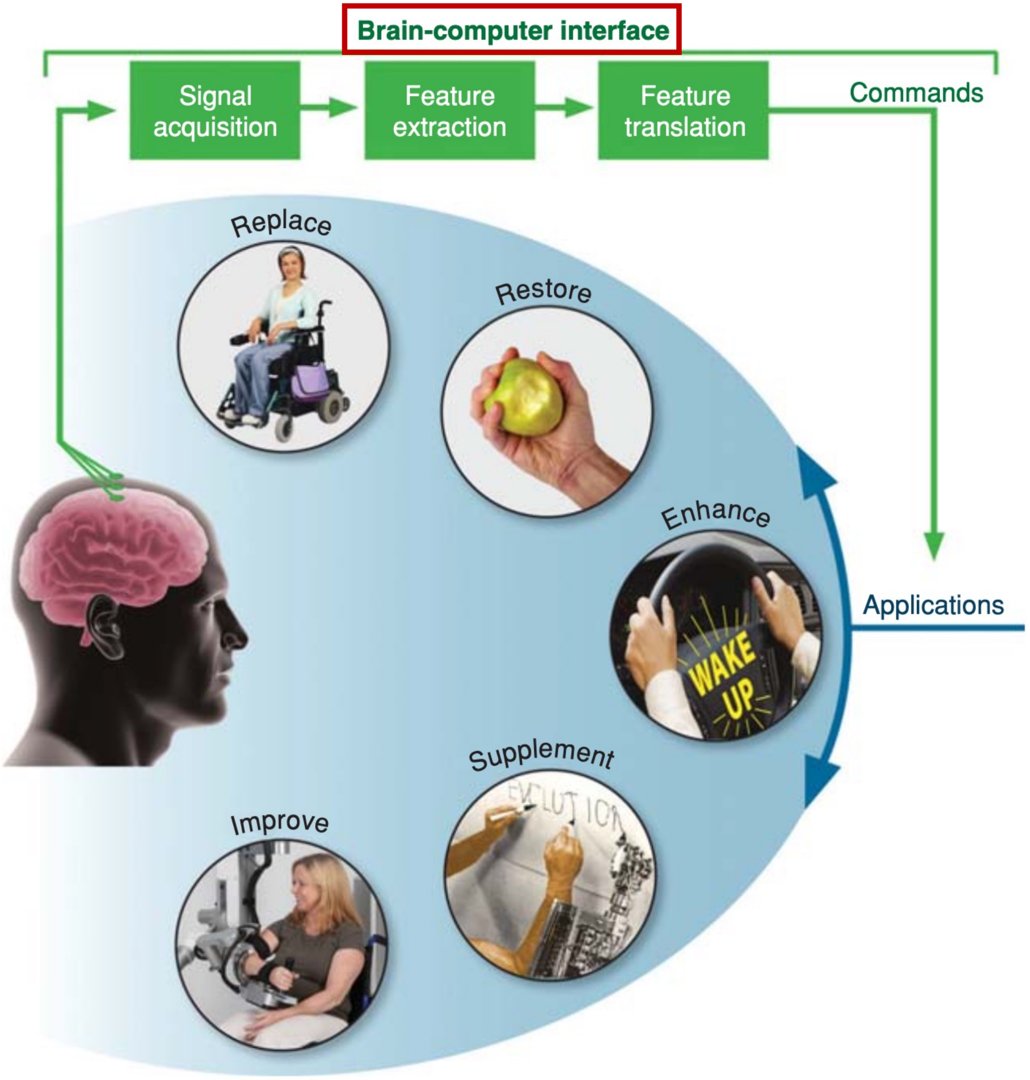
Wolpaw et al. (2012)



Why do we need neural decoding?

Brain-Computer Interfacing

Neural decoding



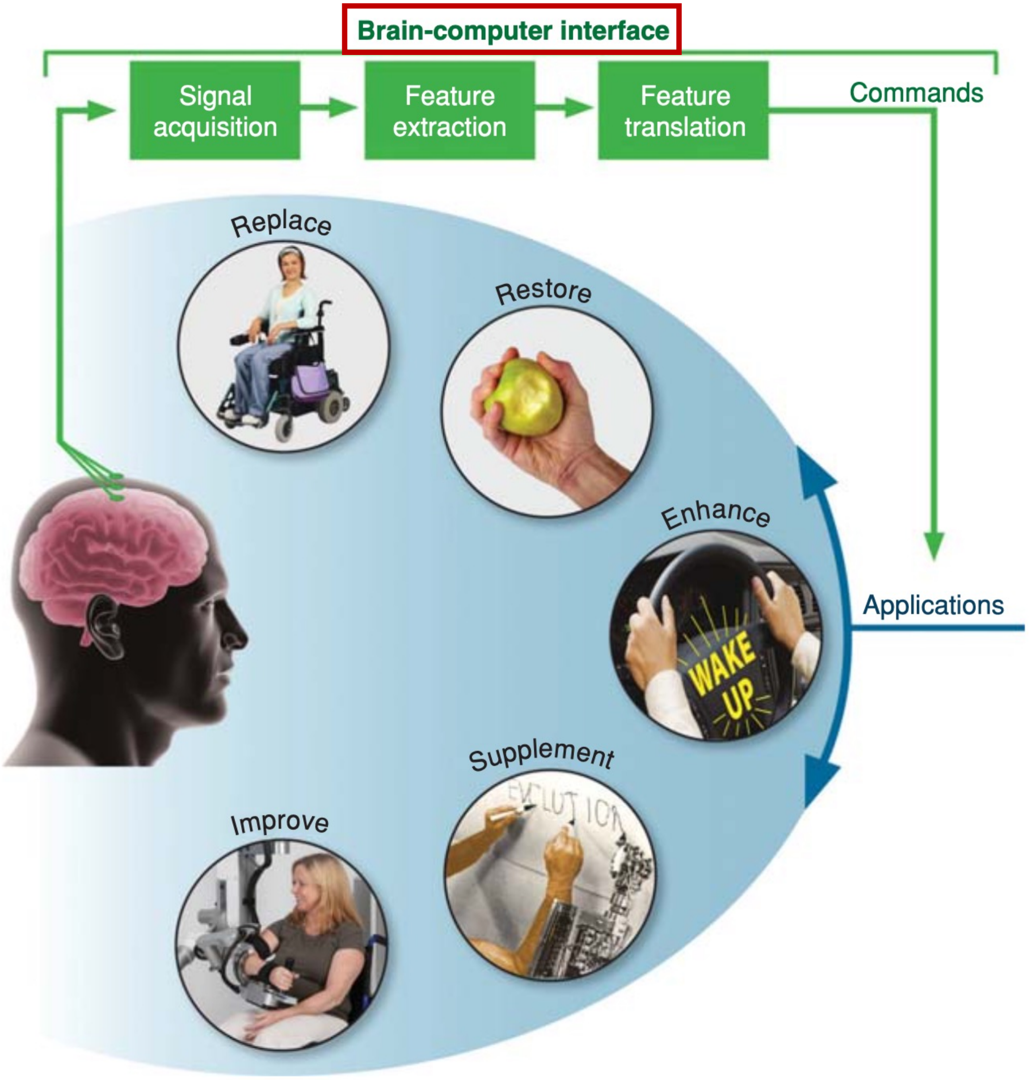
Wolpaw et al. (2012)

Brain-Computer Interface (BCI)
Definition no. 1

A Brain-Computer Interface is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles (Wolpaw et al.)

→<u>BCIs provide a new way for linking our brain with the environment</u> (bypassing physiological pathways)

Neural decoding

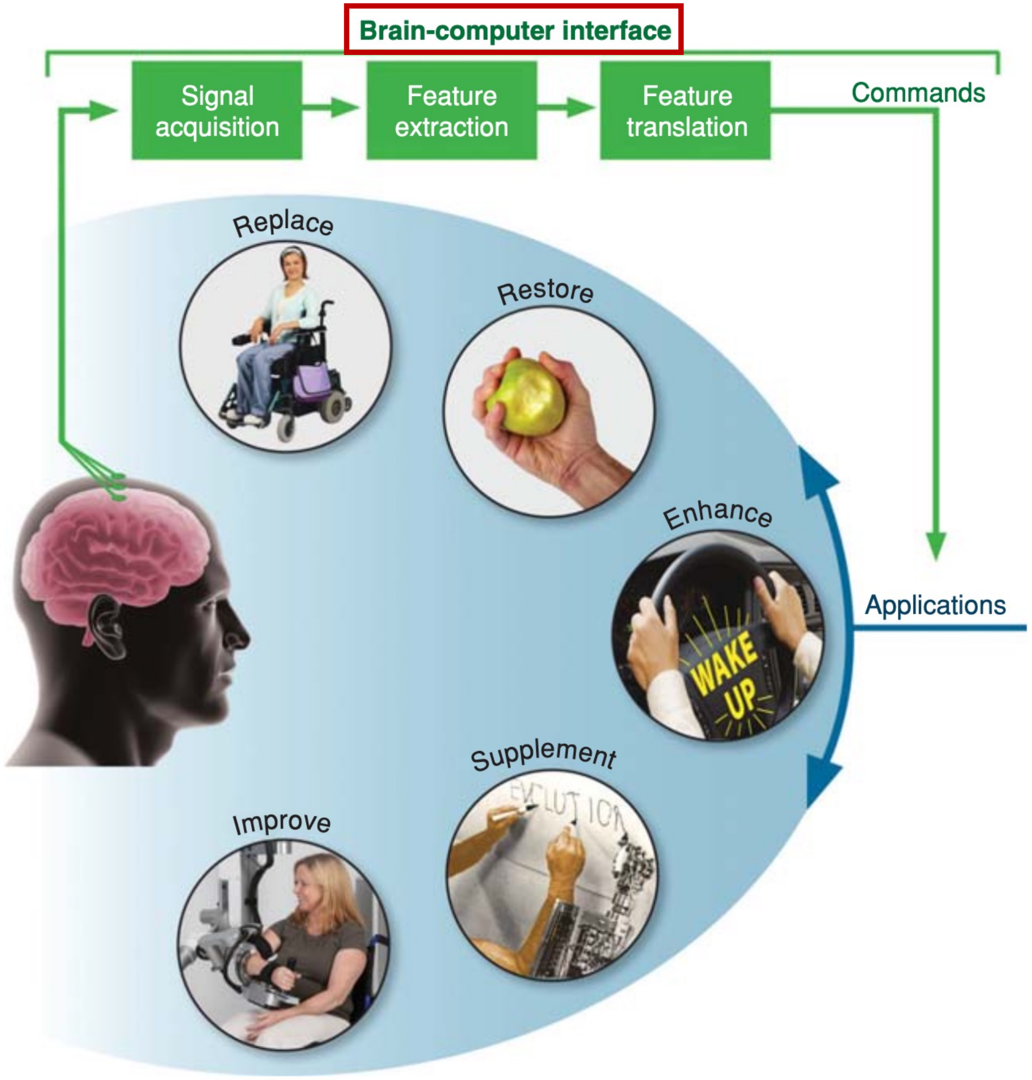


Wolpaw et al. (2012)

Brain-Computer Interface (BCI)
Definition no. 2
A Brain-Computer Interface is a new augmented communication system that translates human intentions reflected by suitable brain signals, into a control signal for an output device such as a computer application or a neuroprosthesis (Blankertz et al.)

→To interact with the environment the <u>brain activity have to be 'translated' into commands</u>

Neural decoding



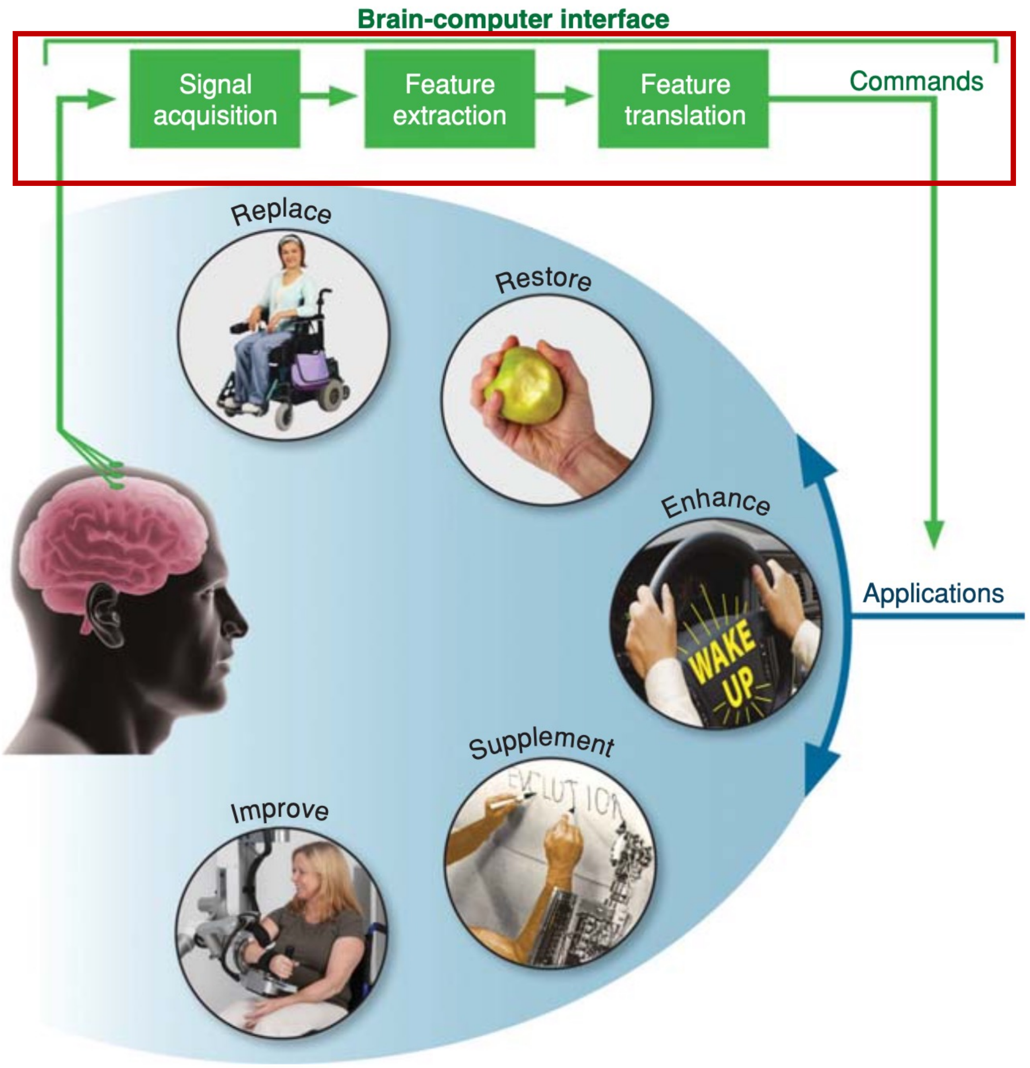
Wolpaw et al. (2012)

Brain-Computer Interface (BCI)
Definition no. 3
A Brain-Computer Interface enables a new real-time interaction between the user and the outside world (Daly and Wolpaw)

→The authors specify that the brain signals have to be translated into commands and then a feedback have to be returned to the user, modifying inturn the users' brain activity

→It is highlighted the real-time component of BCIs, introducing the notion of 'closed-loop' communication between the user and the BCI system via a feedback

