Using neural networks to decode EEG and read your thoughts

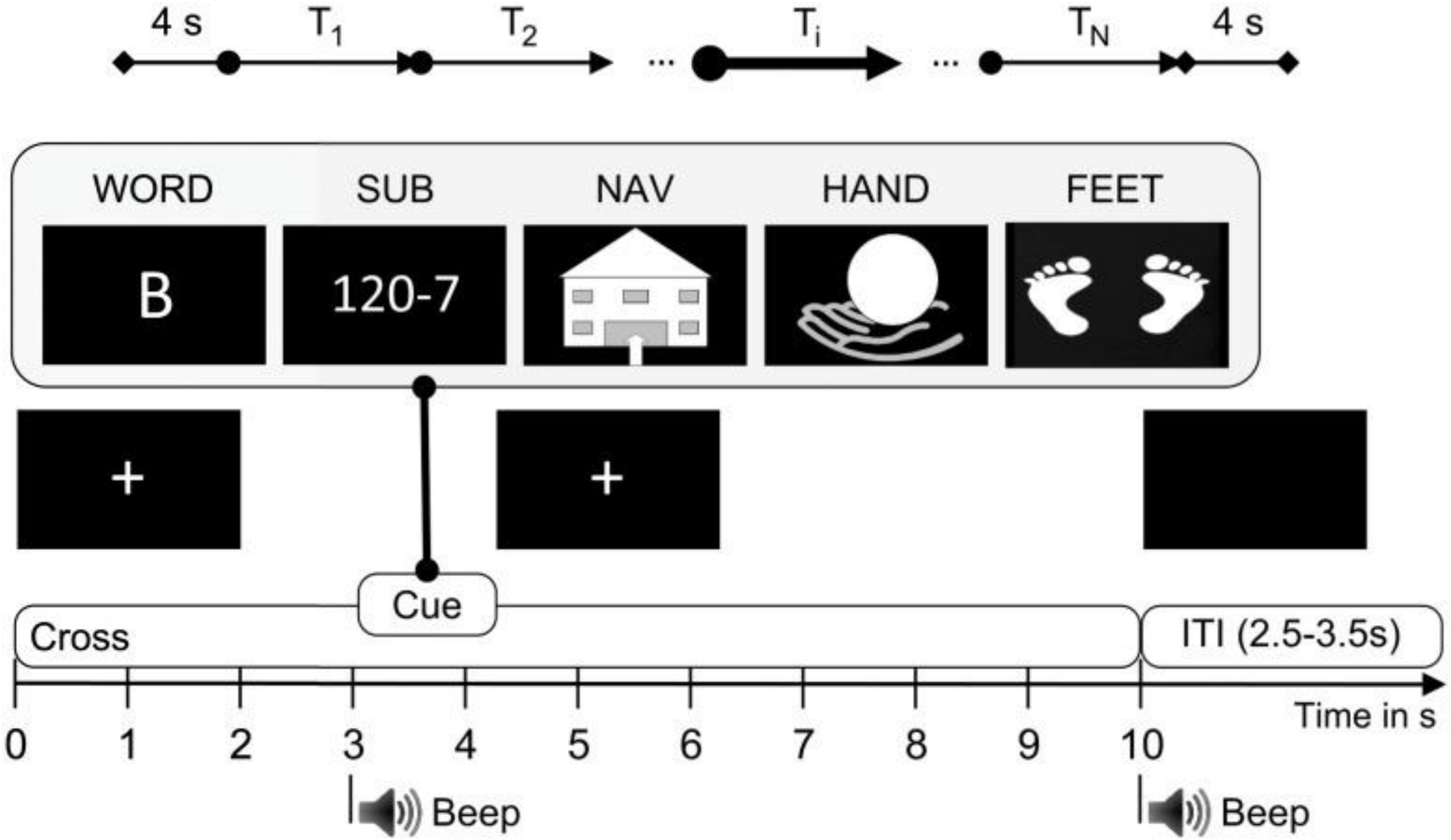
BUILDING A YES/NO CLASSIFIER TO HELP PEOPLE WITH CENTRAL NERVOUS SYSTEM INJURIES COMMUNICATE

