

# Localising the Seizure Onset Zone from SPES Responses Using Deep Learning

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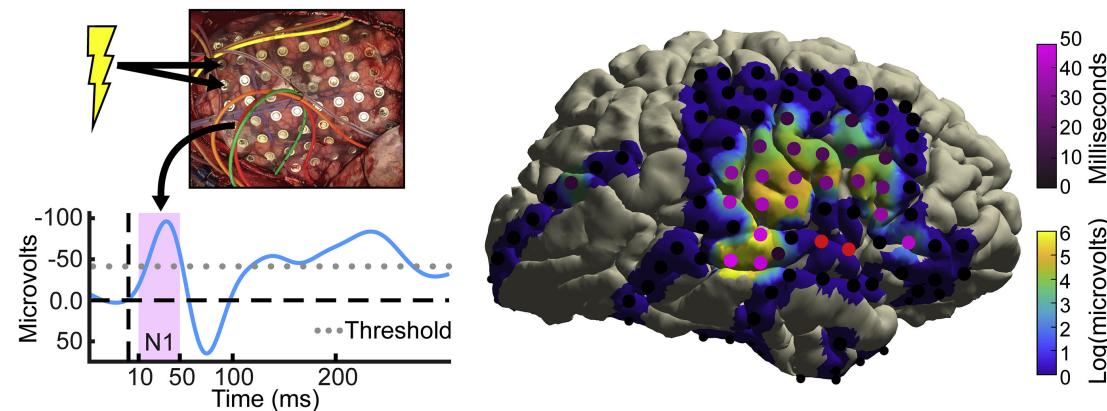


# Outline

- Single-pulse electrical stimulation (SPES)
- Existing deep learning approach for SOZ localisation
- Implementation on open-source dataset
- Modifications to existing method
- Analysis of final model

# Single pulse electrical stimulation (SPES)

- Investigational tool in epilepsy surgery (*Valentin et al., 2005*)
- Electrical stimulus applied through adjacent electrode pairs
- Frequency: typically, between 0.2 – 1 Hz
- Primarily used to 1) probe seizure networks and 2) probe epileptogenicity

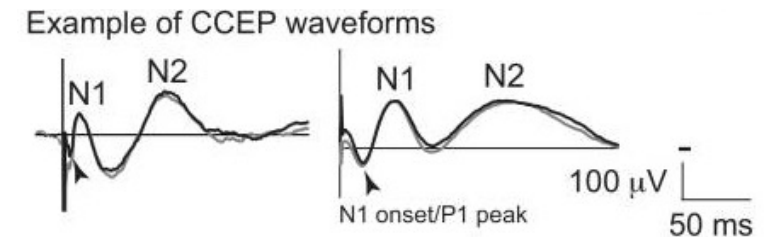


*Dynamic tractography: Integrating cortico-cortical evoked potentials and diffusion imaging. Silverstein et al. (2020)*

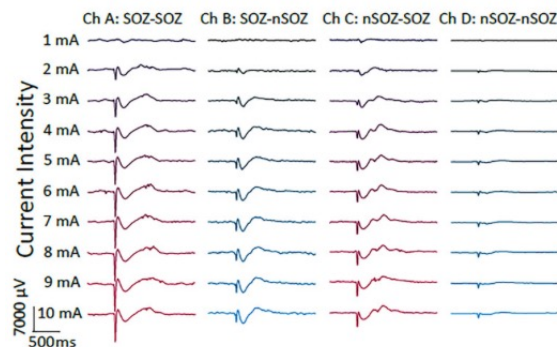
# Early Responses to SPES: Cortico-Cortical Evoked Potentials (CCEPs)

## CCEPs for probing seizure networks

- Emerge within 100ms post-stimulation
- Reflective of effective connectivity
- Consistent across trials: averaged to increase SNR



*Single pulse electrical stimulation to probe functional and pathological connectivity in epilepsy. Matsumoto et al. (2018)*

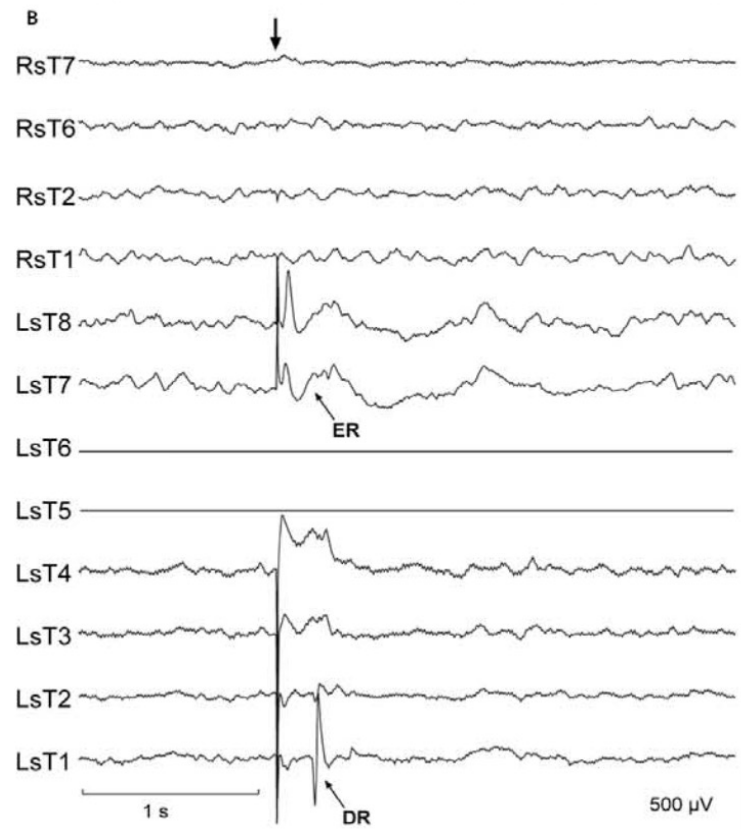


*Stimulation to probe, excite, and inhibit the epileptic brain. Frauscher et al. (2023)*

## CCEPs and epileptogenicity

- Presence not indicative of epileptogenicity
- Some differences in epileptogenic sites: e.g., N1 amplitude is generally larger