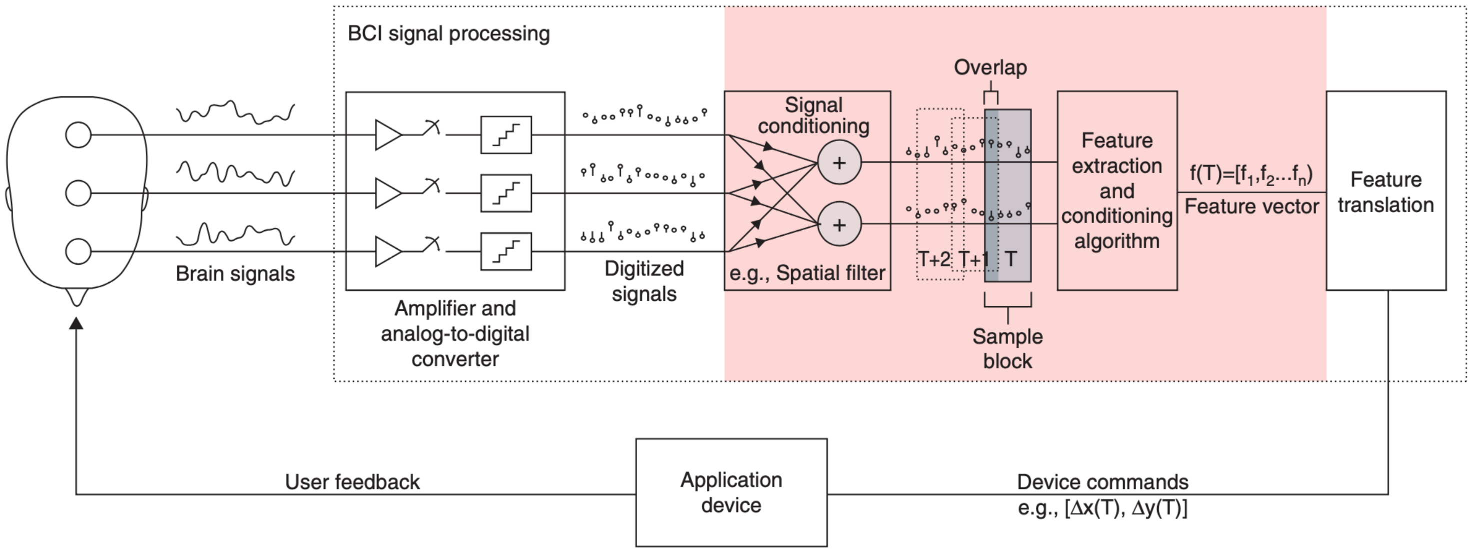
Neural decoding



Wolpaw et al. (2012)

How we implement a BCI?

- **Brain signal acquisition**
- **Signal processing (incl. neural decoding)**
- **Feedback**

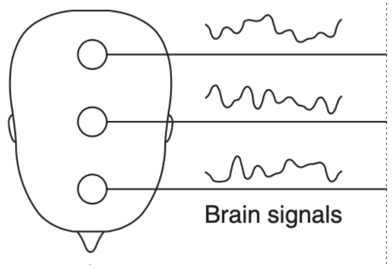


Wolpaw et al. (2012)

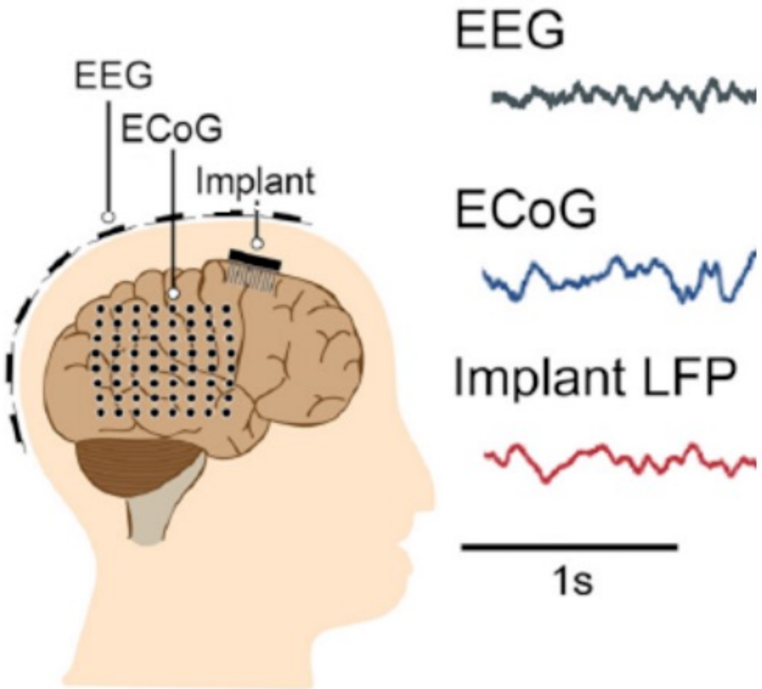
Neural decoding

Brain signal acquisition

- Brain signals: signals related to the brain activity (e.g., the electrical brain activity, measured by electroencephalography)
- Can be recorded:
  - Invasively (e.g., electrocorticography or single-neuron recordings)
  - Non-invasively (e.g., electroencephalography)



Wolpaw et al. (2012)



M. E. J. Obien et al. (2015)

Neural decoding

Signal processing

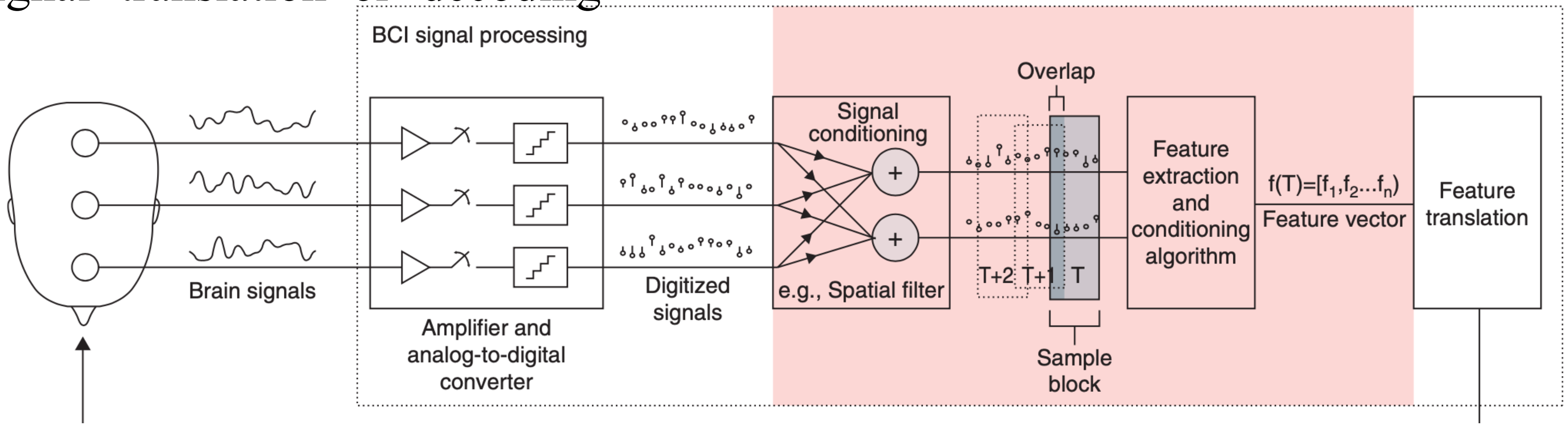
- *Input*: brain signals (e.g., electroencephalogram, EEG)

→processing of the neural time series:

  - Pre-processing (the signal tends to be noisy, especially non-invasively recorded ones)
  - Feature extraction and selection*
  - Classification*

- *Output*: neural signal ‘translation’ or ‘decoding’

*In a traditional machine-learning pipeline (separation between feature extraction, selection and classification)



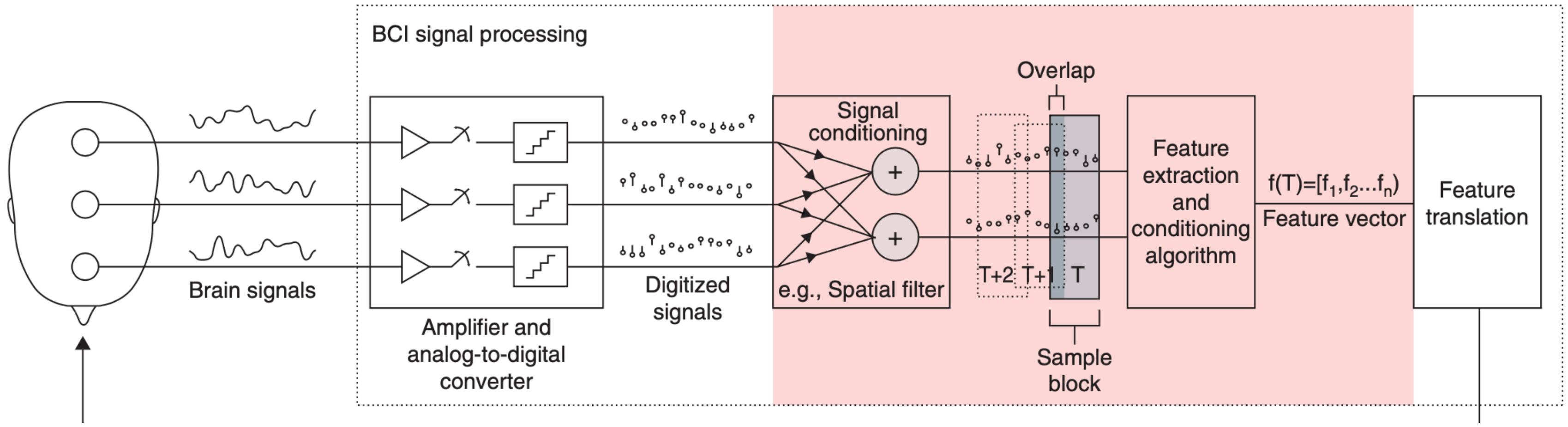
Wolpaw et al. (2012)

Neural decoding

Signal processing

What represents the output?

- Depends on the specific BCI application → move an external device (e.g., a wheelchair or a robotic arm)? communicate with the external world (e.g., composing a sentence)?
- For example, in case the users should move an external device, <u>movement imagery</u> (imagination of right-hand movement) can be decoded



Wolpaw et al. (2012)

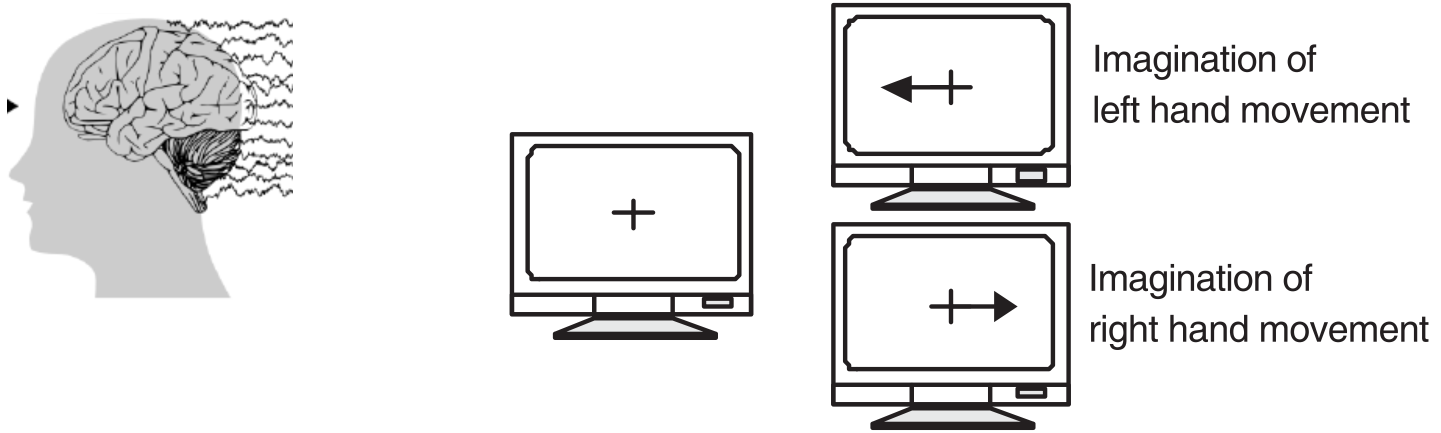
BCI tasks
- Motor imagery
- P300
- SSVEP

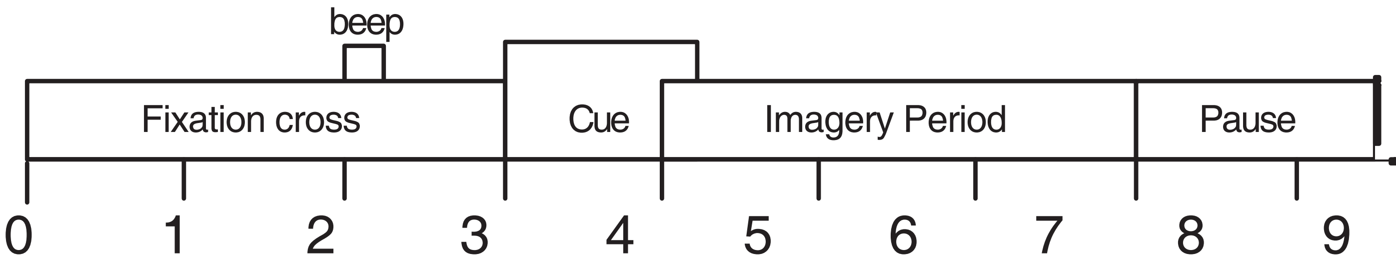
…

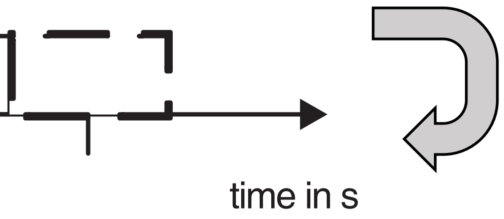
Neural decoding

Signal processing

Example of a motor imagery BCI task: left-hand vs. right-hand movement imagery







Tangermann et al. (2012)

- High-intra subject variability
- Low EEG signal-to-noise-ratio

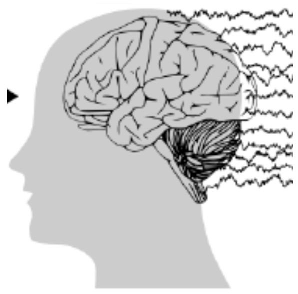
Repeat multiple times, recording multiple examples for each subject to reduce noise with averaging

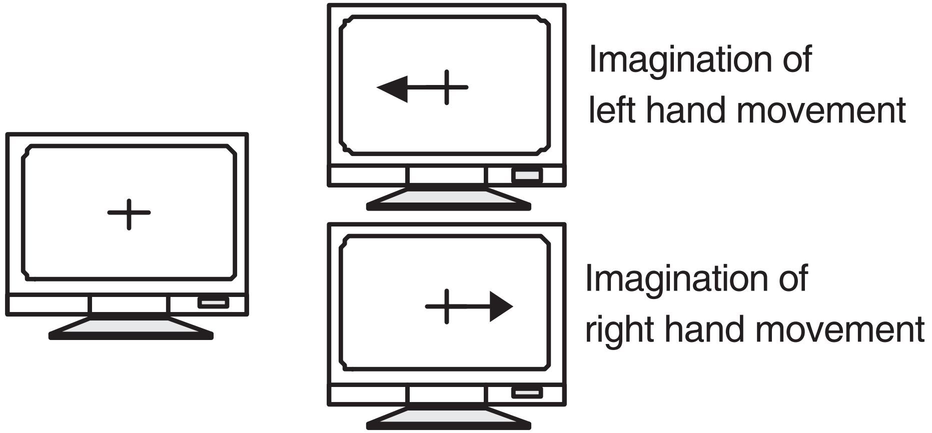
“Trial”: single repetition of the task (e.g., the imagery of one movement condition)