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 most importantly for our purposes – **they released the raw data** so we can use it to try and replicate and improve on their results

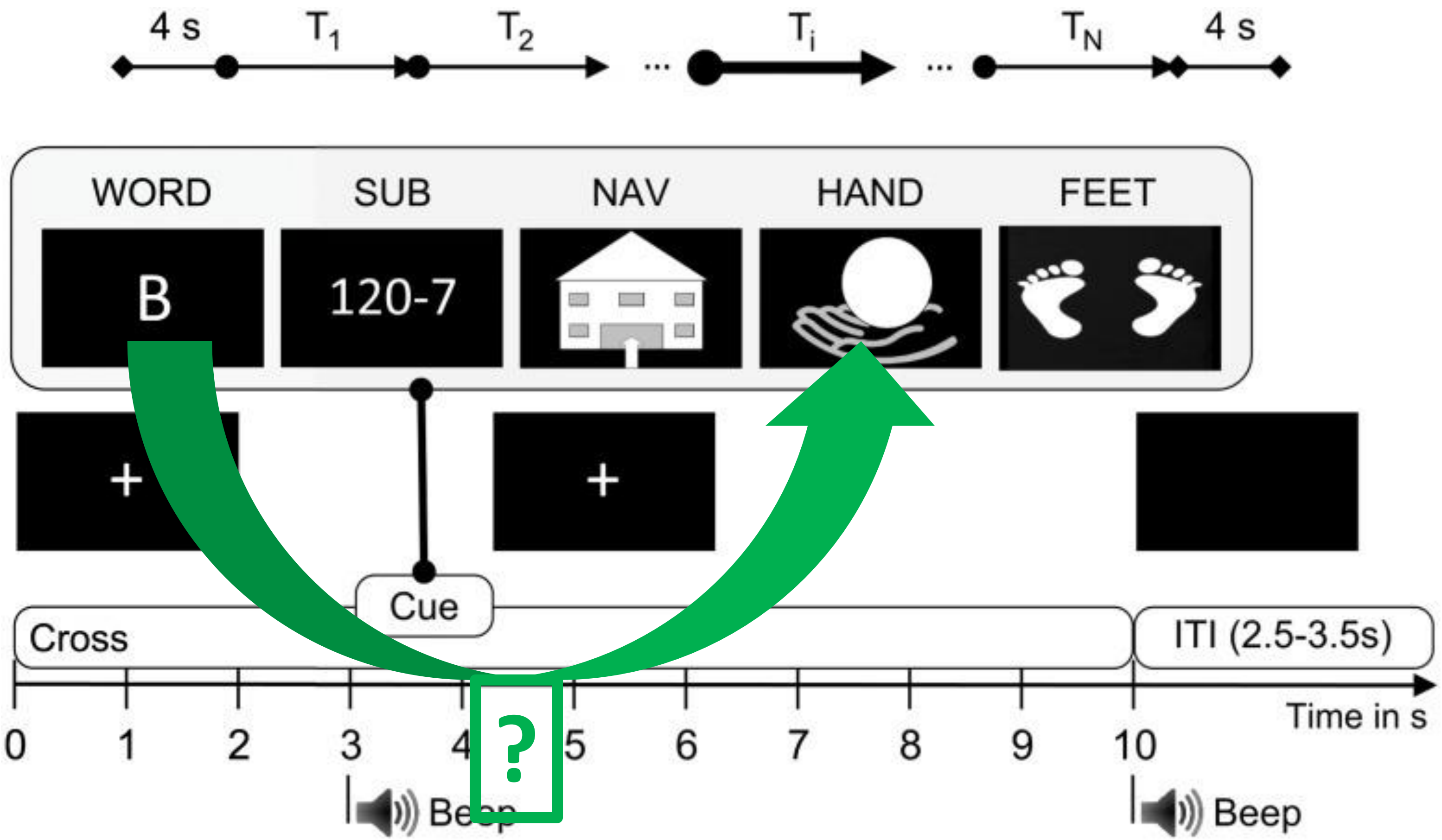
Can we build a model to accurately differentiate between two of those five trial types?