# Delayed responses to SPES



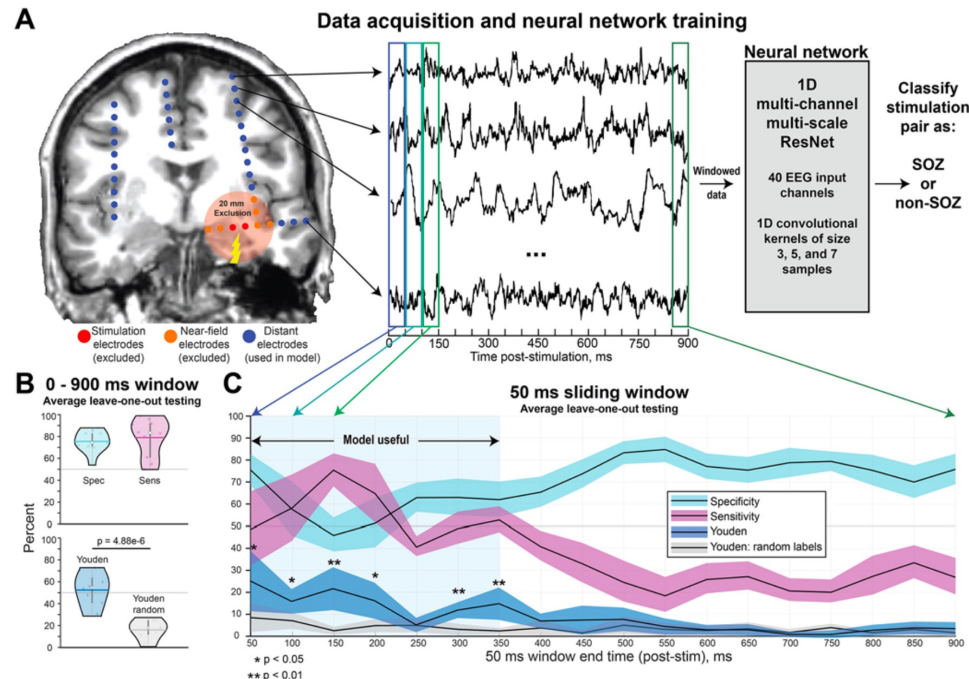
*Single pulse electrical stimulation for identification of structural abnormalities and prediction of seizure outcome after epilepsy surgery: a prospective study. Valentin et al. (2005)*

- Typically occur 100ms – 1s post-stimulation
- Occur in a subset of trials (not time-locked)
- Resemble interictal epileptiform discharges (IEDs)
- Suggestive of increased excitability and potential epileptogenicity  $\Rightarrow$  usually within SOZ
- Complementary to other methods in surgical planning

# Existing deep learning approach

## Localizing seizure onset zones in surgical epilepsy with neurostimulation deep learning

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## Patient demographics:

- Total Patients: 10 (Ages 23–51)
- Temporal lobe epilepsy

## Methodology:

- Electrode Type: S EEG
- Algorithm: Convolutional neural net (CNN)
- Validation: K-fold cross-validation
- Sensitivity: 78.1%
- Specificity: 74.6%

# Applying CNN to an open-source dataset



# Dataset (1)

Brief Communication

<https://doi.org/10.1038/s41593-023-01272-0>

## Developmental trajectory of transmission speed in the human brain

Received: 17 March 2022

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Published online: 9 March 2023

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- Total Patients: 74
- Patients with SOZ Labels: 35
- Temporal and extratemporal lobe epilepsies
- Electrode Type: ECoG



BIDS Validation

Valid

NEMAR

Clone

Files

Download

Metadata

README

### Dataset description

This dataset consists of 74 patients age 4-51 years old where Cortico-Cortical Evoked Potentials (CCEPs) were measured with Electro-CorticoGraphy (ECoG) during single pulse electrical stimulation. For a detailed description see:

- Developmental trajectory of transmission speed in the human brain. D. van Blooij<sup>1</sup>, M.A. van den Boom<sup>1</sup>, J.F. van der Aar, G.J.M. Huiskamp, G. Castegnaro, M. Demuru, W.J.E.M. Zweiphenning, P. van Eijsden, K. J. Miller, F.S.S. Leijten, D. Hermes, Nature Neuroscience, 2023, <https://doi.org/10.1038/s41593-023-01272-0>  
<sup>1</sup> these authors contributed equally.

This dataset is part of the RESpect (Registry for Epilepsy Surgery Patients) database, a dataset recorded at the University Medical Center of Utrecht, the Netherlands. The study was approved by the Medical Ethical Committee from the UMC Utrecht.



# Dataset (2)

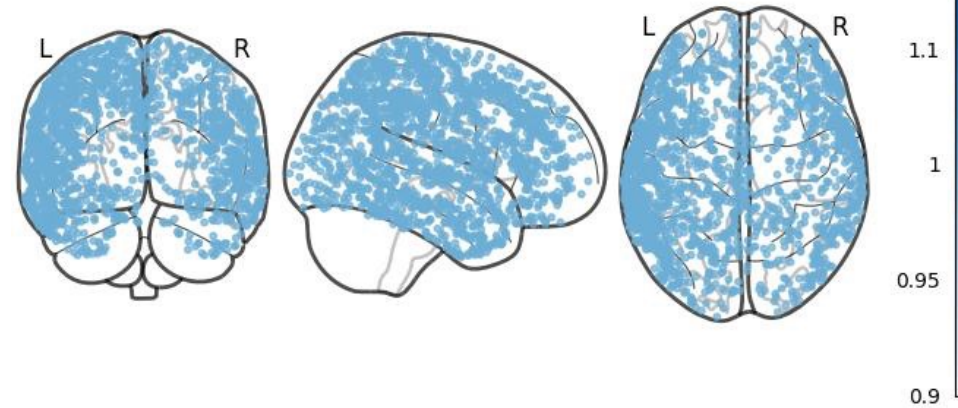
## Patient demographics:

- Mean age: 22.1 years
- 53% Male, 47% Female

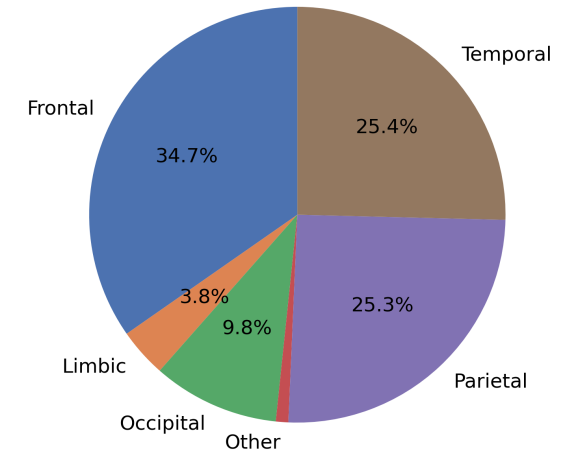
## SPES parameters:

- Intensity: 4 – 8 mA
- Frequency: 0.2 Hz
- Ten monophasic stimuli
- Pulse Width: 1 ms