Neural decoding

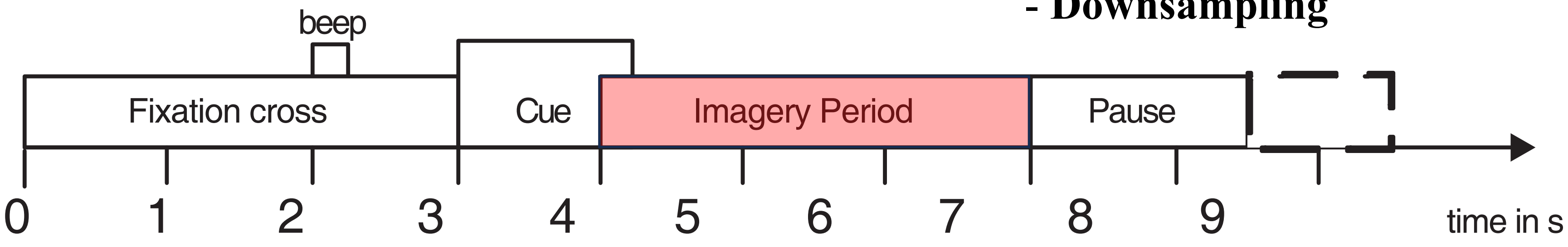
Signal processing

Example of a motor imagery BCI task: left-hand vs. right-hand movement imagery





Example of signal pre-processing steps:
- **Band-pass filtering** (e.g., 4-40 Hz for sensorimotor neural correlates)
- **Epoching** (i.e., windowing): cut the EEG into specific windows of interest ('epochs'), by considering the activity with respect to an 'epoching event' (e.g., the motor imagery onset)
- **Remotion of artifacts (e.g., eye blinks)**
- **Downsampling**



Tangermann et al. (2012)

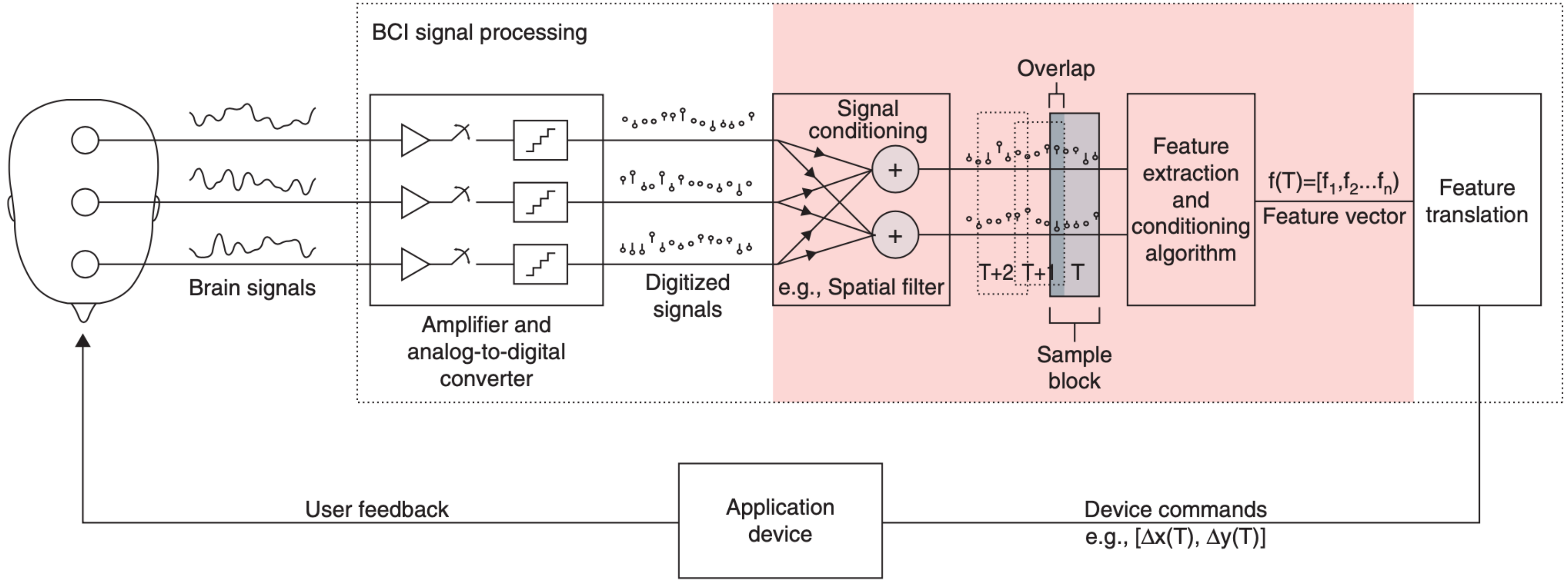
Neural decoding

Feedback

- *Input*: neural signal translation (e.g., right-hand motor imagery detected)

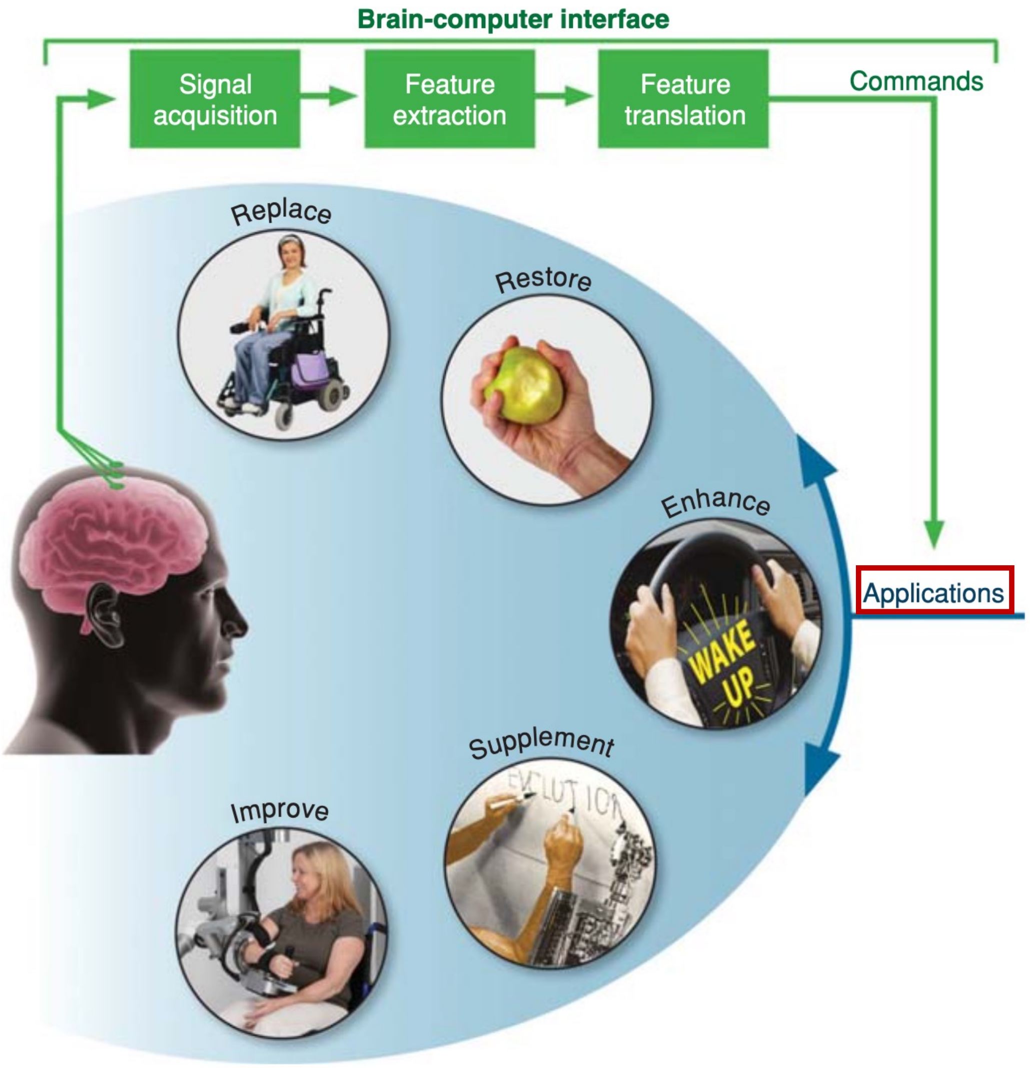
→depending on the translation, a command is processed and transmitted to a device (e.g., robotic arm / hand)

- *Output*: user feedback (e.g., execution of the movement using a robotic device)



Wolpaw et al. (2012)

Neural decoding



Wolpaw et al. (2012)

Main applications

<u>Medical</u>

- *Prevention* (e.g., alcoholism)
- *Detection and diagnosis* (e.g., brain and sleep disorders)
- *Rehabilitation* (e.g., brain stroke, disability, psychological disorders)
  →Robot-assistance for rehabilitation

https://www.youtube.com/watch?v=nFwNWNDwxQQ

- *Restoration* (e.g., locked-in syndrome)
  →Speller https://www.youtube.com/watch?v=wKDimrzvwYA

<u>Games and Entertainment</u>

→ Game controller https://www.youtube.com/watch?v=jXpjRwPQC5Q
→ 2020 BCI races https://www.youtube.com/watch?v=cwdURh0izxM
→ Drone controller https://www.youtube.com/watch?v=2xBNpotE4aI

<u>Security and Authentication</u>

…

Outline

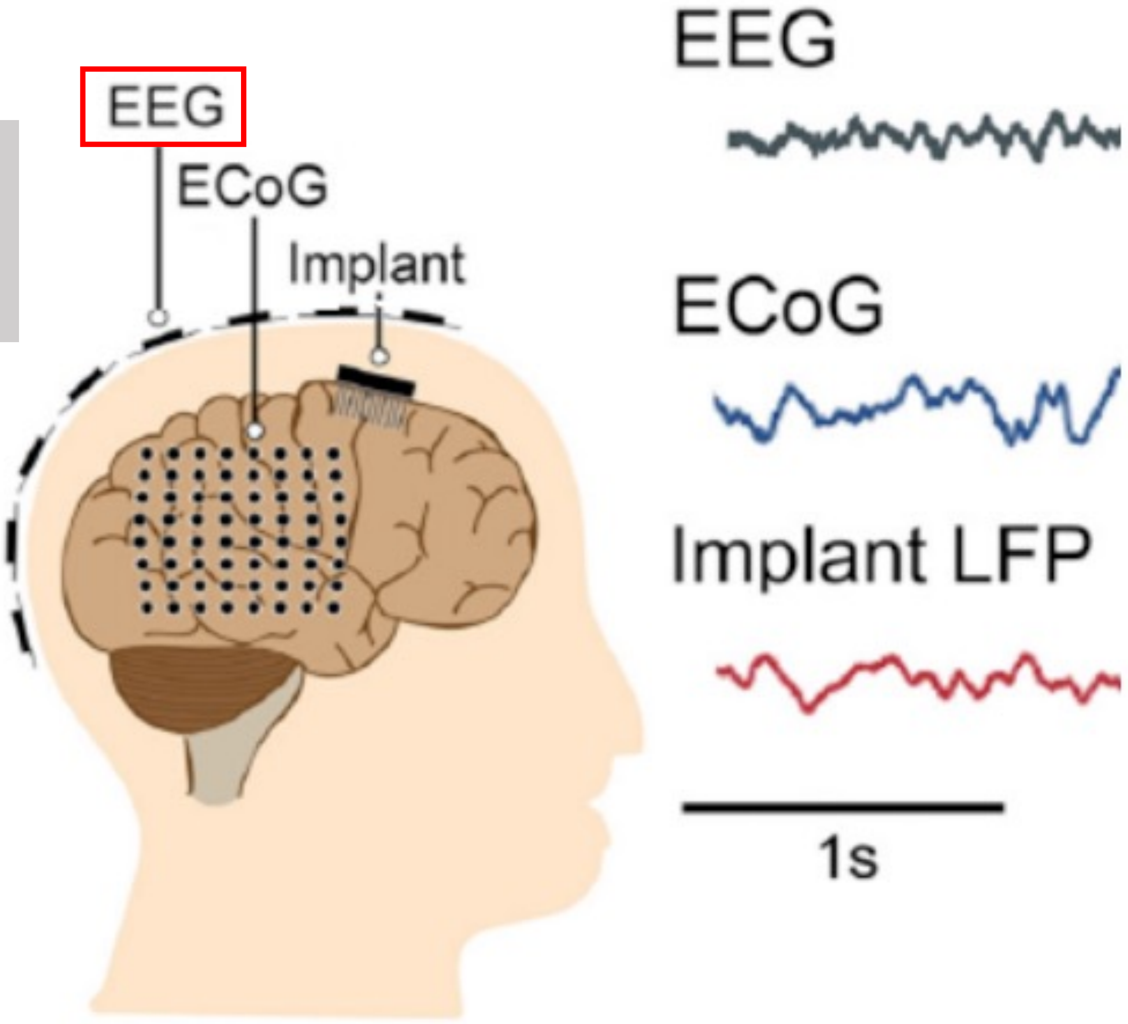
- Neural decoding
- **Electroencephalography (EEG)**
- EEG decoding via convolutional neural networks

Electroencephalography

Basics

Electroencelphalogram (EEG): macroscopic **scalp-level signals** that reflects the **syncronized electric activity of large populations of neurons**

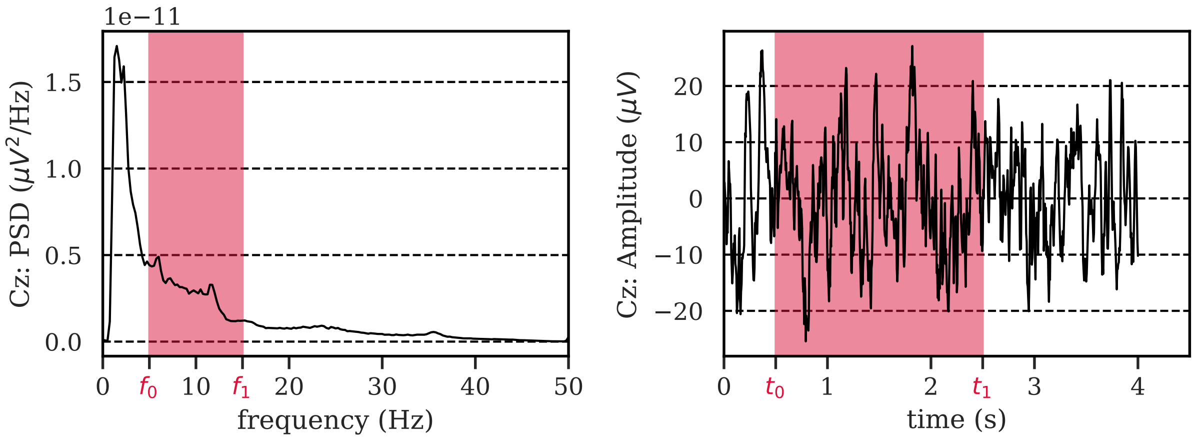
- Scalp-level recordings → significant contribution of neurons near to the scalp (i.e., pyramidal neurons of the human cortex)
- Non-invasive recording: allows the development of non-invasive BCIs (differently from electrocorticography (ECoG) or local field potential (LFP) implants)