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*

Finding a yes/no predictor against 50% baseline accuracy



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200 trials conducted each day, 80 data points in each pairwise combination

Day 1	
Trial type	**Times conducted**
Word	40
Subtraction	40
Navigation	40
Hand	40
Feet	40
Total	**200**

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80 data points for each pairwise combination, split into train and test

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Day 2

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Can't look at it until testing final model

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

1. **Frequency filtering** (low pass and high pass filters)

2. Use **signal-space projections (SSP)** and **independent component analysis (ICA)**

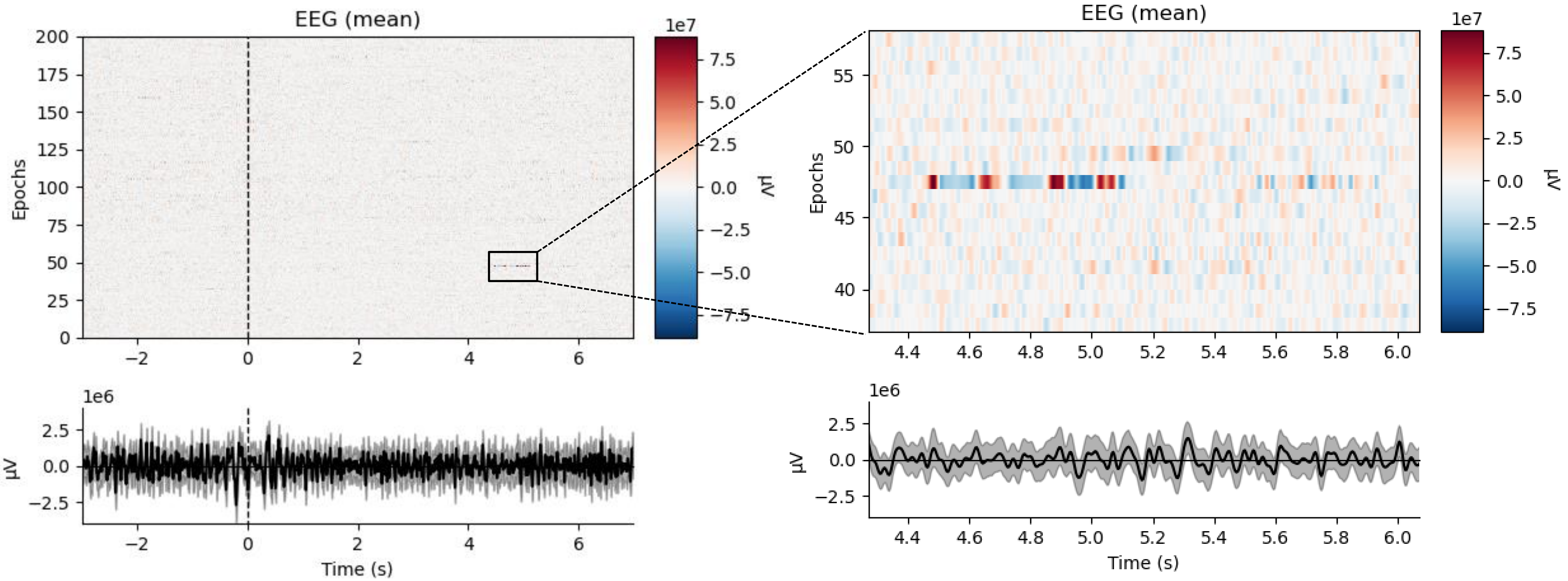
3. **Baseline correction**

4. **Decimate data** (e.g., take every 2nd, 4th, and 8th samples)

5. **Drop trials** based on peak-to-peak amplitude or lack of peak to trough amplitude