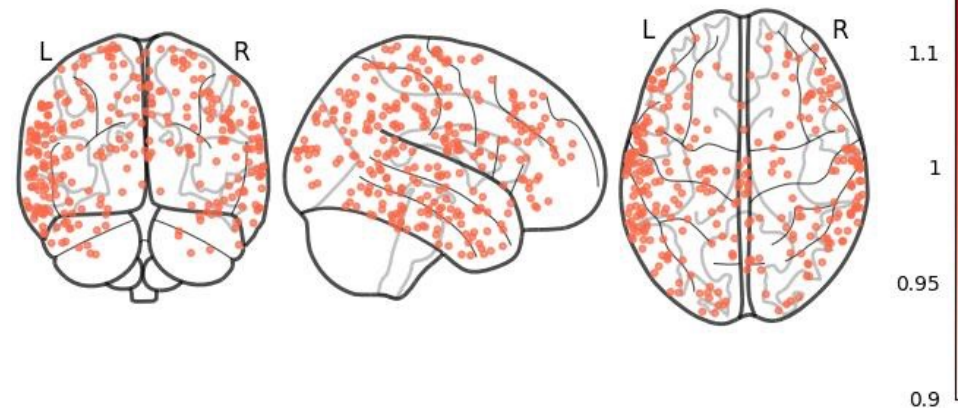
All channels



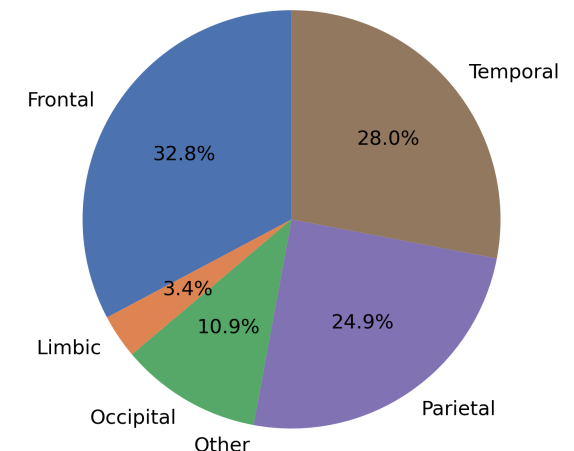
Dataset breakdown by lobe (n = 2052)



SOZ channels



SOZ breakdown by lobe (n = 293)



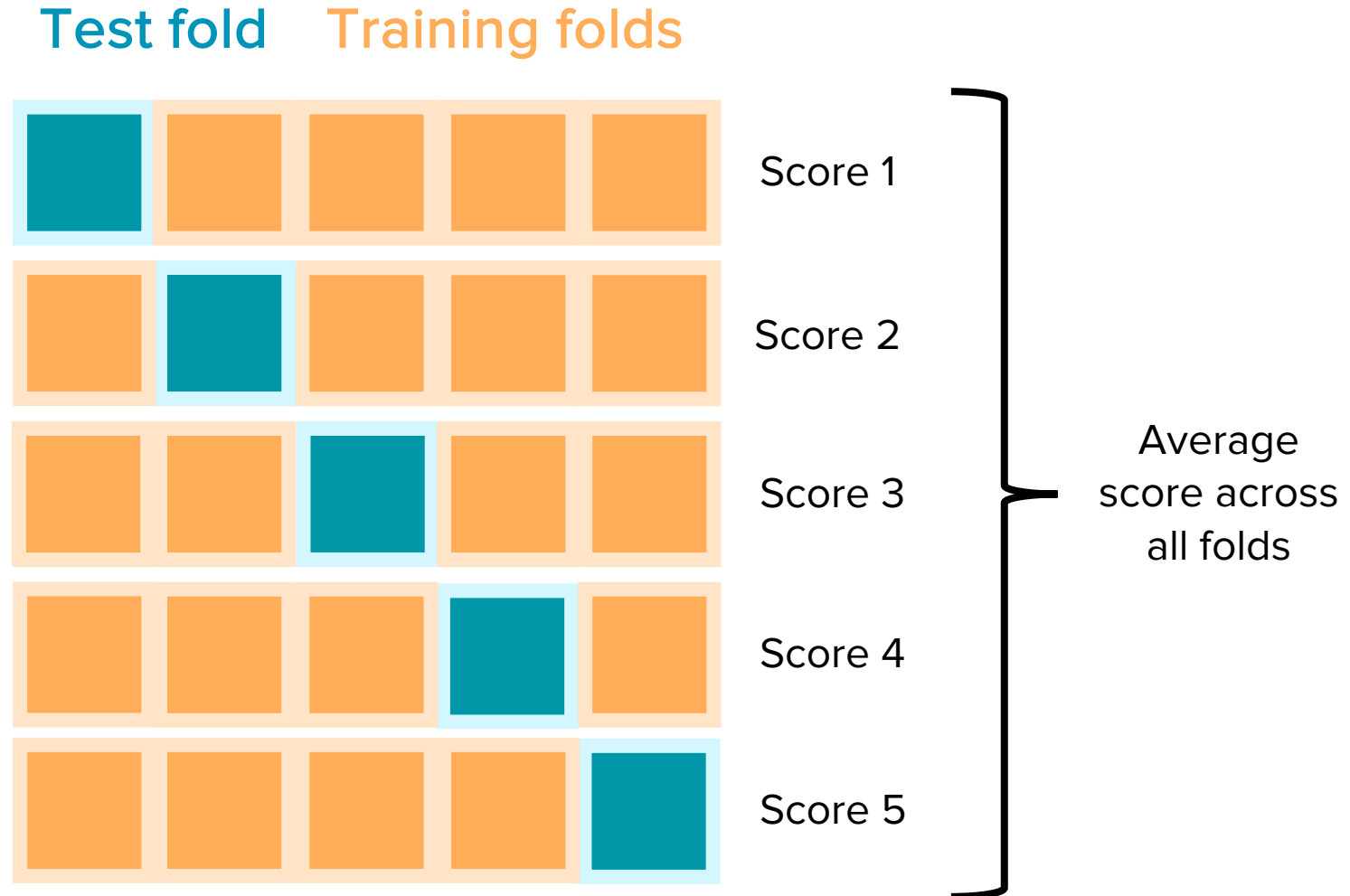
# Model training strategy

## Training strategy:

- k-fold cross validation ( $k = 5$ )
- 28 patient training sets
- 7 patient test sets