M. E. J. Obien et al. (2015)

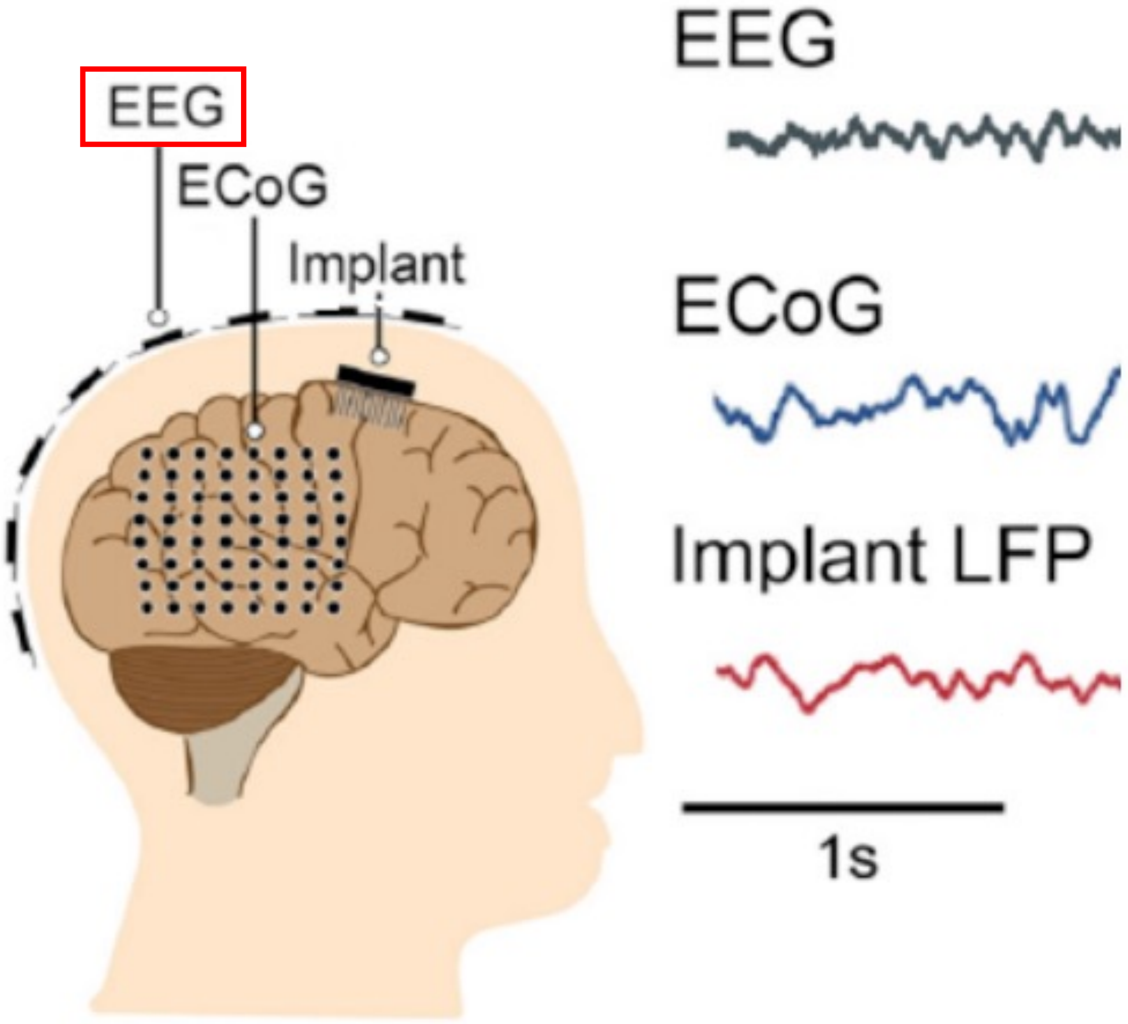
Electroencephalography

Basics



D. Borra et al. (2024, under review)

- Non-invasive recording
- Low signal-to-noise ratio
- Amplitude up to ~ 50-100 μV
- Relevant freq. < 100 Hz
- Limited cost (from ~ 3 to 30 k€) compared to other technologies (e.g., functional MRI)
- Resolution:
  - ➢Great in time (sampl. freq. up to ~1 kHz)
  - ➢Scarce in space (up to ~ 200 sites)



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Electroencephalography

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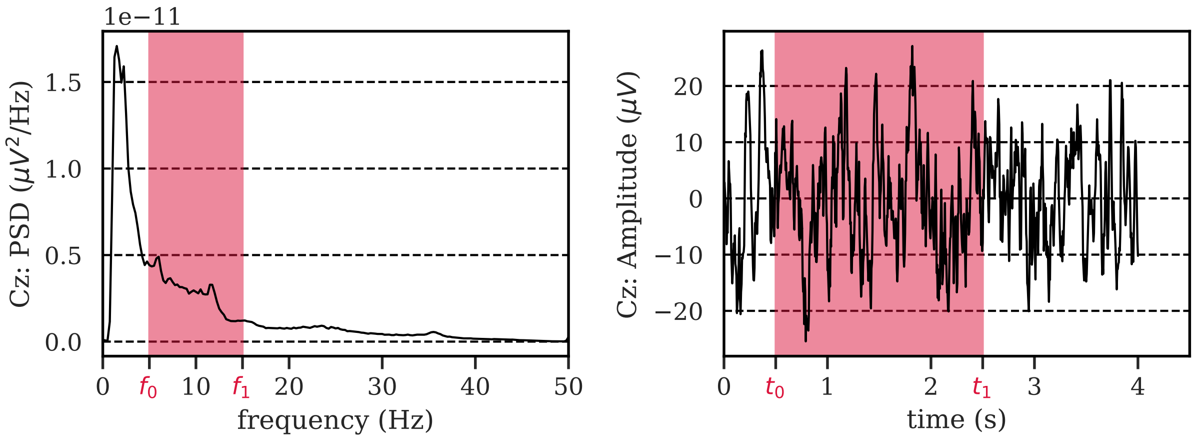


D. Borra et al. (2024, under review)

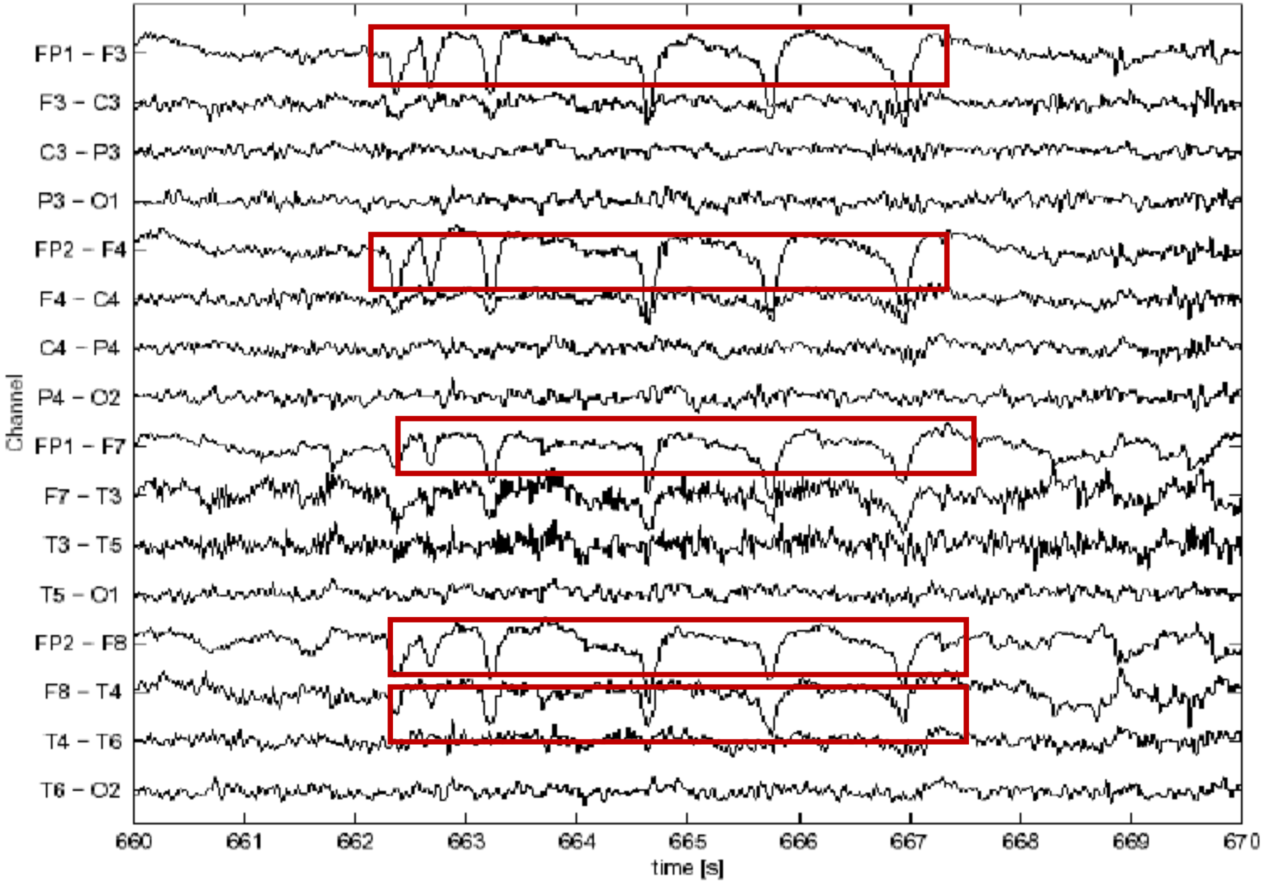
…low-signal-to-noise ratio and small amplitudes (~ µV)

→EEG is highly contaminated by artifacts (e.g., eye blinks, eye movements, muscle activity, heart activity, etc.)

…EEG can also be simulated by models (e.g., with neural mass models)

https://cs.brown.edu/people/epavlick/eeg/eeg.html

Example of eye-related artifacts in EEG recordings

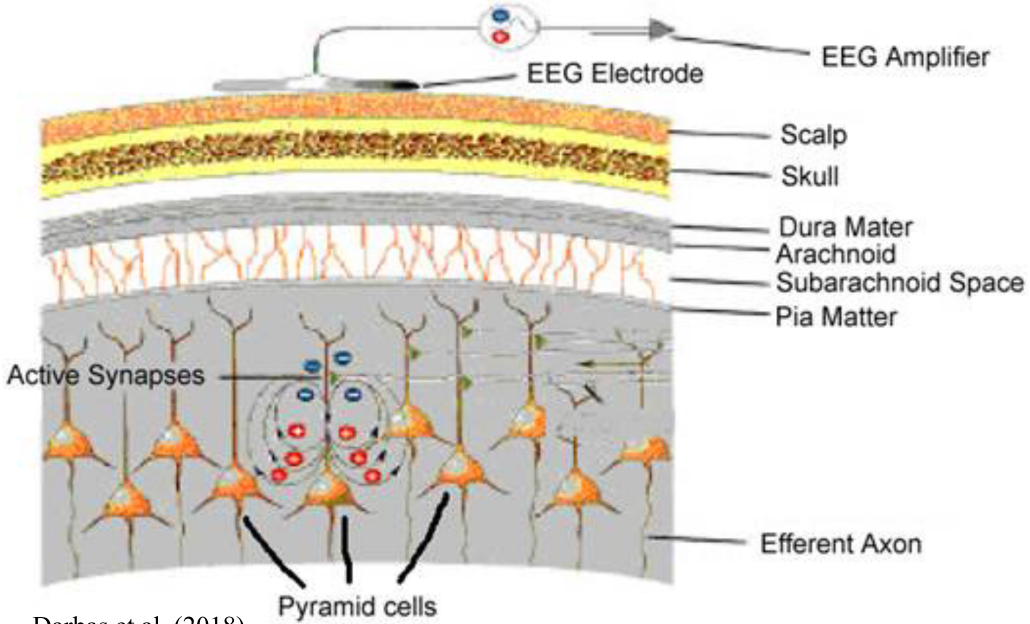


V. Krishnaveni et al. (2005)

Electroencephalography

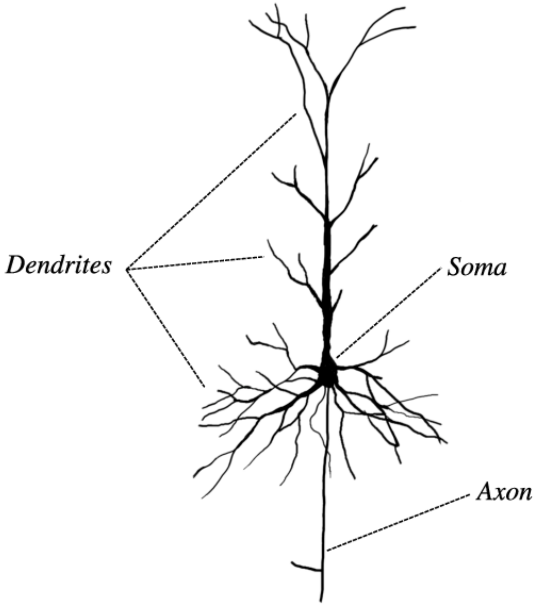
Basics: neural generators

- Projections of pyramidal neurons have coherent organization
  - ➢ Parallel to each other
  - ➢ Perpendicular to the cortex surface



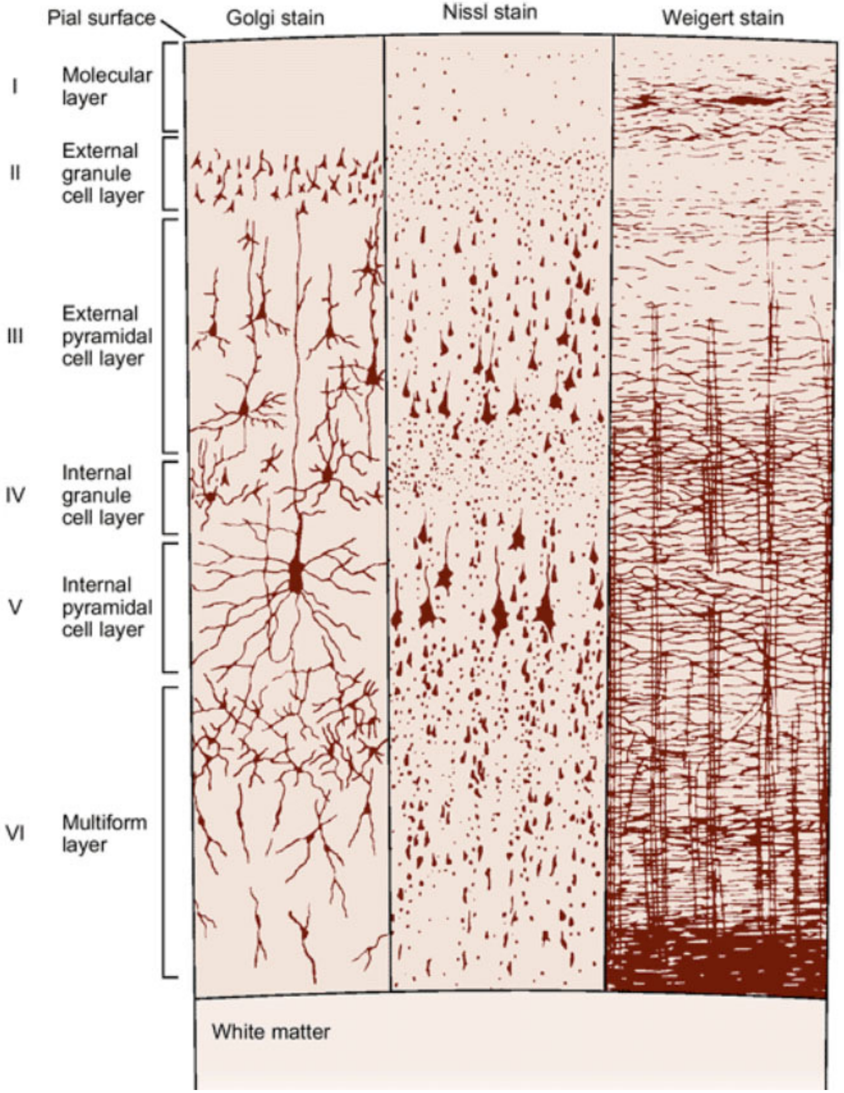
Darbas et al. (2018)