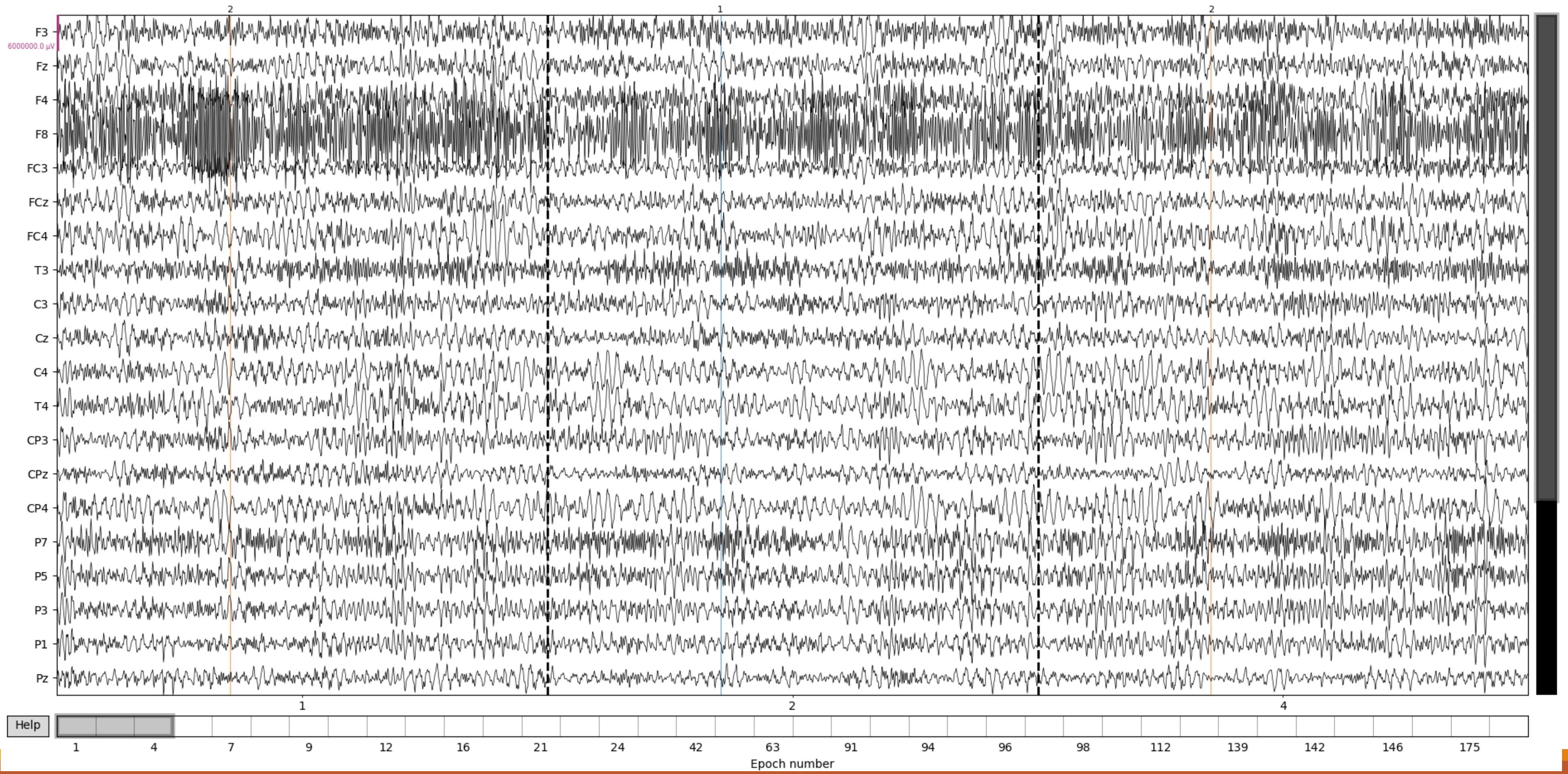
6. **Common Spatial Patterns (CSP)** to reduce dimensionality of data