## Reported metrics:

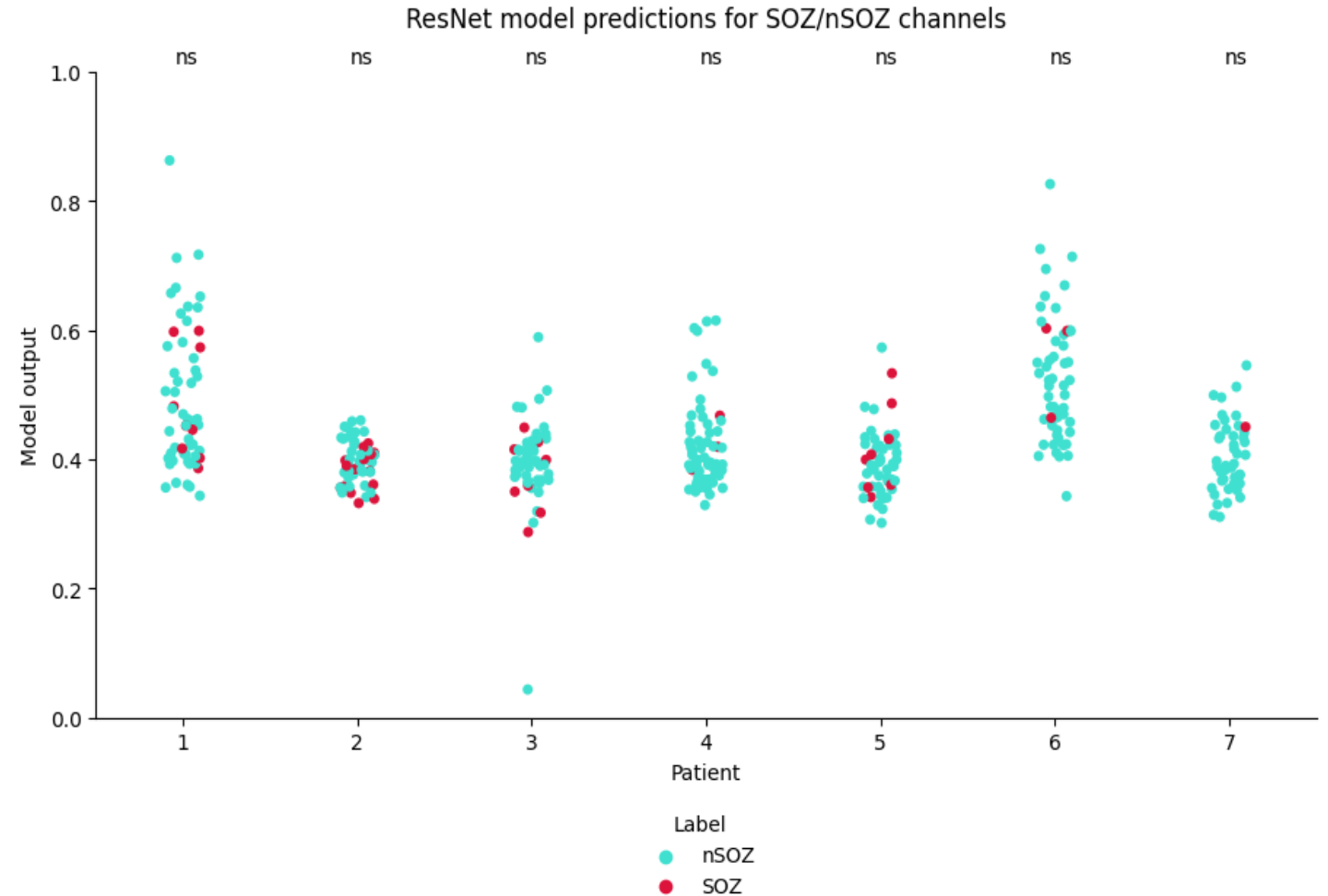
- Area under the precision-recall curve (AUPRC)
- Area under the receiver operating characteristic (AUROC)



# Baseline model performance

Model	AUPRC	AUROC
Random	0.14	0.50
CNN	0.17	0.48

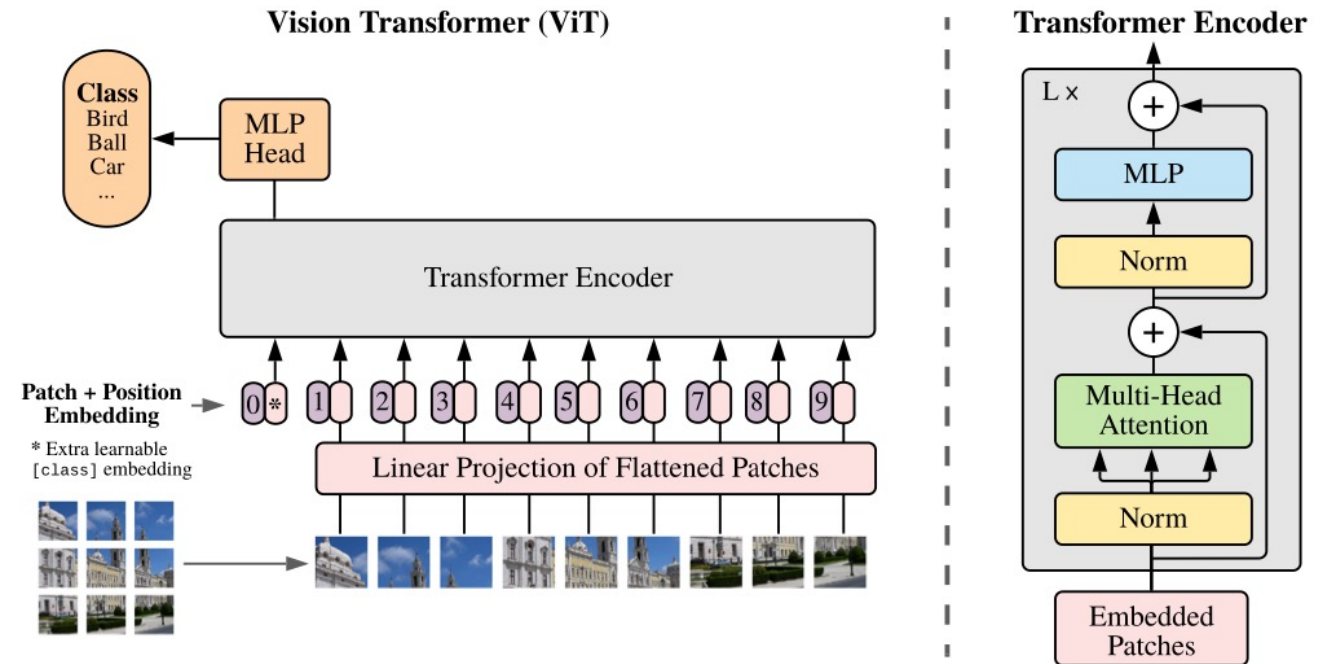
- Poor performance: doesn't beat random classifier



# Modifying methodology to improve performance

# Modification 1: Use a Transformer

- CNN limited by fixed channel input; Transformer better suited to patient-specific channel placements (spatial attention).
- Efficiently models cross-channel interactions.
- Global context understanding.
- Common in NLP (e.g., ChatGPT), but we adapt a Vision Transformer