Pyramidal neuron



F. Walter et al. (2016)

Cerebral cortex

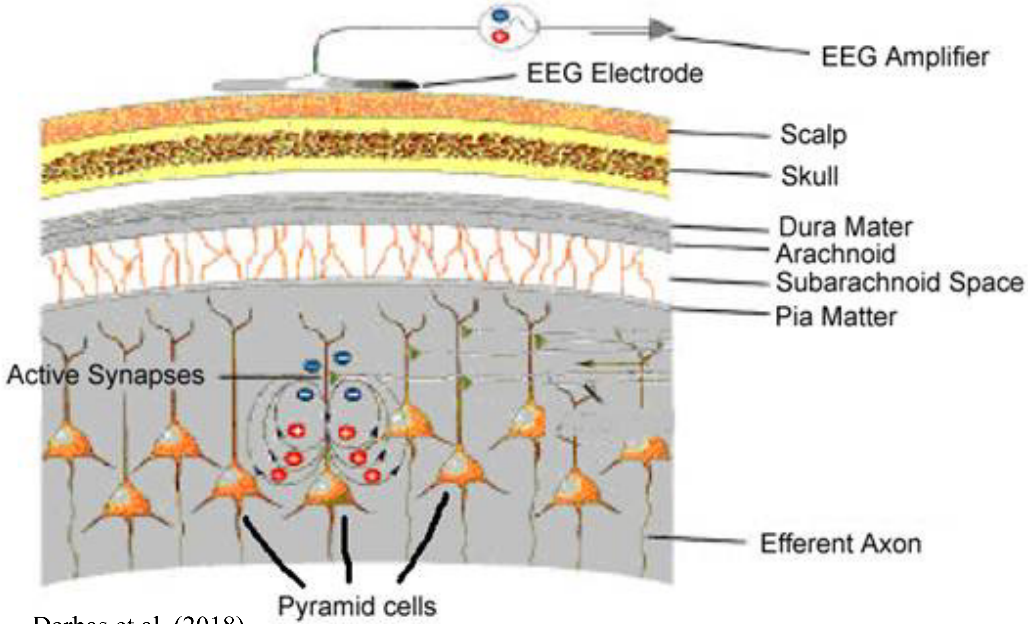


Kandel et al. (2000)

Electroencephalography

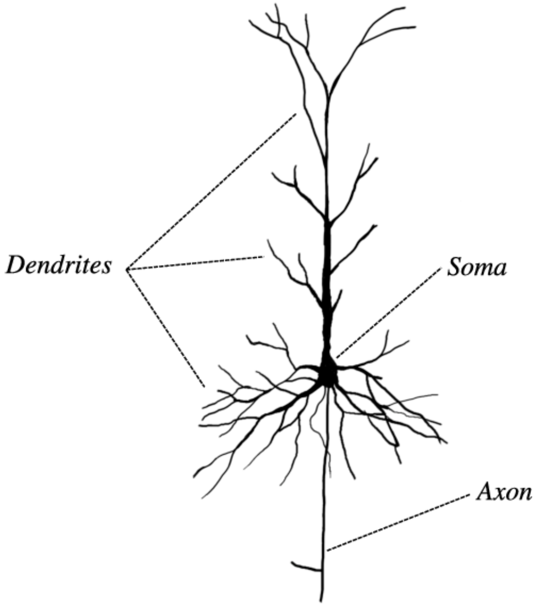
Basics: neural generators

Due to the peculiar structure and organization of projections of **pyramidal neurons**, these neurons are the **principal generators of the surface EEG signals**



Darbas et al. (2018)

Pyramidal neuron



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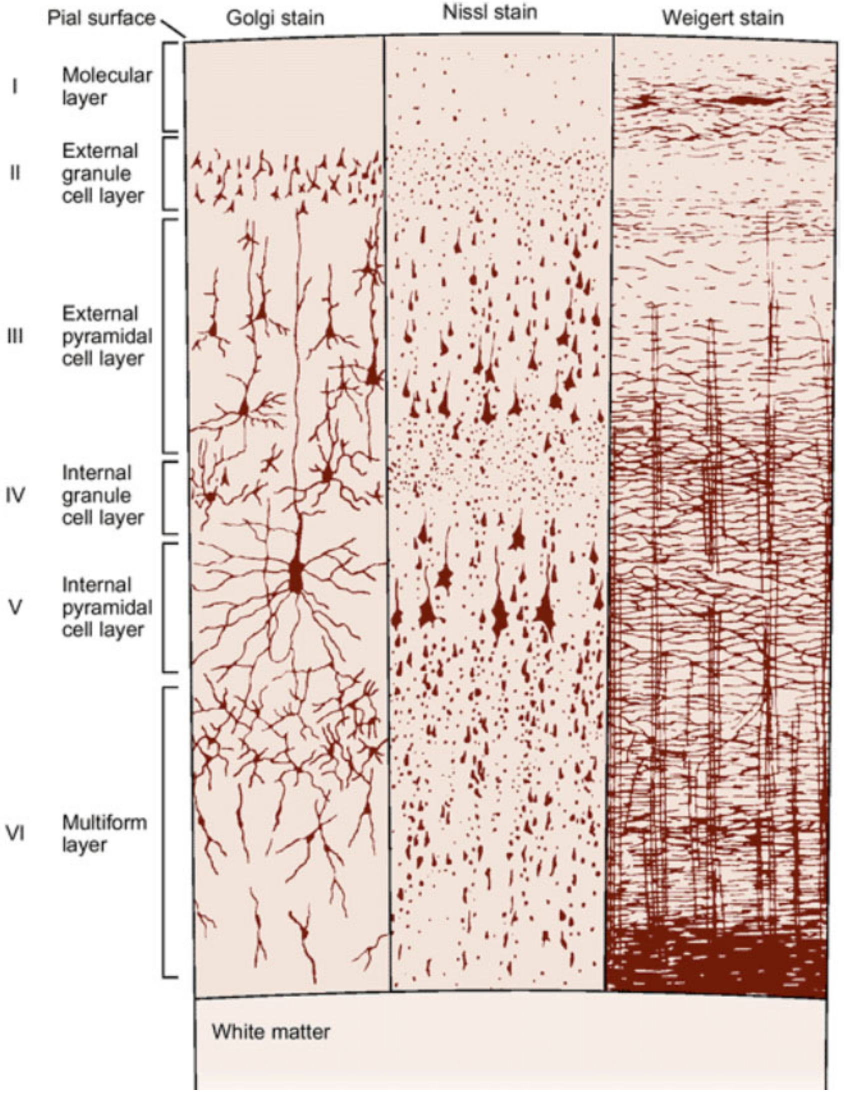


Kandel et al. (2000)

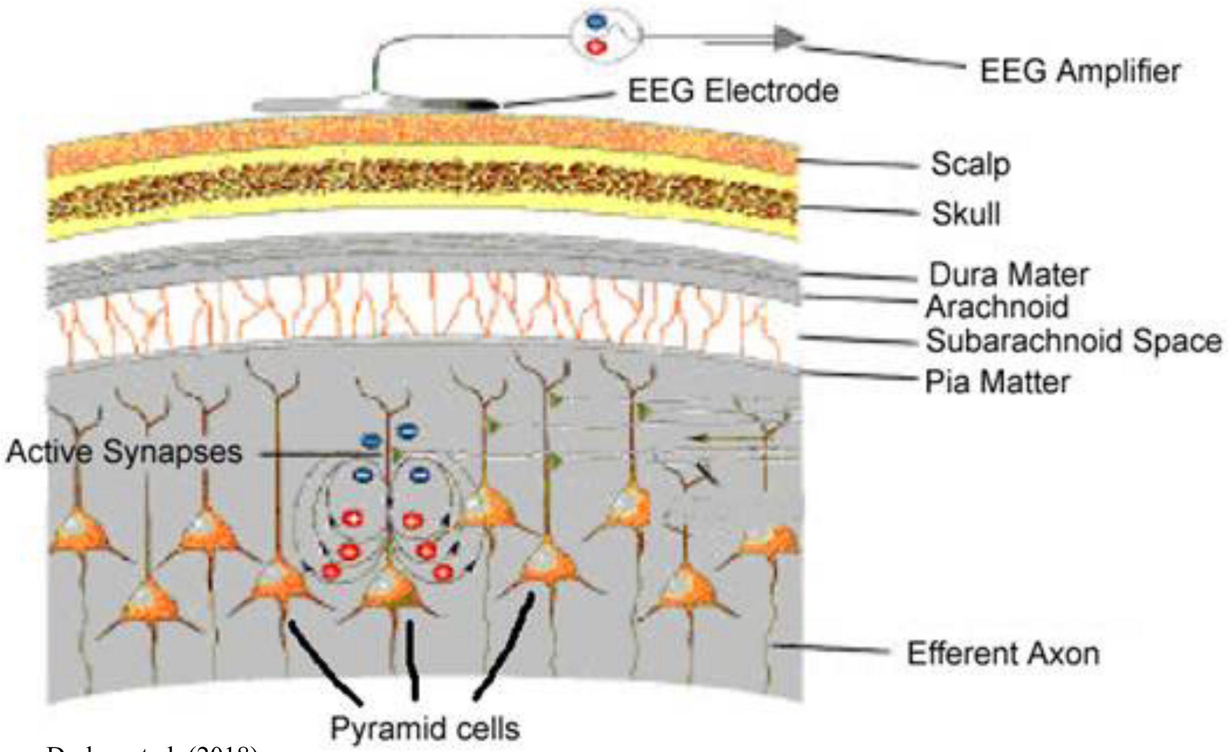
Electroencephalography

Basics

…summing up

Electroencelphalogram (EEG): macroscopic **scalp-level signals** that reflects the **syncronized electric activity of large populations of neurons**

Due to the peculiar structure and organization of projections of **pyramidal neurons**, these neurons are the **principal generators of the surface EEG signals**



Darbas et al. (2018)

Electroencephalography

Setup

Non-invasive electrodes for surface recordings on the scalp

1. Disc/cup electrodes

- 0.5-1 cm diameter
- Ag, AgCl
- Placed on the scalp by using conductive and adhesive gel
- Long preparation times

2. EEG cap with mounted electrodes

- Disc electrodes mounted on an elastic cap, available in different measures (e.g., small, medium, large)
- Already placed at specific positions
- Shorter preparation times

... what about the location of the electrodes?

Example of single EEG passive electrode

g.tec medical engineering GmbH, Austria (taken from g.tec web-site)

Example of active EEG electrodes pre-mounted on an EEG cap

Hole for inserting the conductive gel (not adhesive in this case)

g.tec medical engineering GmbH, Austria (taken from g.tec web-site)

Electroencephalography

Setup

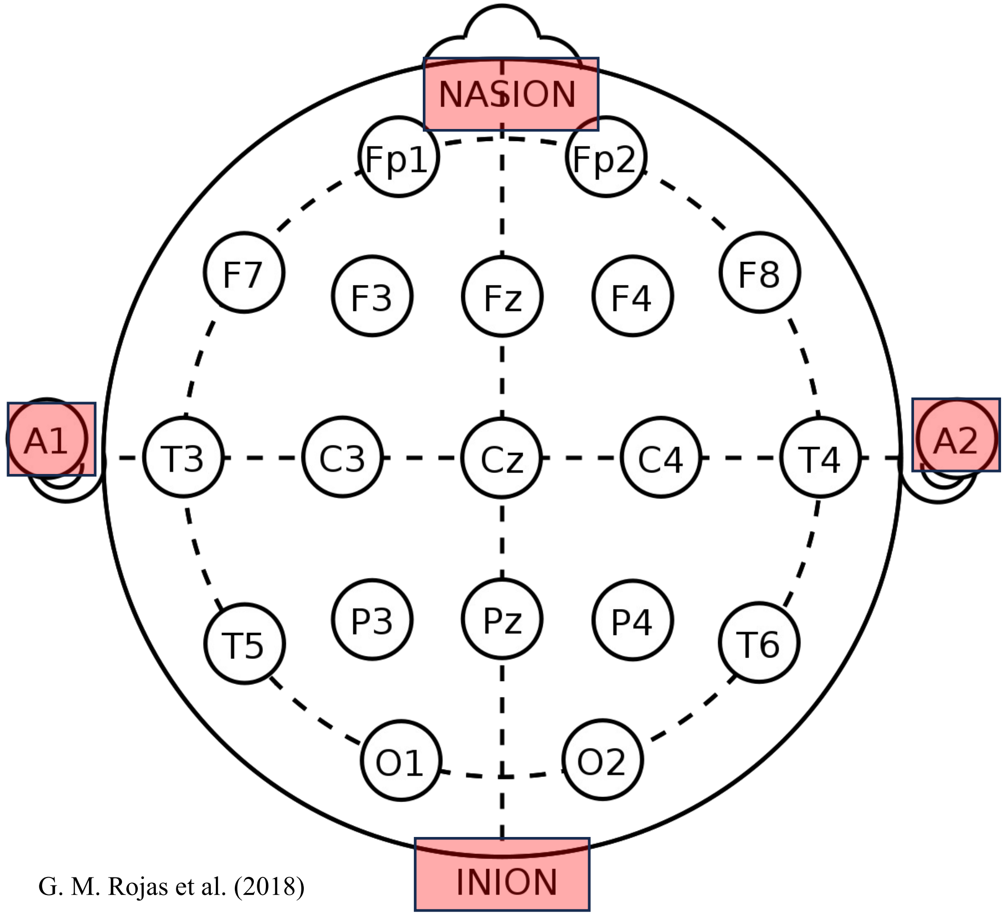
EEG electrode standard locations

- Crucial for comparing recordings of different subjects or of the same subject recorded in different days (i.e., different recording sessions)

Standard 10/20

- Defined in 1958 for the standard location of 21 electrodes
- 4 reference points (NASION, INION, A1, A2)

… extensions of this standard exist, to handle more electrodes (e.g., 10/10 standard up to 75 electrodes, 10/5 standard up to 300 electrodes)