Dropping trials, visualized

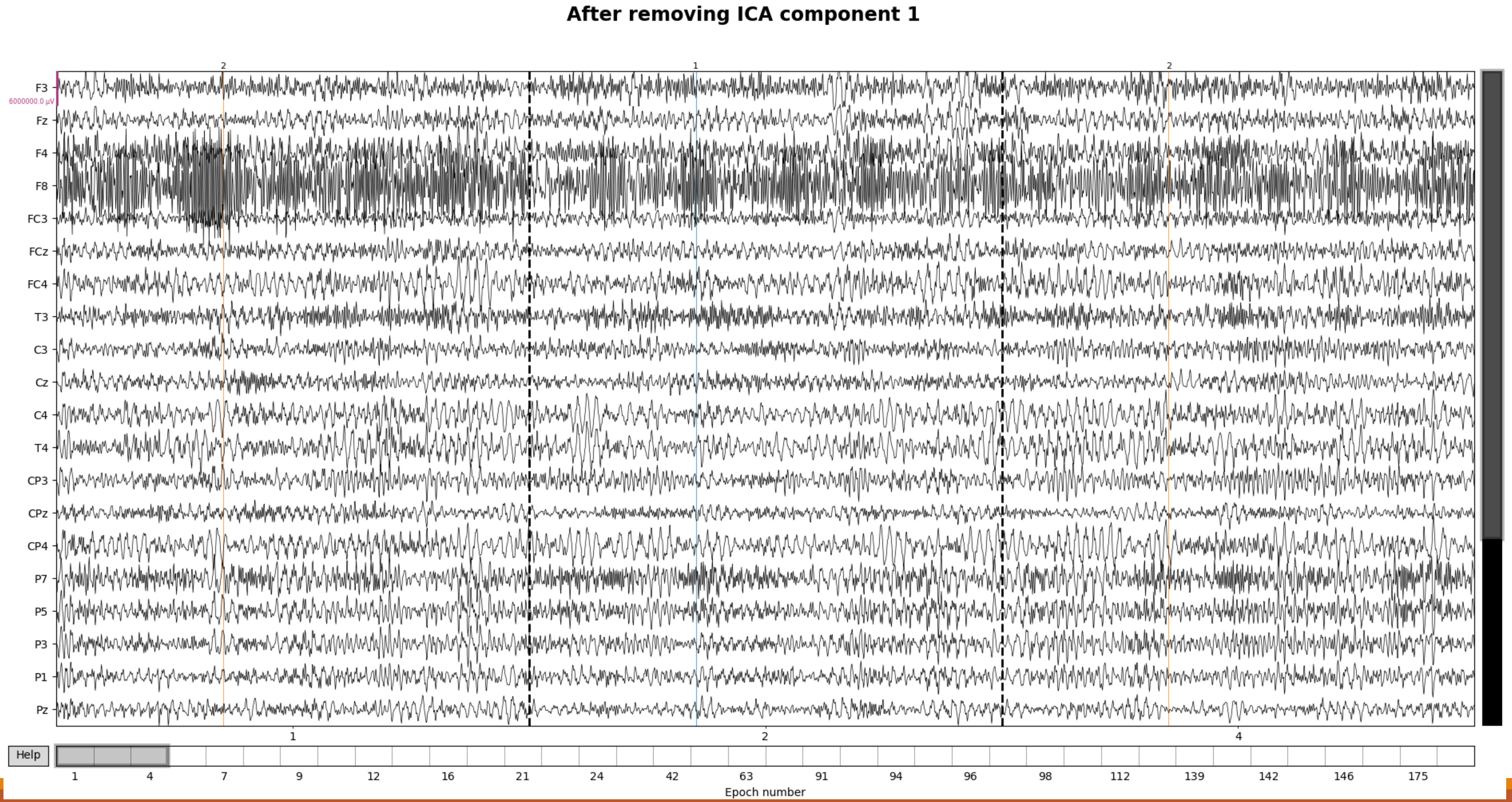


ICA visualized (1 of 2)