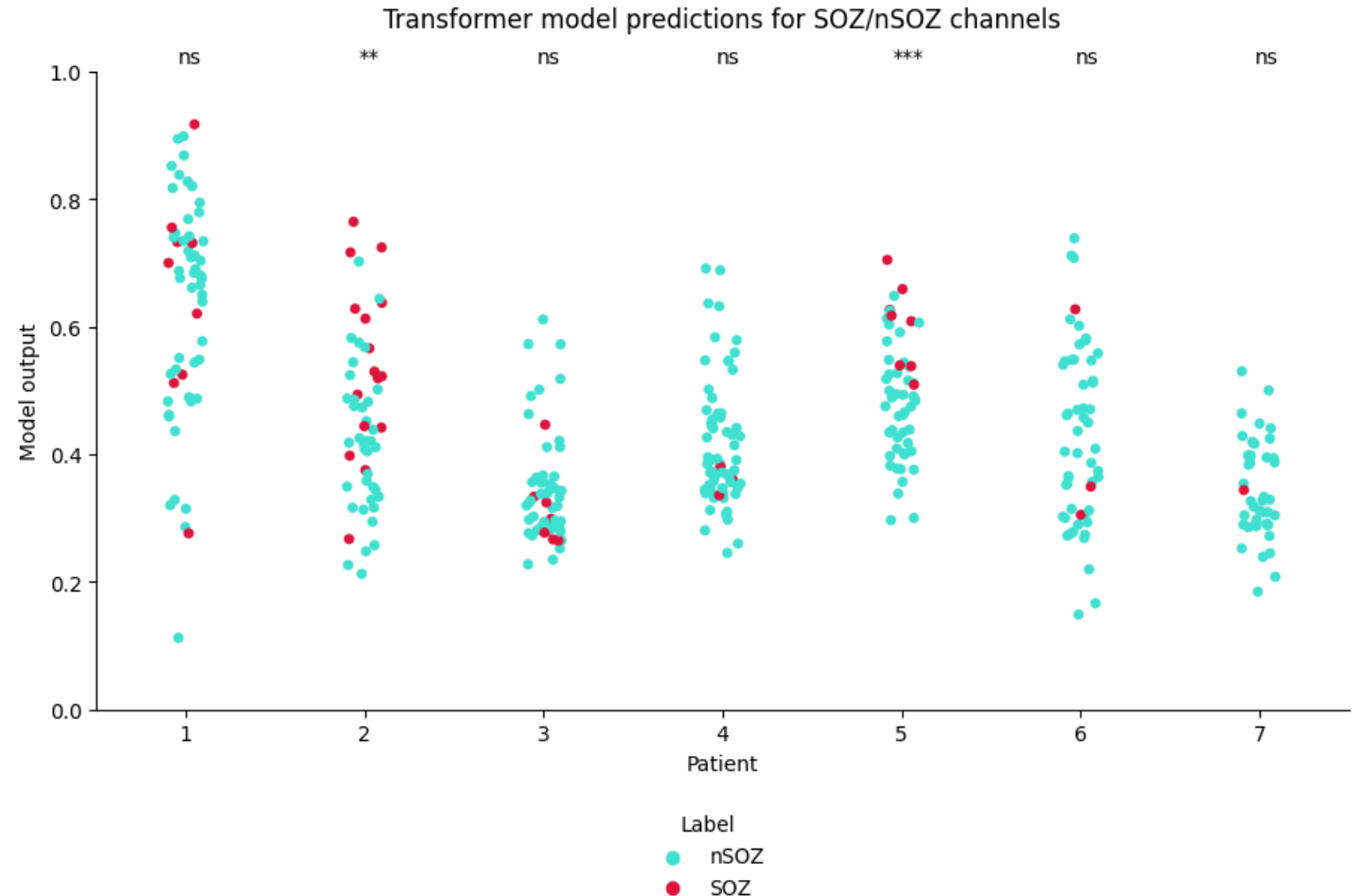


*An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. Dosovitskiy et al. (2020)*

# Transformer model performance

Model	AUPRC	AUROC
Random	0.14	0.50
CNN	0.17	0.48
Transformer	0.22	0.58

- Improvement over CNN, but still poor

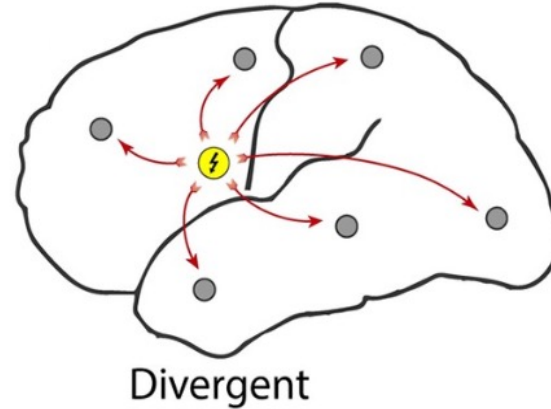


# Modification 2: Add convergent paradigm

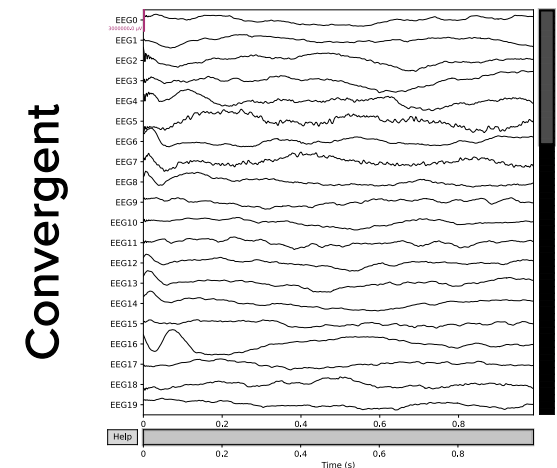
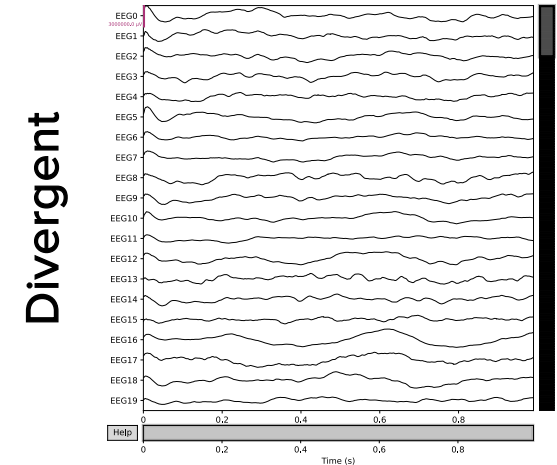
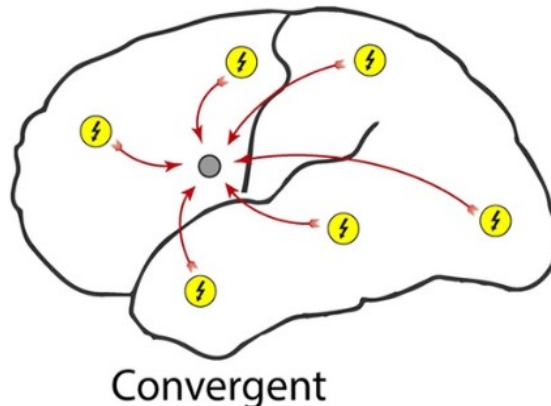
- Current method uses a divergent paradigm
- Convergent paradigm is better suited to observing the epileptogenicity responses introduced in earlier slides