G. M. Rojas et al. (2018)

Each electrode is labelled with a letter and a number (positive: right hemisphere, negative: left hemisphere)

…if you are interested into EEG and BCIs: https://www.gtec.at/spring-school-2024/

Outline

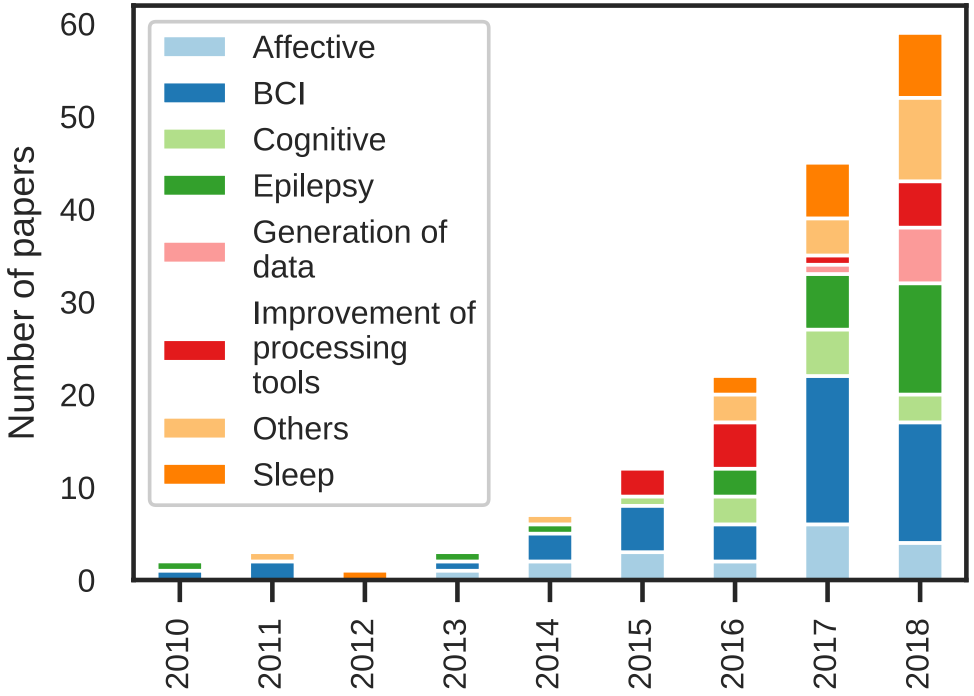
- Neural decoding
- Electroencephalography (EEG)
- **EEG decoding via convolutional neural networks**

EEG decoding via convolutional neural networks

Why deep neural networks instead of traditional machine learning?

- Light pre-processing of neural time series
- Automatic feature learning directly on time series
- High performance (esp. on single-trial decoding)

No. of publications about deep neural networks for EEG



Y. Roy et al. (2019)

EEG decoding via convolutional neural networks

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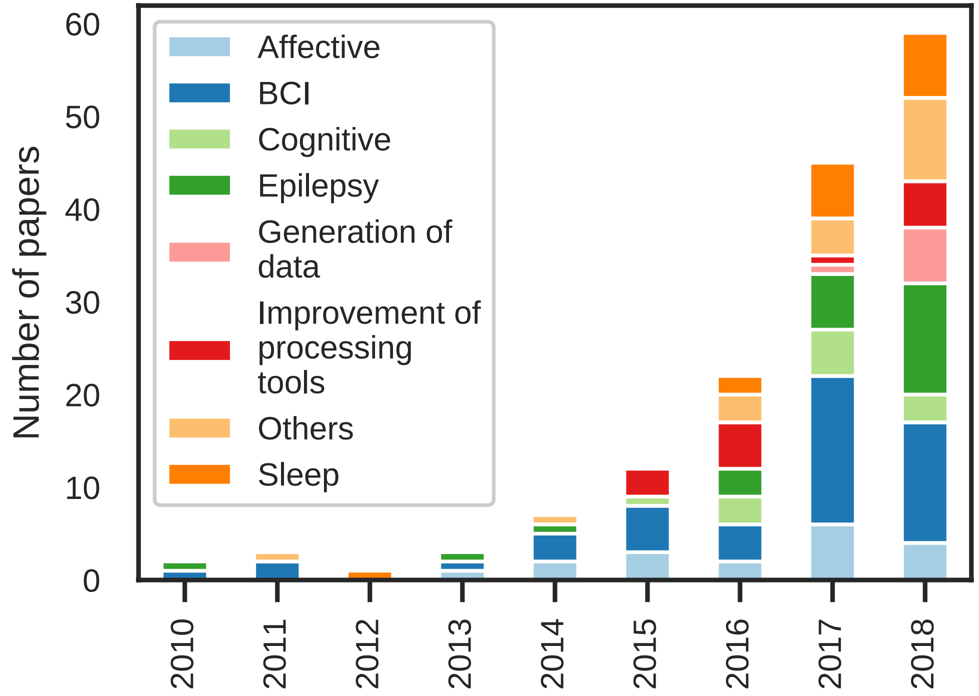

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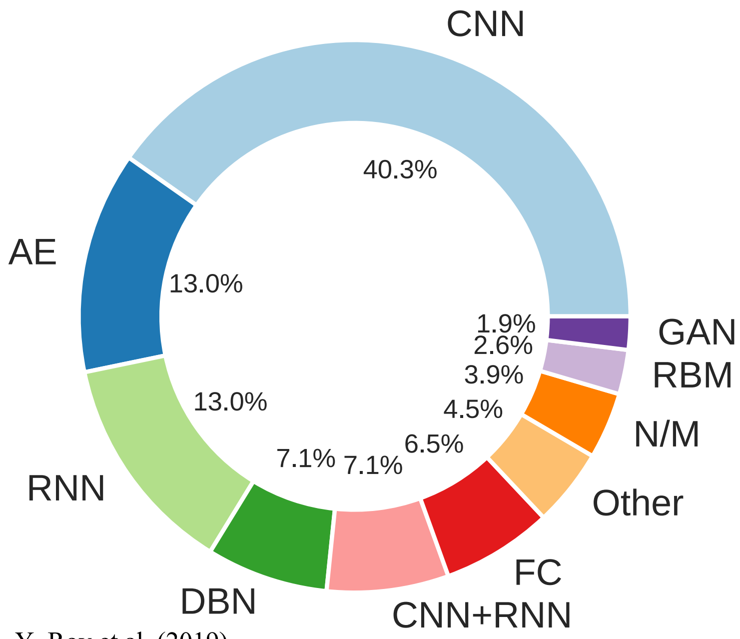
Deep neural networks for EEG



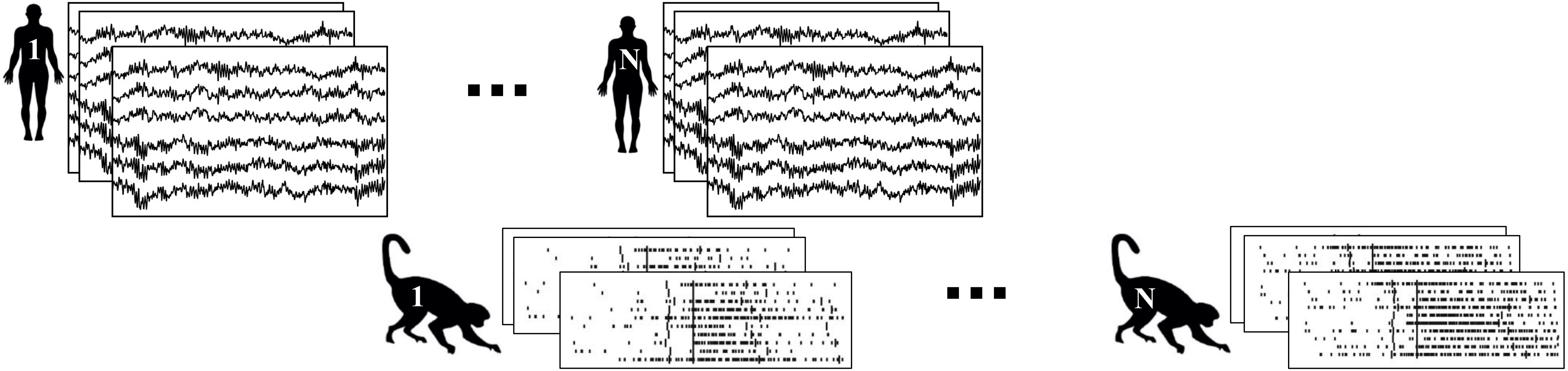
Y. Roy et al. (2019)

Why CNNs among other deep learning solutions?

- Good ratio decoding performance/number of trainable parameters
- More interpretable

EEG decoding via convolutional neural networks

...repeated trials recorded on many subjects/animals



D. Borra (2022)

How networks can be trained on neural time series?

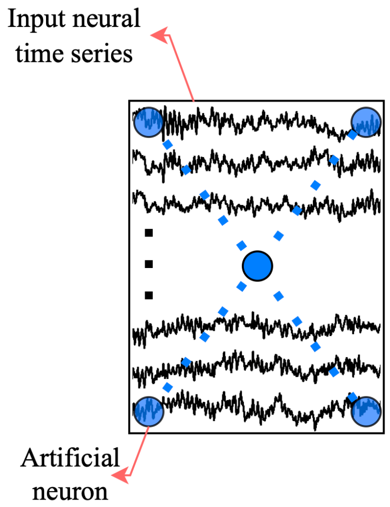
Two main training strategies:

- *Within-subject*: training and testing with within-subject data (e.g., *leave-one-session-out*, where a ‘session’ is an EEG recording session)
- *Leave-one-subject-out*: training with cross-subject data, testing on held out subject

EEG decoding via convolutional neural networks

Typical neural network structure

Input layer



→ **Input layer**: multi-variate neural activity

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EEG decoding via convolutional neural networks

Typical neural network structure

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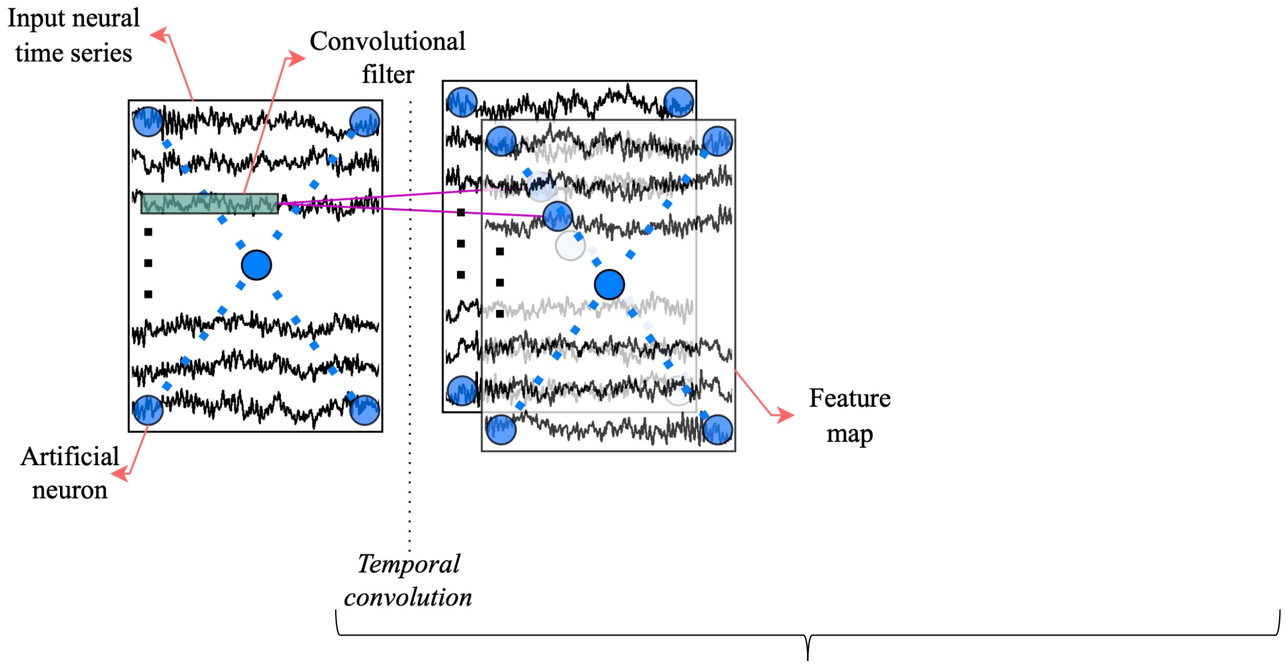

D. Borra (2022)

Hidden layers

→ **Input layer**: multi-variate neural activity

→ **Hidden layers**:

1. *Temporal convolution*: learns how to filter (via a bank of trainable filters) the input channels

EEG decoding via convolutional neural networks

Typical neural network structure

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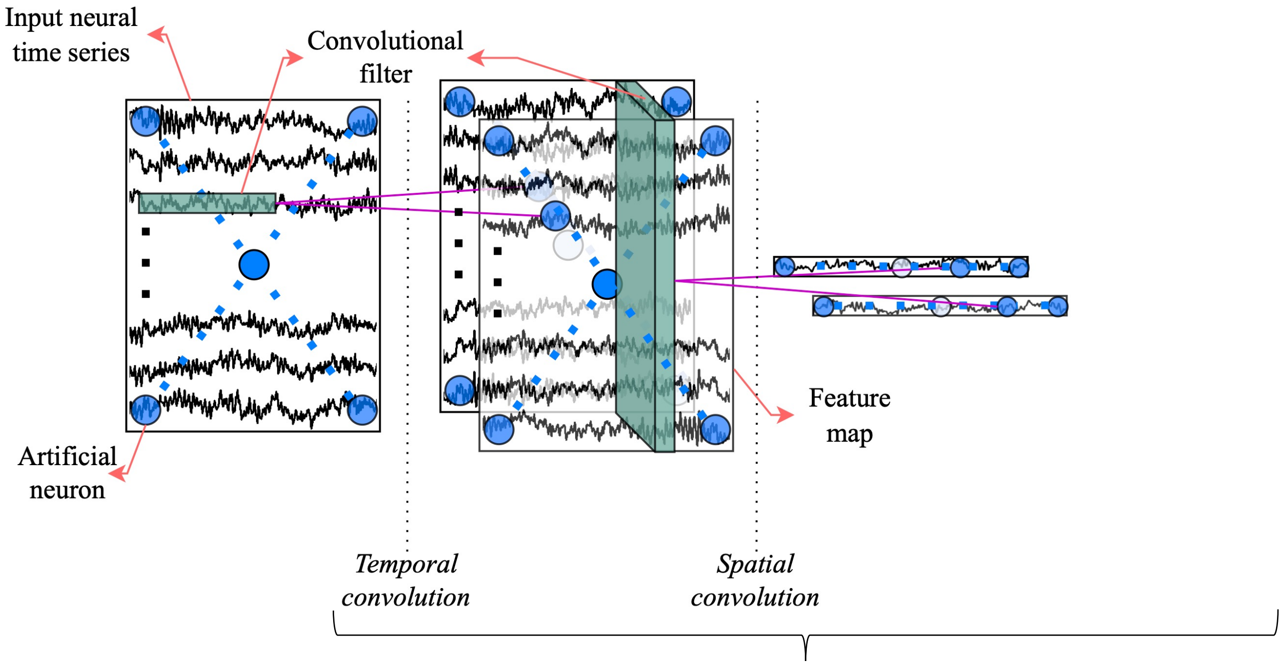

