# Using neural networks to decode EEG and read your thoughts

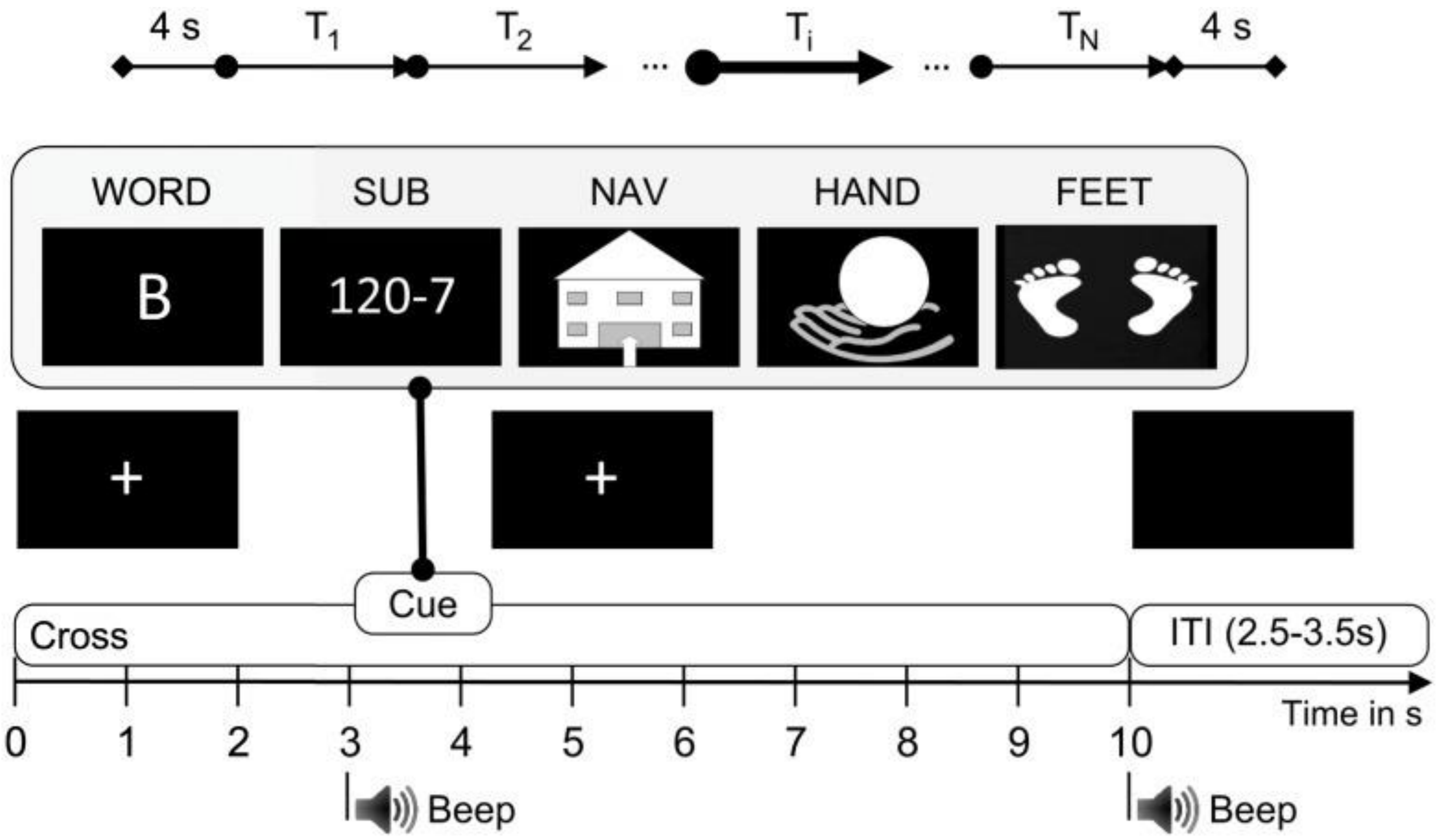
BUILDING A YES/NO CLASSIFIER TO HELP PEOPLE WITH CENTRAL NERVOUS SYSTEM INJURIES COMMUNICATE

# We are seeking to replicate and improve on the results of a recent scientific study

- The original study sought to **create the best yes/no binary predictor for nine participants with spinal cord injuries or major strokes**.
  - Each participant came for two sessions several days apart
  - At each session they wore an array of thirty EEG electrodes and were asked to think about five different mental tasks forty times per task, for a total of 200 trials per session.
- And most importantly for our purposes – **they released the raw data** so we can use it to try and replicate and improve on their results

Can we build a model to accurately differentiate between two of those five trial types?