## Modification 2:

- For a given site, also consider responses when other sites stimulated



*Basis profile curve identification to understand electrical stimulation effects in human brain networks. Miller et al. (2021)*









# Modification 3: Add standard deviation

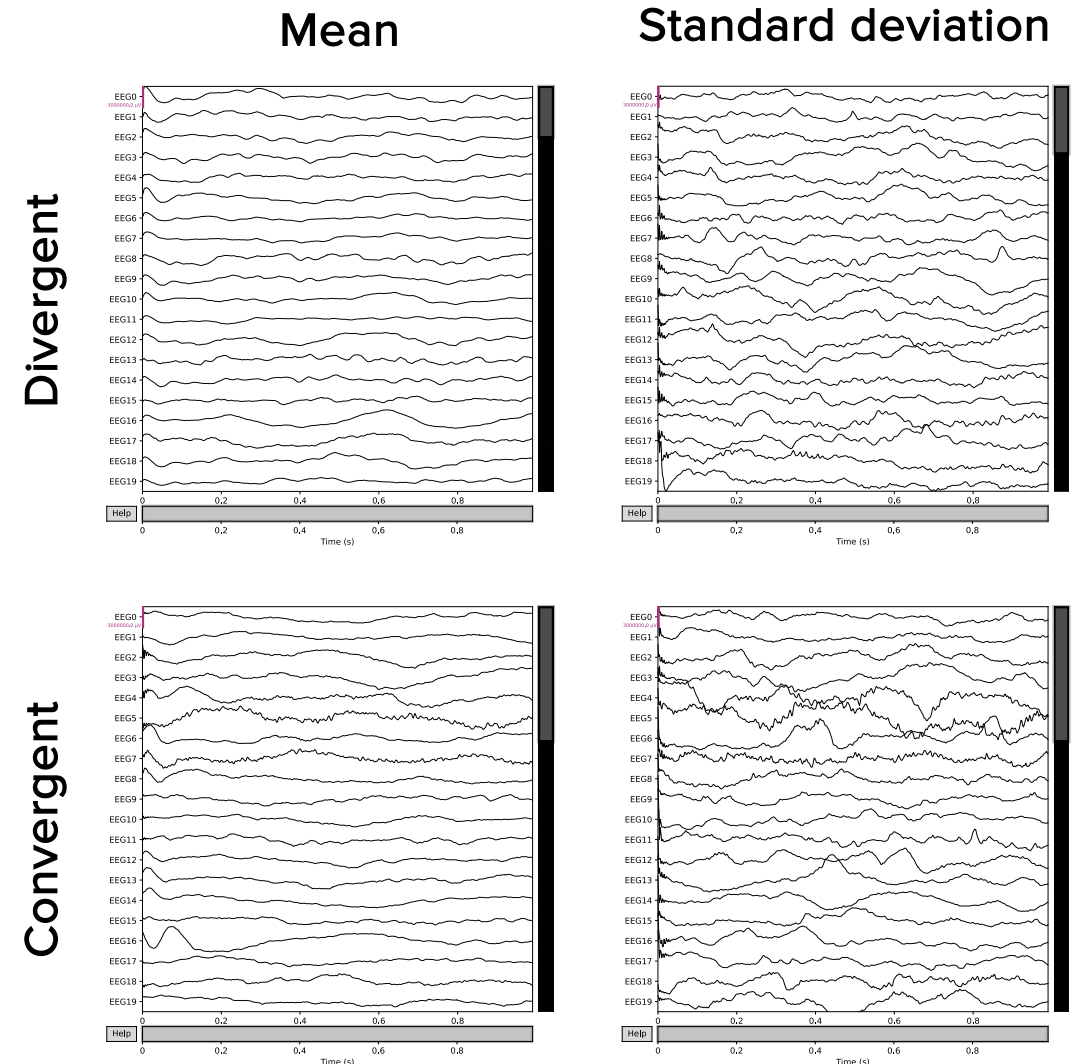
- Averaging responses across trials eliminates delayed responses
- Other information is potentially lost:

**Quantifying trial-by-trial variability during cortico-cortical evoked potential mapping of epileptogenic tissue**

Eli J. Cornblath<sup>1</sup>  | Alfredo Lucas<sup>1,2</sup>  | Caren Armstrong<sup>3</sup> | Adam S. Greenblatt<sup>1</sup> | Joel M. Stein<sup>4</sup> | Peter N. Hadar<sup>1</sup>  | Ramya Raghupathi<sup>1</sup> | Eric Marsh<sup>1,3,5</sup> | Brian Litt<sup>1</sup> | Kathryn A. Davis<sup>1</sup> | Erin C. Conrad<sup>1</sup> 

## Modification 3:

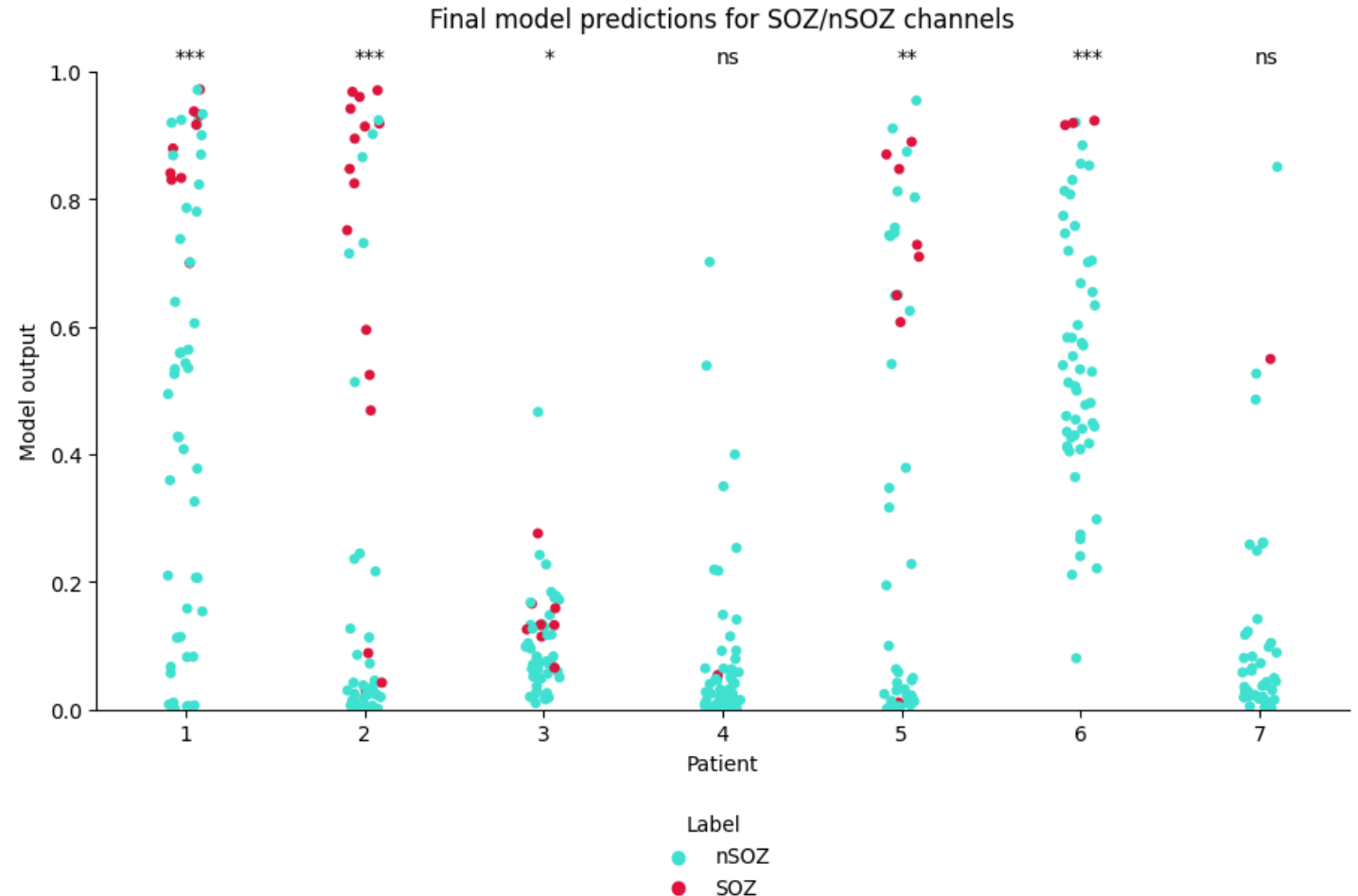
- As well as mean, incorporate standard deviation across trials