D. Borra (2022)

Hidden layers

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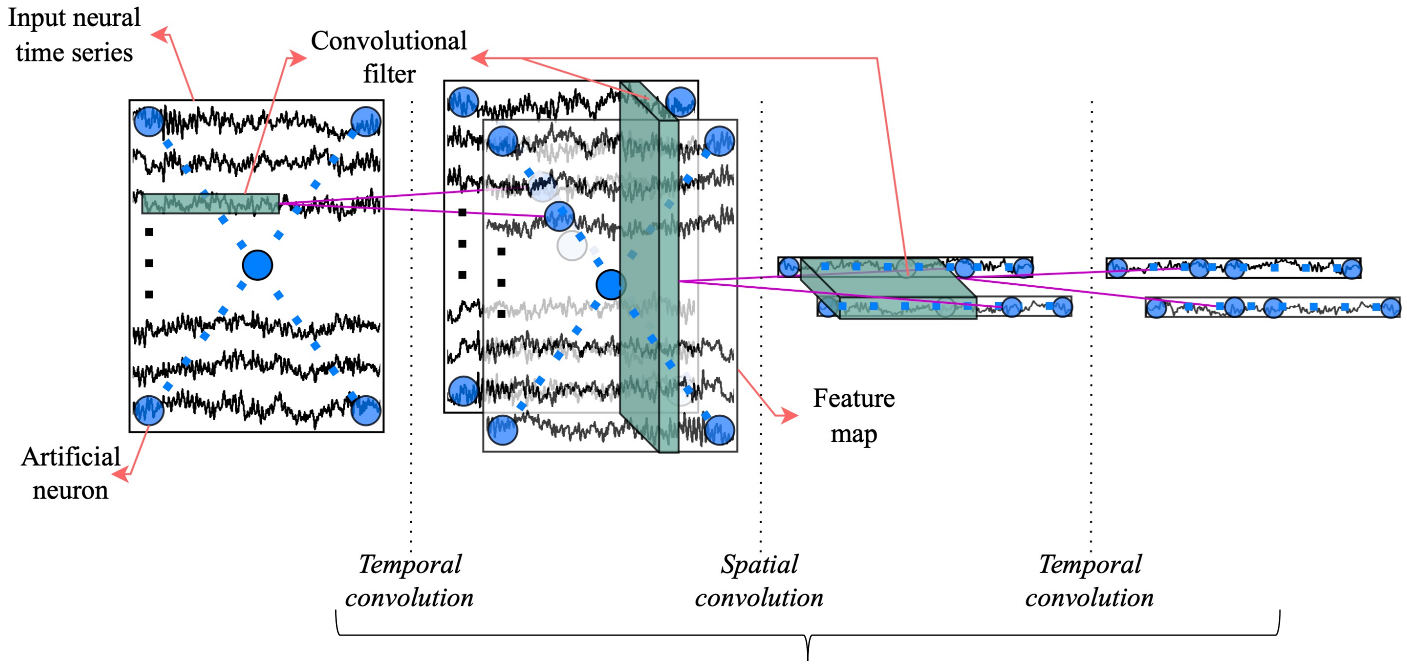
EEG decoding via convolutional neural networks

Typical neural network structure

Input layer



D. Borra (2022)

Hidden layers

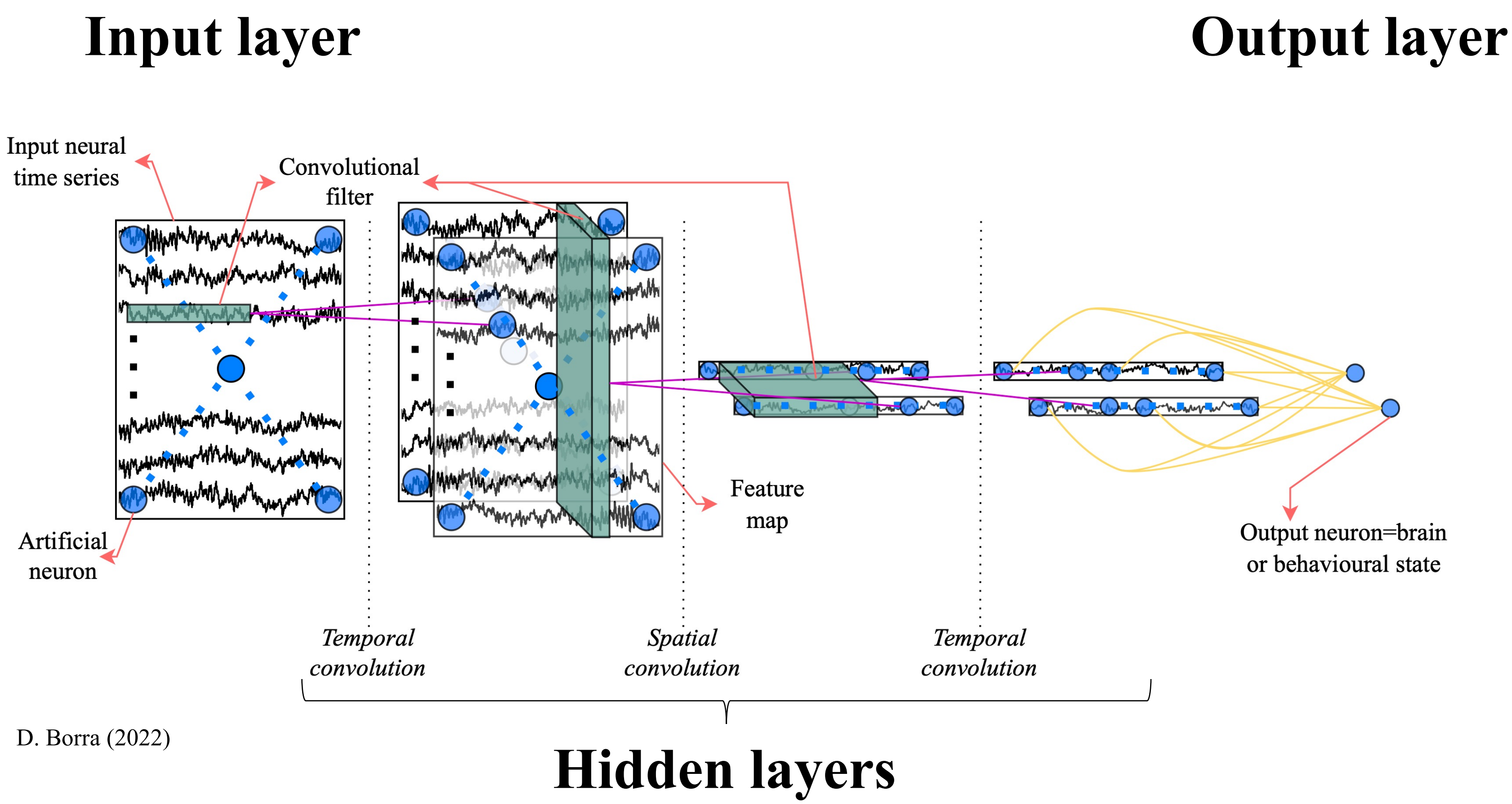
→ **Input layer**: multi-variate neural activity

→ **Hidden layers**:

1. *Temporal convolution*: learns how to <u>filter</u> (via a bank of trainable filters) <u>the input channels</u>
2. *Spatial convolution*: learns the <u>optimal combinations of channels</u> from the filtered versions of the input
3. *Deep temporal convolutions*: learn how to further <u>recombine the information in the temporal domain</u>

EEG decoding via convolutional neural networks

Typical neural network structure



D. Borra (2022)

→ **Input layer**: multi-variate neural activity

→ **Hidden layers**:

1. *Temporal convolution*: learns how to <u>filter</u> (via a bank of trainable filters) <u>the input channels</u>
2. *Spatial convolution*: learns the <u>optimal combinations of channels</u> from the filtered versions of the input
3. *Deep temporal convolutions*: learn how to further <u>recombine the information in the temporal domain</u>

→ **Output layer**: finalize decoding from the extracted feature maps

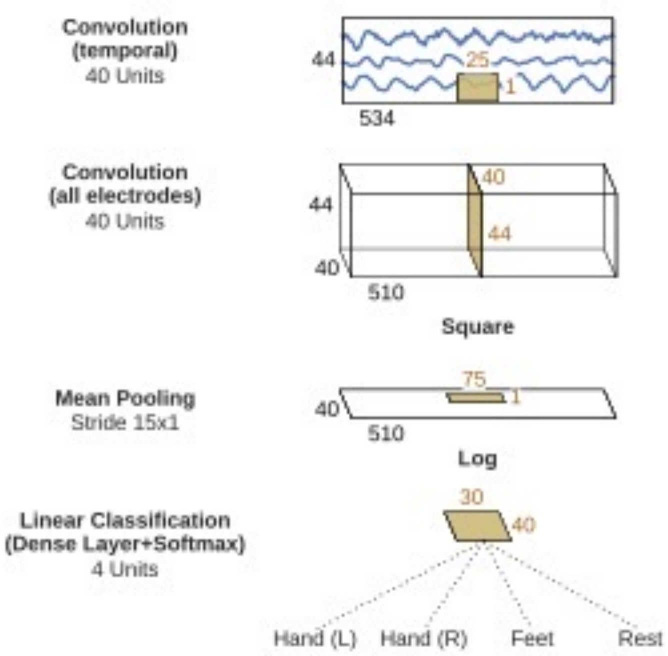
EEG decoding via convolutional neural networks

State-of-the-art CNNs

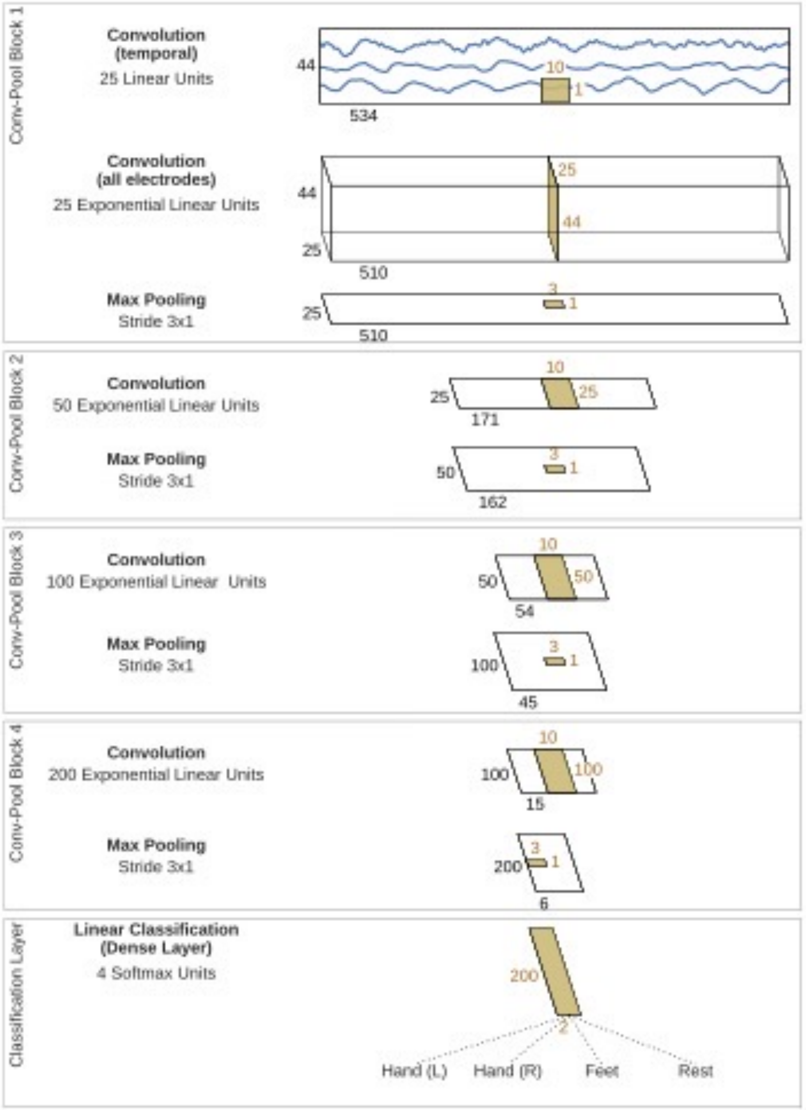
<u>ShallowConvNet and DeepConvNet (R. T. Shirrmeister et al. 2017)</u>

- Among the first successful CNNs proposed for EEG decoding in mot imagery tasks (not general-purpose networks)
- Shallow variant (ShallowConvNet)
  - ➢ 2 convolutional layers
  - ➢ 1 fully-connected output layer
- Deep variant (DeepConvNet):
  - ➢ 5 convolutional layers
  - ➢ 1 fully-connected output layer

* It forces the extraction of power-related features from the time series (constrain)



R. T. Shirrmeister et al. (2017)



R. T. Shirrmeister et al. (2017)

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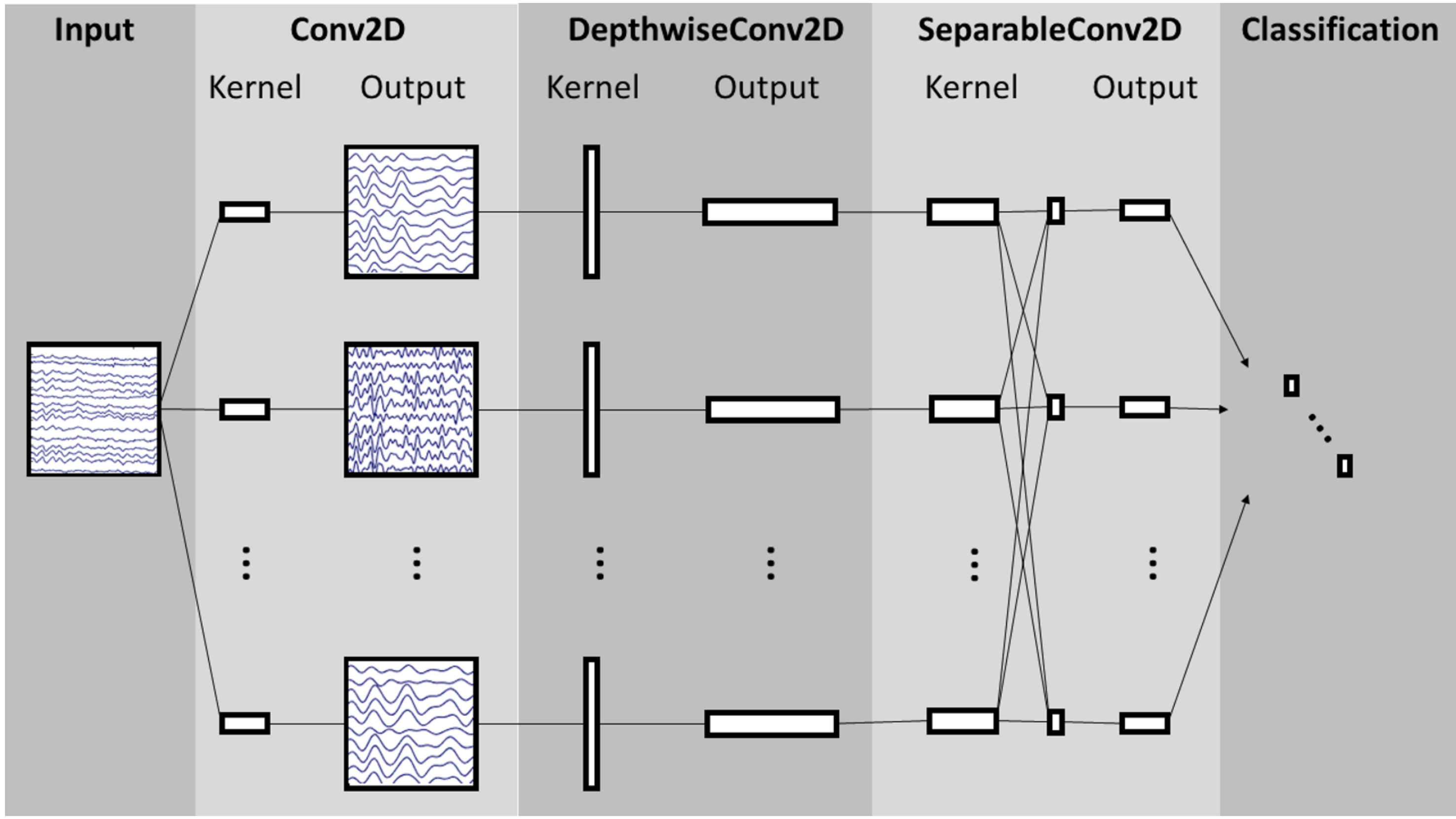
State-of-the-art CNNs