# Details of the original study

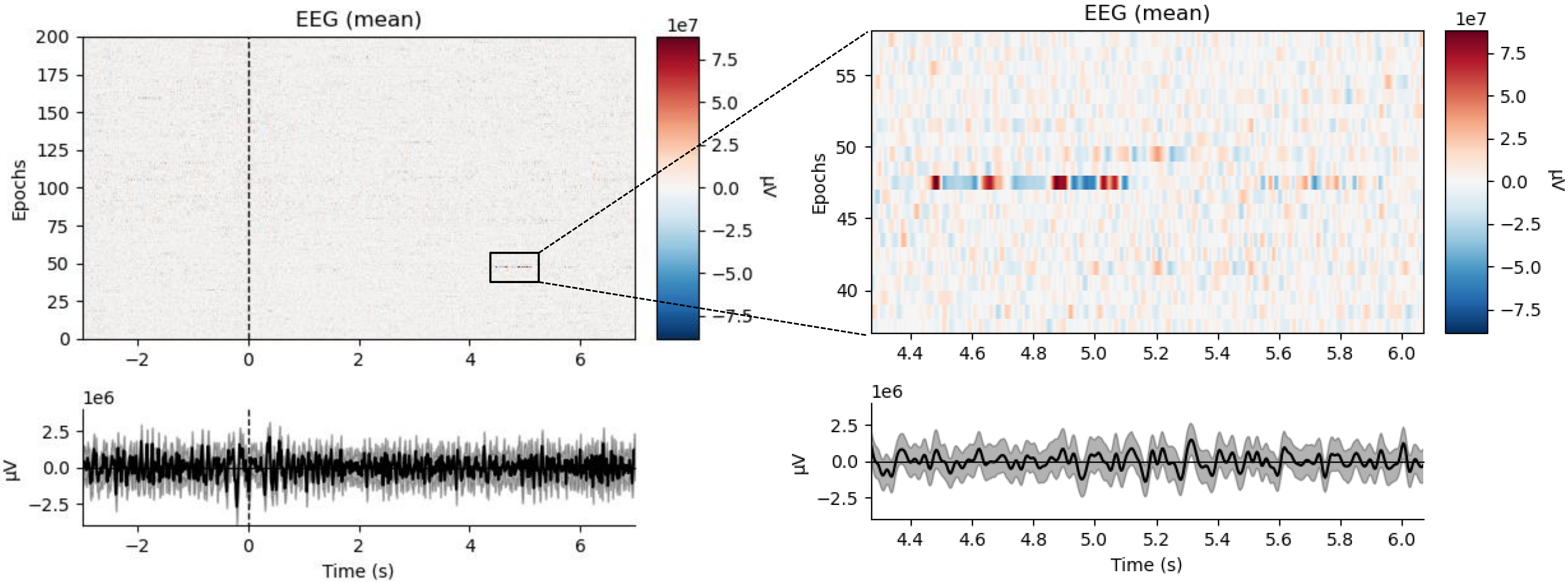



Source: Reinhold Scherer, Josef Faller, Elisabeth V. C. Friedrich, Eloy Opisso, Ursula Costa, Andrea Kübler, and Gernot R. Müller-Putz: *Individually Adapted Imagery Improves Brain-Computer Interface Performance in End-Users with Disability*