# Full model performance

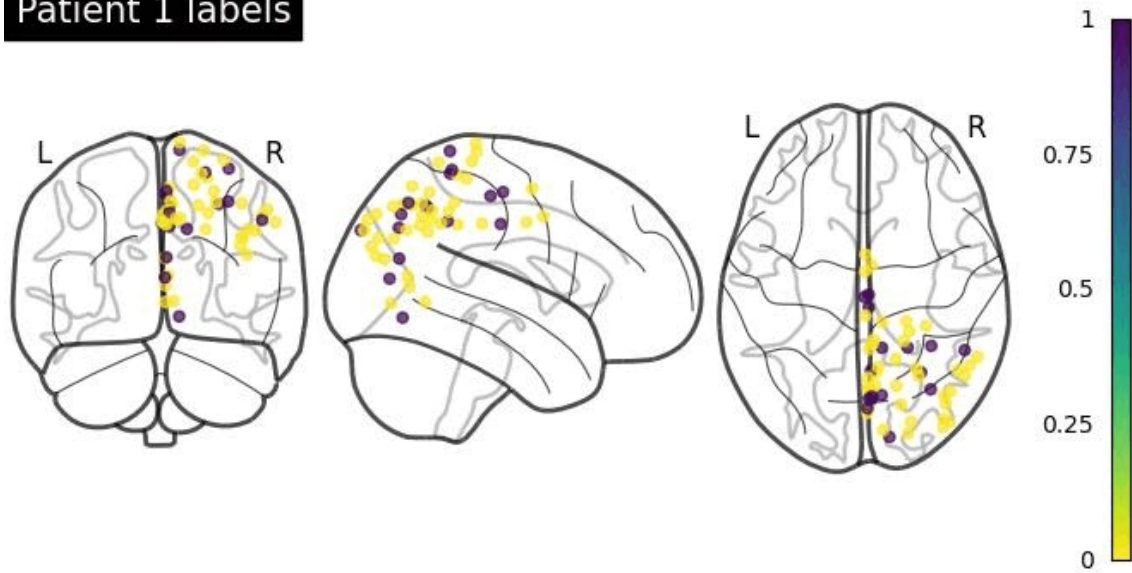
Model	AUPRC	AUROC
Random	0.14	0.50
CNN	0.17	0.48
Transformer	0.22	0.58
Full model	0.37	0.74