EEGNet (V. J. Lawhern et al. 2018)

- 3 convolutional layers
- 1 fully-connected output layer



V. J. Lawhern et al. (2017)

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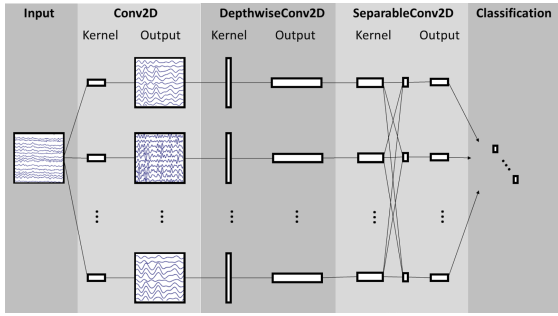
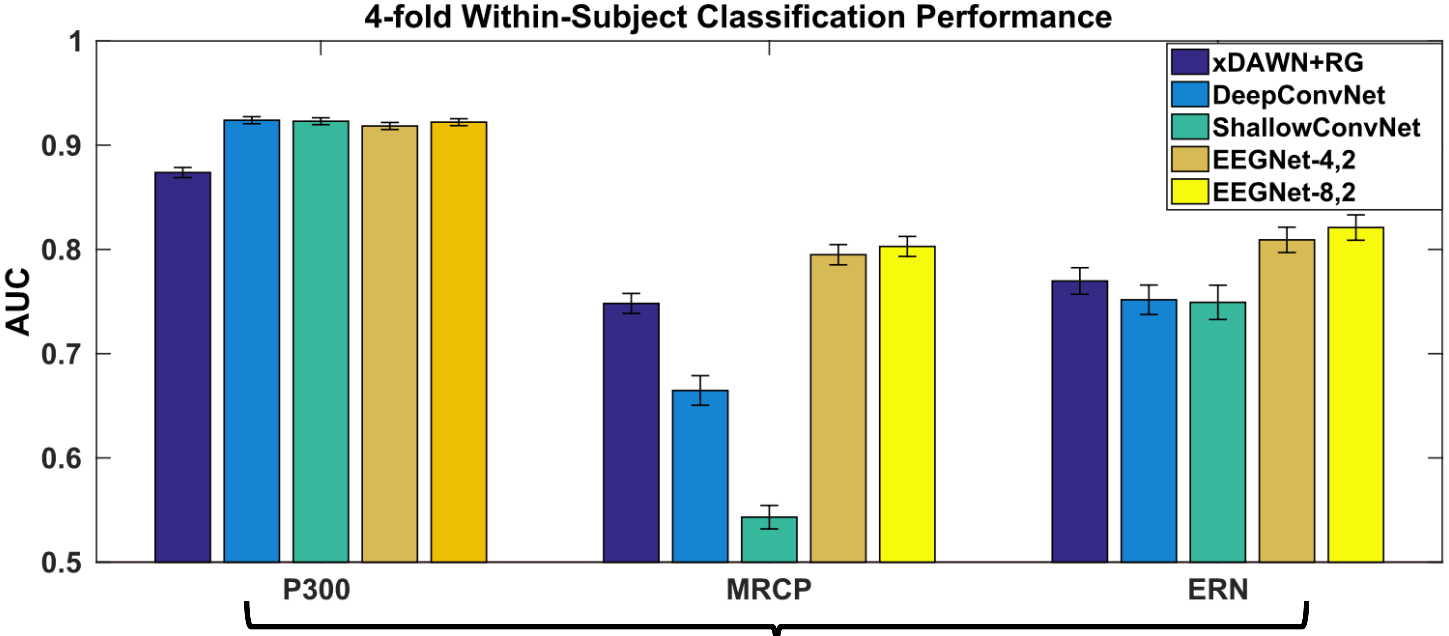


EEGNet (V. J. Lawhern et al. 2018)

- 3 convolutional layers
- 1 fully-connected output layer

- State-of-the-art performance on a variety of EEG decoding tasks (e.g., motor imagery decoding)
- Architectures inspired from EEGNet won international competitions for P300 and SSVEP decoding (Simões et al. (2020), An et al. (2022)).



V. J. Lawhern et al. (2017)

Different EEG decoding tasks (cognitive and motor decoding tasks)

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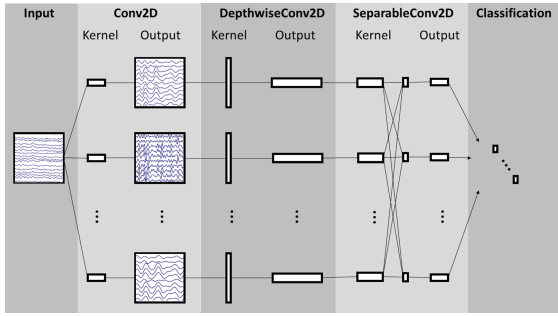
State-of-the-art CNNs

EEGNet (V. J. Lawhern et al. 2018)



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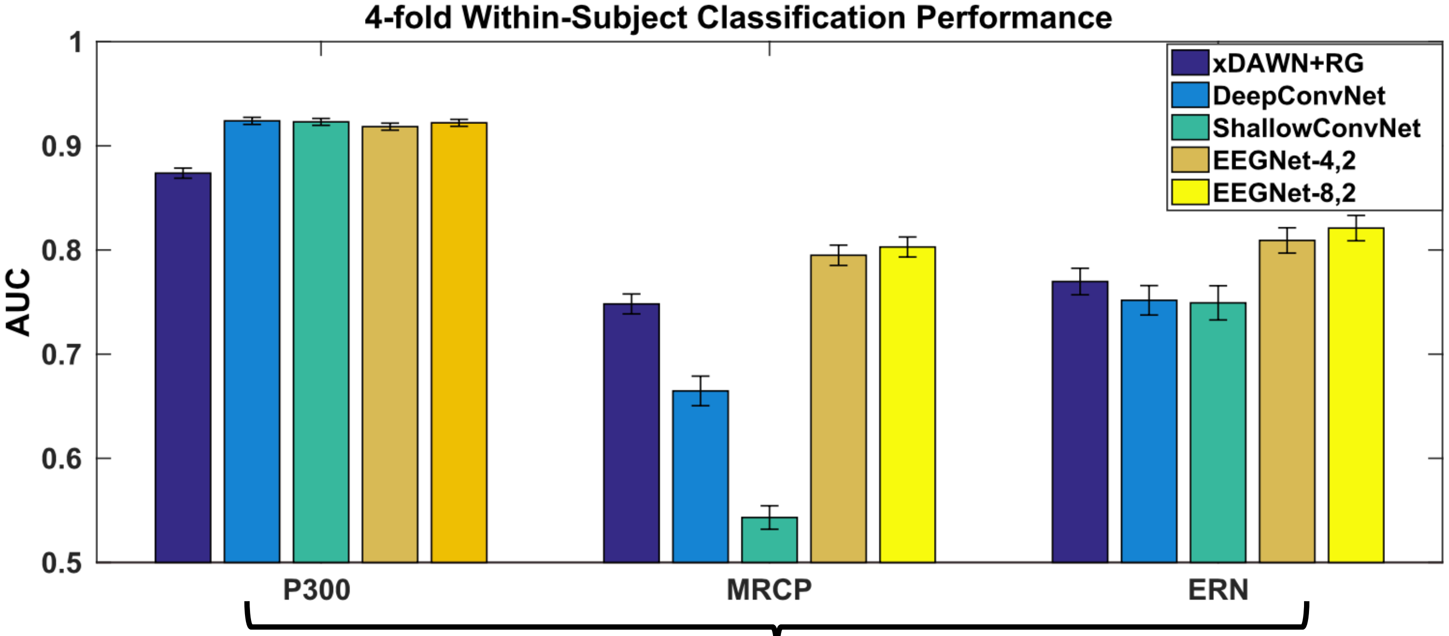
- Widely used as base architecture for designing novel CNNs for EEG



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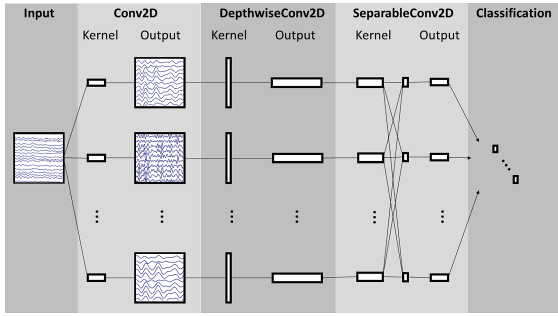
State-of-the-art CNNs



EEGNet (V. J. Lawhern et al. 2018)

- IFMBE Scientific Challenge won by an adaptation of EEGNet for decoding P300 neural response for a BCI aimed at improving social skills in autistic patients (Borra et al., 2019)
- Patients used the BCI in a virtual reality environment for improving social attention

- > +8% accuracy improvement compared to other CNNs / deep neural networks (RNNs)
- > +10% accuracy improvement compared to other machine learning approaches

M. Simões, D. Borra et al. (2020)

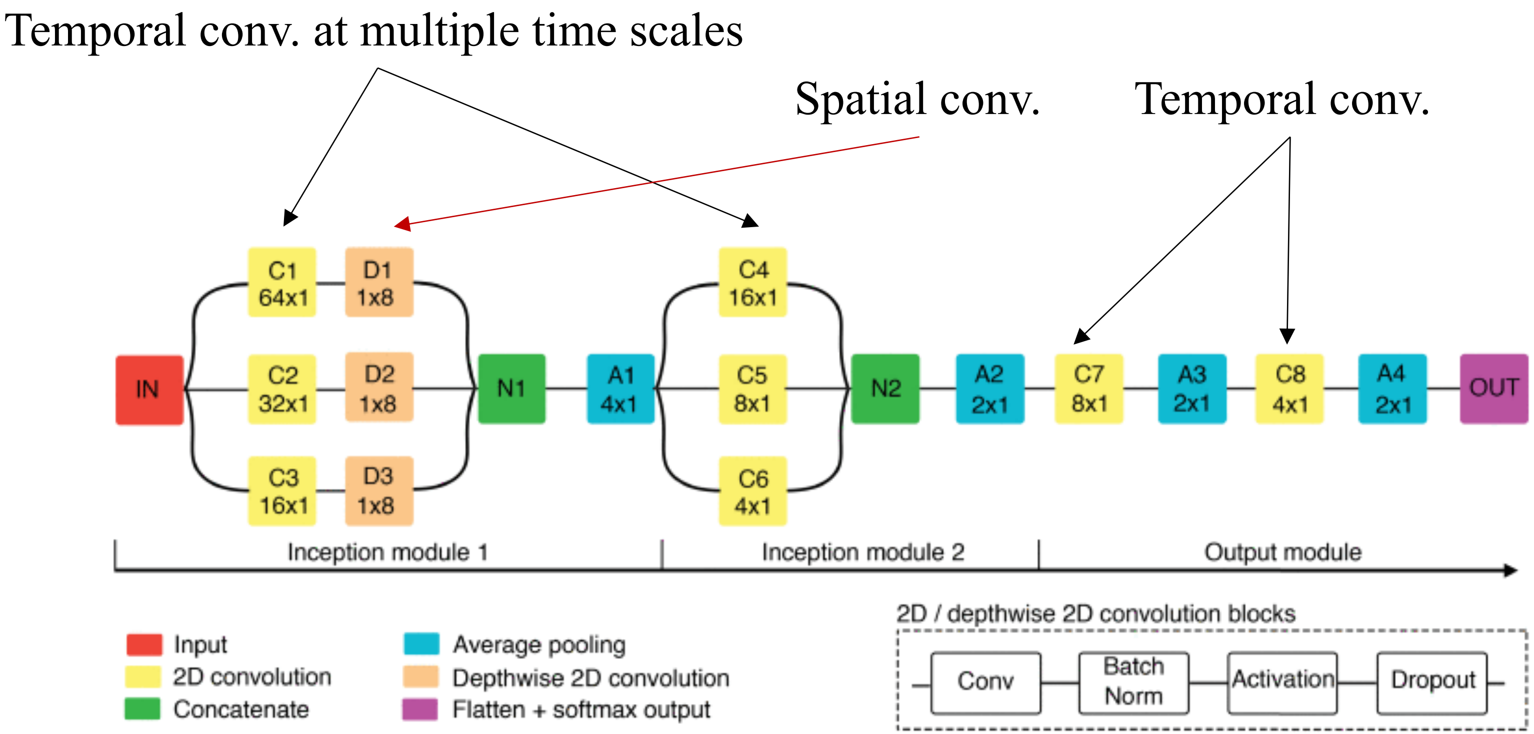
EEG decoding via convolutional neural networks

State-of-the-art CNNs

<u>EEG-Inception (E. Santamaría-Vazquez et al. 2020)</u>

- 11 convolutional layers
- 1 fully-connected output layer

- Example of useful cross-contamination from other domains (Inception modules in CNNs for image processing)
- Learning temporal features at multiple time scales via Inception modules
- Improvement of 5.1% in P300 decoding



E. Santamaría-Vázquez et al. (2020)

EEG decoding via convolutional neural networks

How to properly benchmark deep neural networks for EEG?

… EEG studies benchmark new decoding pipelines (e.g., new networks) :

- using different experimental protocols (e.g., using or not hyperparameter tuning, differing in the parameters set for hyperparameter tuning, etc.)
- using private datasets (50% studies in a recent review, see Roy et al. 2019)
- without sharing codes with the community (only <15% share codes, see Roy et al. 2019)

→ Lack in **reproducibility**, **reliability** and **robustness** of performance validation of existing solutions

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- Comprehensive and standardized protocol

Proposes a standardized experimental protocol including a comprehensive hyperparameter tuning

- Public datasets

Relies on MOABB, that provides public EEG datasets under a single Python package

http://moabb.neurotechx.com/docs/index.html

- Open source
- Decoding pipeline easy to define and share

SpeechBrain MOABB

https://github.com/speechbrain/benchmarks/tree/main/benchmarks/MOABB

THANK YOU FOR YOUR ATTENTION

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The speaker Davide Borra declares no conflict of interest