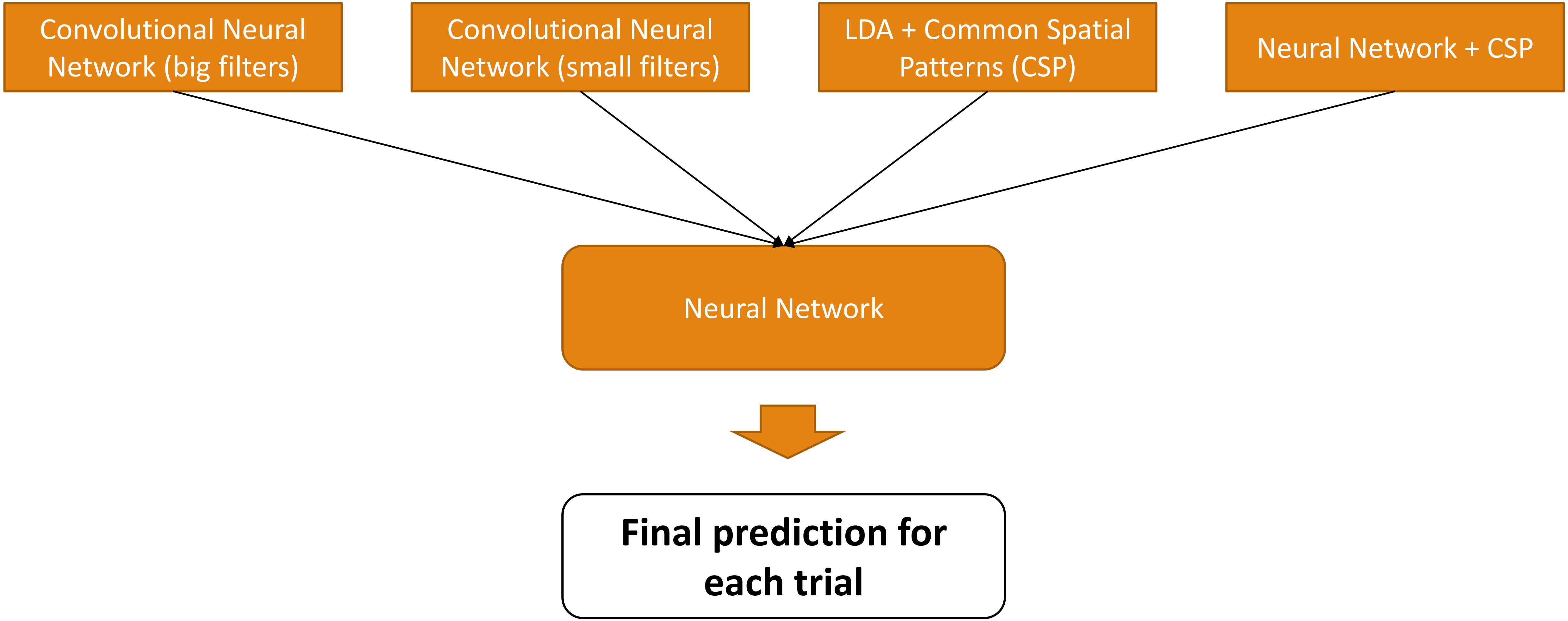
Before removing ICA components



ICA visualized (1 of 2)



I combined several methods to try and solve the problem – **unique model for each subject**



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

Mental task pairs / Participant	E TPR	E TNR	F TPR	F TNR	J TPR	J TNR	G TPR	G TNR	L TPR	L TNR	H TPR	H TNR	C TPR	C TNR	D TPR	D TNR	A TPR	A 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

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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. Use **different ensemble model** – neural network is overfitting
2. Utilize a **Reiman geometry** method for a new L1 model
    1. Supposed to outperform CSP on EEG problems
3. Implement a **rebiasing** method
    1. Essentially using the first few trials of session 2 to adjust the model to the shifted EEG patterns
4. 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)
5. Rerun analysis with **fewer dropped channels**
    1. The key to success here is more data – I should drop as little as possible