- Considerable improvement over previous methods



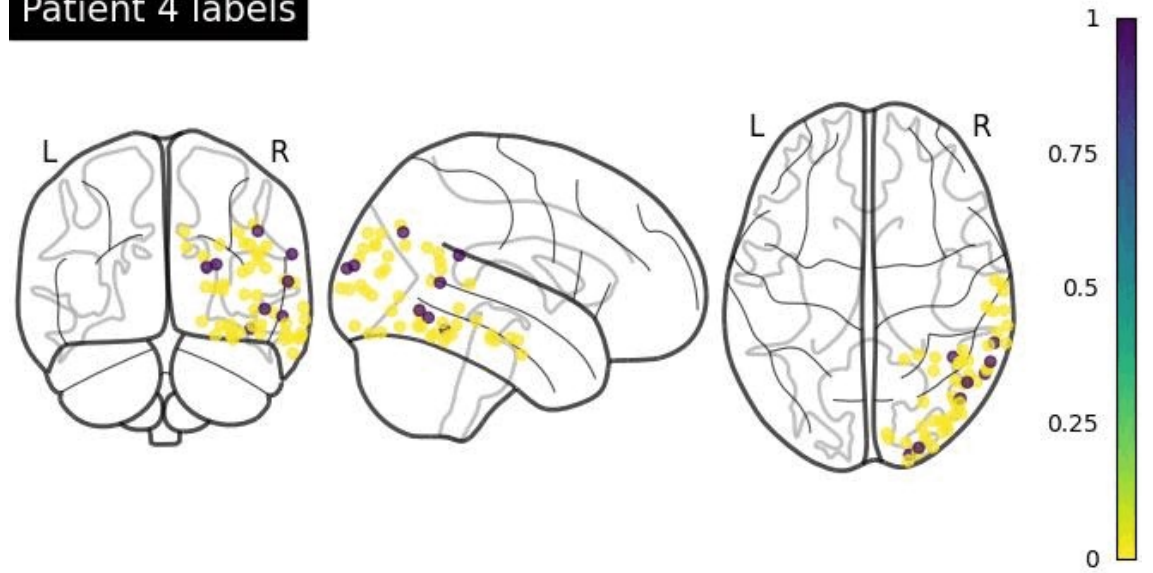
# Predictions visualised

Patient 1 labels



AUROC = 0.88

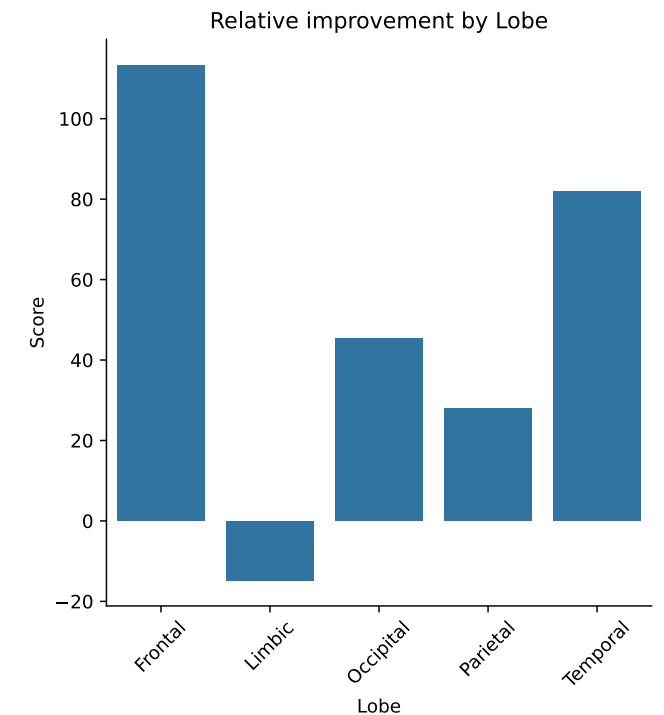
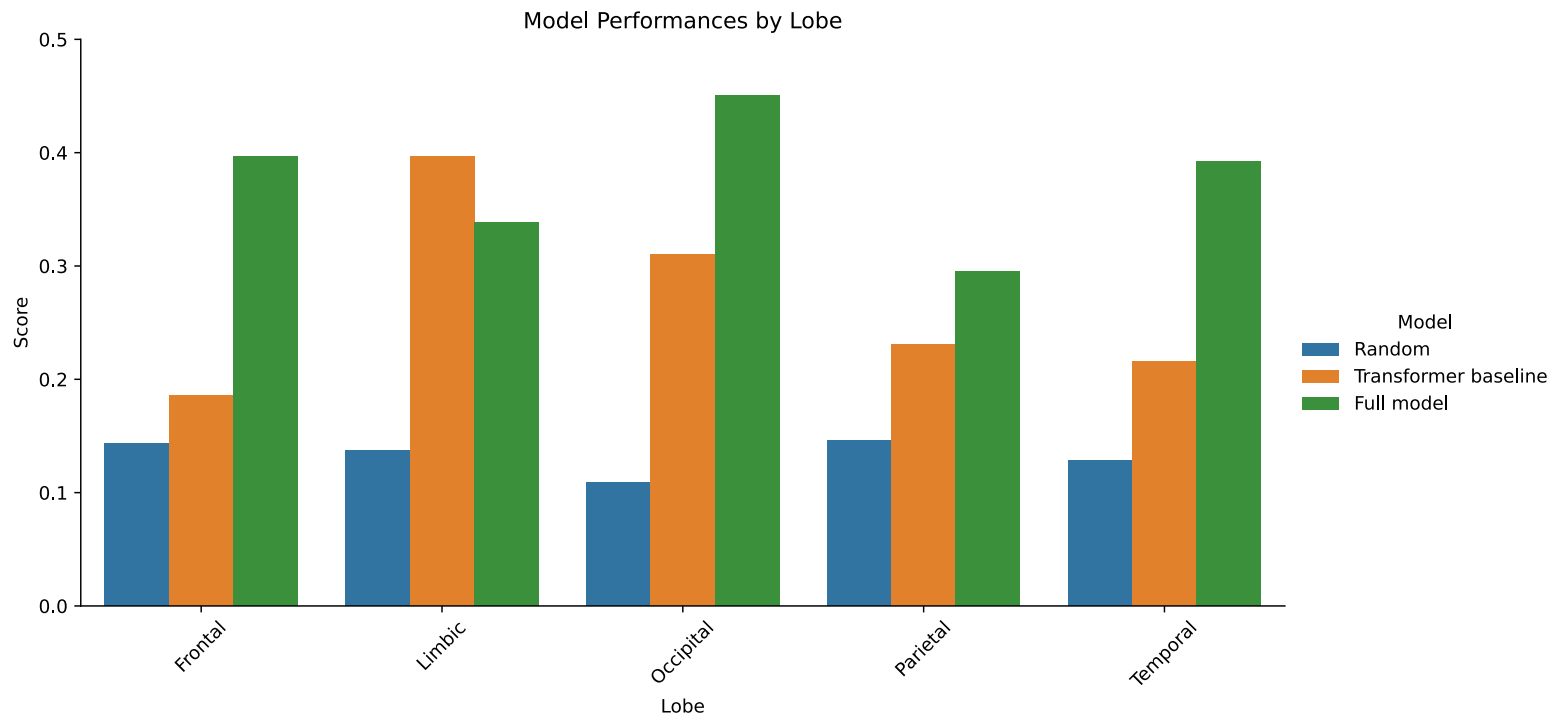
Patient 4 labels



AUROC = 0.77

# Performance by lobe

- Delayed responses are typically seen in frontal and temporal lobes
- **Hypothesis:** modifications will have improved performance for these the most



# Conclusion

## Transformers:

- Better suited to handling diverse channel configurations than CNNs
- Show promise for wide application in intracranial EEG analysis

## Performance increase:

- Mostly from data restructuring – exploiting known SPES characteristics

## Efficiency (Trained/Tested on MacBook Pro 2021)

- Pre-processing and model training: Under 20 minutes
- Applying model on a new patient: Less than 1 minute

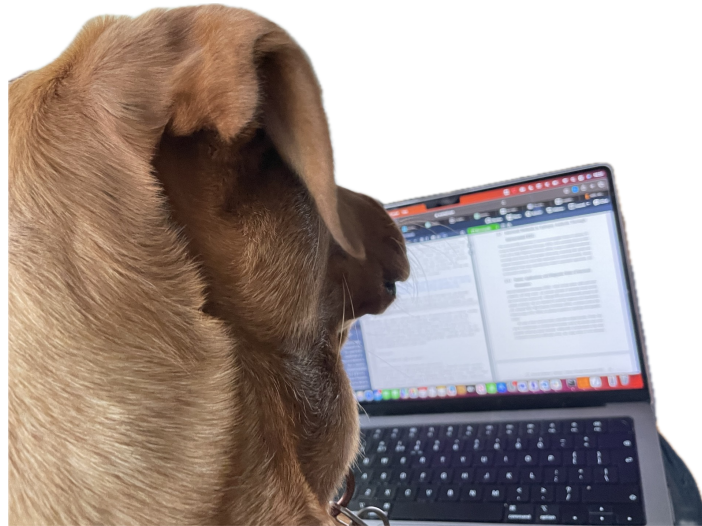
# Challenges and Future Directions

- Enhance validity with external validation
- Integrate channel locations for improved accuracy
- Predict outcome given removal of a channel (requires outcome labels)
- Black box: point to salient features?

## Clinical Utility:

- Offers a way of efficiently processing large amounts of stimulation data
- Requires a think about how to truly help clinicians

# Thanks for listening!



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