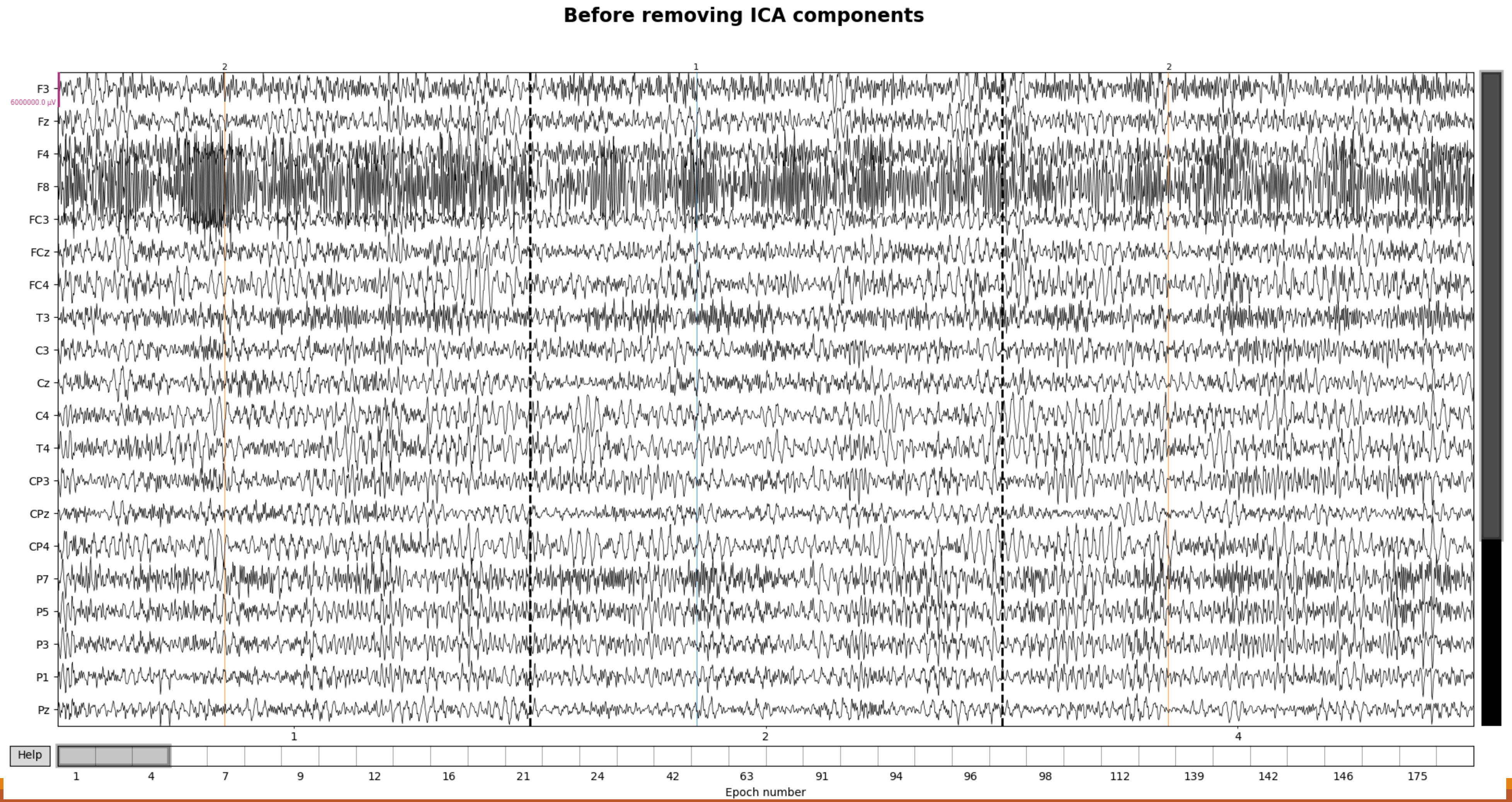
# A number of signal processing methods were tried to improve signal quality

1. **Frequency filtering** (low pass and high pass filters)
    1. Fourier transformations are very cool
    2. Helped some, but not as much as I would have liked
2. Use **signal-space projections (SSP)** and **independent component analysis (ICA)**
    1. Essentially methods for reducing dimensionality of data
    2. Signal space projectors were fairly impactful
3. **Baseline correction** (subtract mean reading for each channel in pre-stimulus period from all signals in each trial)
    1. Unsurprisingly didn't help a bit
4. **Decimate data** (e.g., take every $2^{nd}$, $4^{th}$, and $8^{th}$ samples)
    1. Helped some models, hurt others
5. **Drop trials** based on peak-to-peak amplitude or lack of peak to trough amplitude
    1. Certainly helpful, but was not able to be programmatic about choices. Room for a custom tool or new tool within MNE built on top of scipy here.
6. **Common Spatial Patterns (CSP)** to reduce dimensionality of data
    1. By far the most impactful transformation that I tested

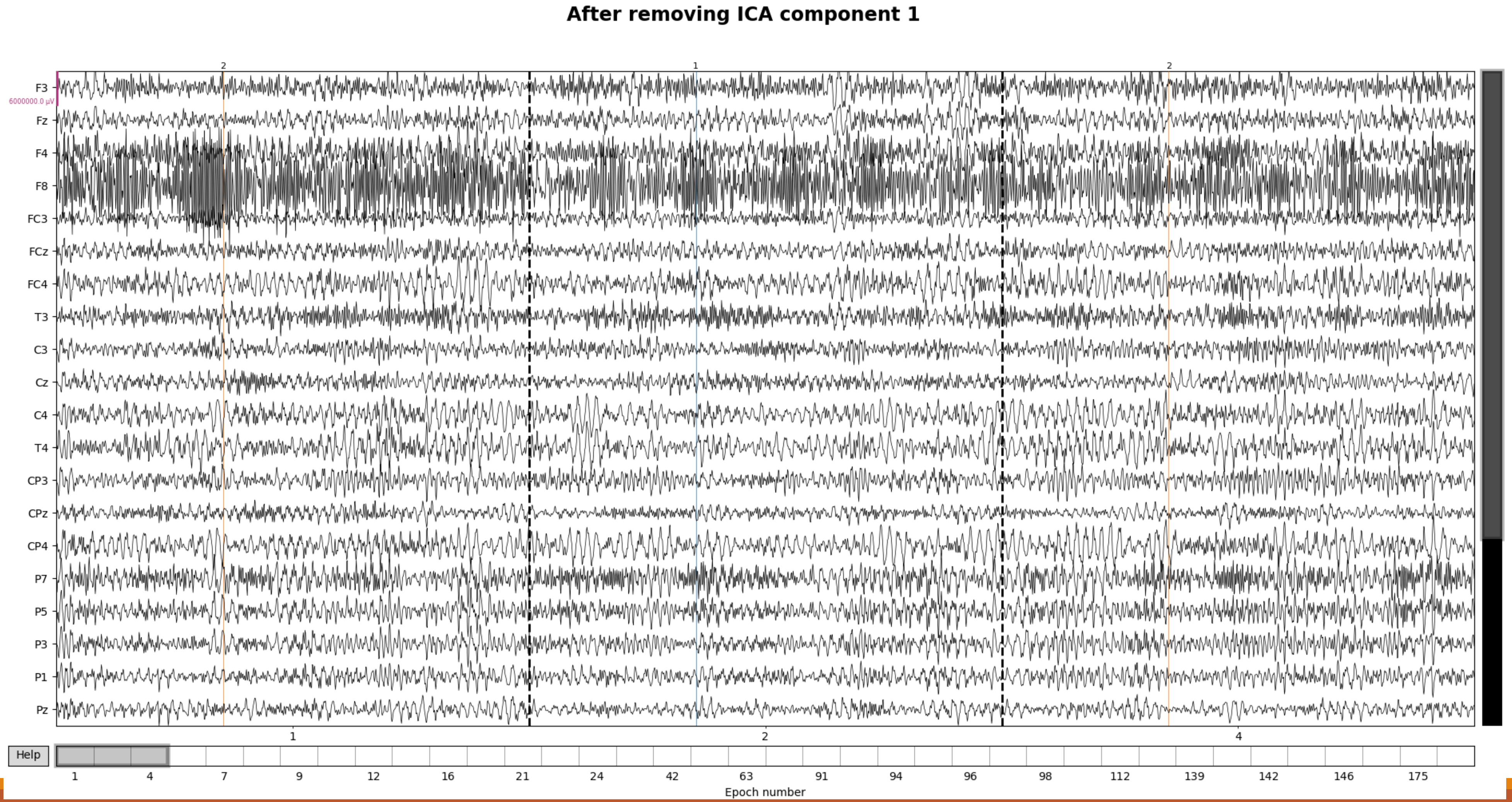
# Dropping trials, visualized



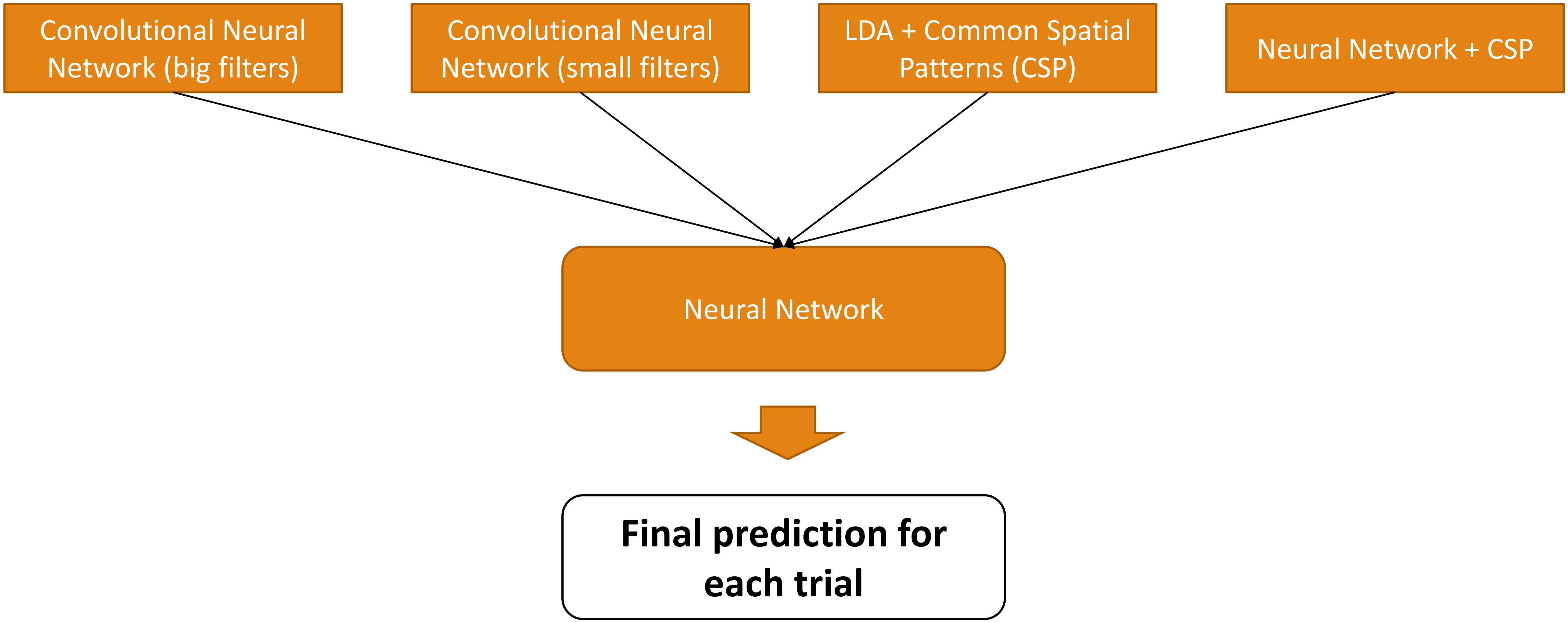
# ICA visualized (1 of 2)



# ICA visualized (1 of 2)



# I combined several different kinds of models to try and solve the problem



# The original study achieved 80% average accuracy across the nine subjects

| Mental task pairs | E | | F | | J | | G | | L | | H | | C | | D | | A | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Participant | TPR | TNR | TPR | TNR | TPR | TNR | TPR | TNR | TPR | TNR | TPR | TNR | TPR | TNR | TPR | TNR | TPR | TNR | *md (n)* |
| WORD vs. HAND | 90 | 78 | 97 | 88 | 75 | 89 | 70 | 81 | 89 | 79 | 79 | 76 | 59 | 79 | 82 | 88 | 89 | 36 | 82 (7) |
| SUB vs. HAND | 76 | 83 | 70 | 82 | 81 | 89 | 70 | 77 | 69 | 97 | 90 | 55 | 48 | 79 | 61 | 82 | 72 | 91 | 76 (8) |
| SUB vs. FEET | 84 | 89 | 91 | 63 | 87 | 63 | 70 | 84 | 56 | 84 | 60 | 71 | 81 | 85 | 85 | 52 | 88 | 58 | 74 (6) |
| WORD vs. FEET | 87 | 100 | 88 | 66 | 75 | 73 | 87 | 55 | 96 | 88 | 64 | 71 | 77 | 85 | 91 | 52 | 68 | 68 | 74 (5) |
| WORD vs. NAV | 80 | 68 | 71 | 74 | 94 | 57 | 60 | 88 | 59 | 63 | 79 | 83 | 64 | 81 | 82 | 91 | 89 | 37 | 72 (7) |
| NAV vs. HAND | 68 | 87 | 55 | 94 | 68 | 70 | 84 | 65 | 73 | 72 | 69 | 72 | 67 | 71 | 84 | 73 | 67 | 61 | 72 (6) |
| NAV vs. FEET | 86 | 84 | 77 | 63 | 57 | 70 | 81 | 52 | 70 | 91 | 69 | 74 | 62 | 85 | 66 | 77 | 57 | 87 | 71 (6) |
| SUB vs. NAV | 64 | 73 | 82 | 65 | 68 | 68 | 58 | 84 | 78 | 53 | 67 | 83 | 67 | 71 | 58 | 81 | 78 | 67 | 69 (3) |
| WORD vs. SUB | 63 | 92 | 79 | 79 | 78 | 68 | 50 | 73 | 70 | 63 | 68 | 67 | 73 | 56 | 82 | 58 | 64 | 84 | 69 (4) |
| HAND vs. FEET | 70 | 68 | 70 | 66 | 56 | 80 | 74 | 65 | 48 | 84 | 62 | 74 | 63 | 80 | 48 | 87 | 79 | 52 | 68 (1) |

□ TP(N)R < 70 ▒ 70 ≥ TP(N)R < 80 ■ TP(N)R ≥ 80

Source: Reinhold Scherer, Josef Faller, Elisabeth V. C. Friedrich, Eloy Opisso, Ursula Costa, Andrea Kübler, and Gernot R. Müller-Putz: *Individually Adapted Imagery Improves Brain-Computer Interface Performance in End-Users with Disability*

# Unfortunately I wasn't able to match that accuracy on session 2 data

| Subject | A | | C | | D | | E | | F | | G | | H | | J | | L | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| % Acc. (TPR, TNR) | 87 | 10 | 48 | 85 | 0 | 100 | 0 | 100 | 73 | 27 | 100 | 0 | 88 | 6 | 97 | 49 | 54 | 36 |

Extremely **unbalanced positive vs negative accuracy** rates show the model has not successfully adapted to the shift to session 2.

**Overall average accuracy is only 55%**

# Next steps

1. Utilize a **Reiman geometry** method
    1. Supposed to outperform CSP on EEG problems
2. Implement a **rebiasing** method
    1. Essentially using the first few trials of session 2 to adjust the models to the shifted EEG patterns
3. Make **CNN models more generalizable**
    1. Resample the data (e.g., instead of looking at data from 0 - 5 seconds, create three sections of data 0 – 3 1 – 4 2 - 5)
4. Rerun analysis with **fewer dropped channels**
    1. The key to success here is more data – I should drop as little as possible