Predicting the Spatial Origin of EEG Independent Components from their Spectral-Temporal Features

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What type of data?

- Electroencephalography (EEG)
  - Records electrical activity of the brain
  - Made up of many electrodes on scalp surface
  - Non-invasive
  - Used in diagnoses, research and brain-computer interfaces
- EEG readings contain multiple sources at once
- Independent component analysis (ICA) [1]
  - Creates independent components (IC)
  - Characterized spatially with topographic map (topo-map)
  - Characterized temporally by autocorrelation function and power spectral density (PSD)
- ICs can be of many types
  - Wanted biological sources: brain ICs
  - Unwanted biological sources: eye blink, heart, muscles, etc.
  - Noise: powerline noise, motion artifacts
- The dataset was originally used to classify ICs [2]

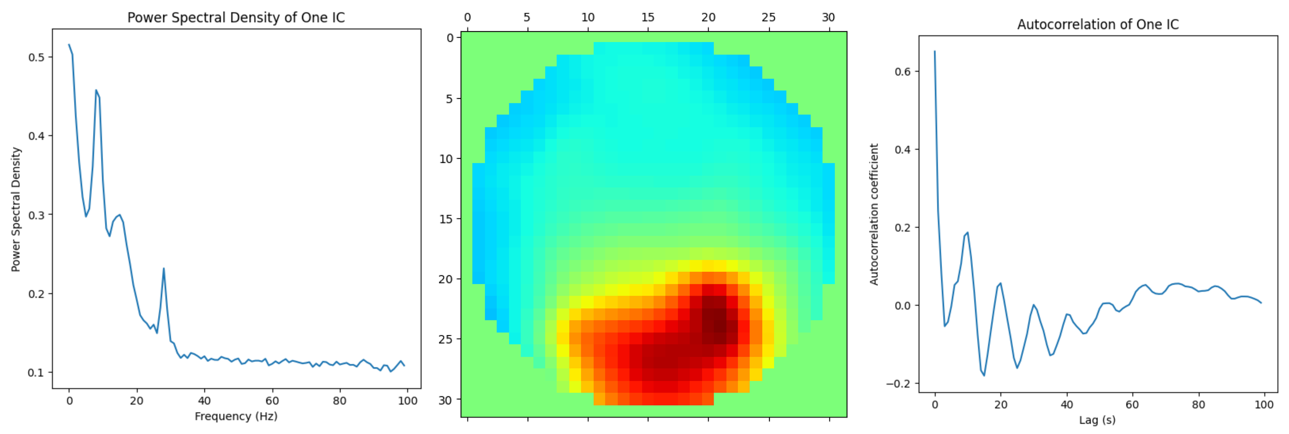

Figure 1: Example Data of a PSD, Topo-map, and Autocorrelation Function.

What is Contrastive Learning?

- Machine learning method of embedding
- Places paired items into shared vector space
- Our project does this with multimodal data
  - Spectral-Temporal features: PSD and autocorrelation function
  - Spatial features: topo-map
- Equation 1 is used to characterize the loss function [3]

$$\ell_{i,j} = -\log \frac{\exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)}$$

Equation 1: NT-Xent loss function from SimCLR paper[3].

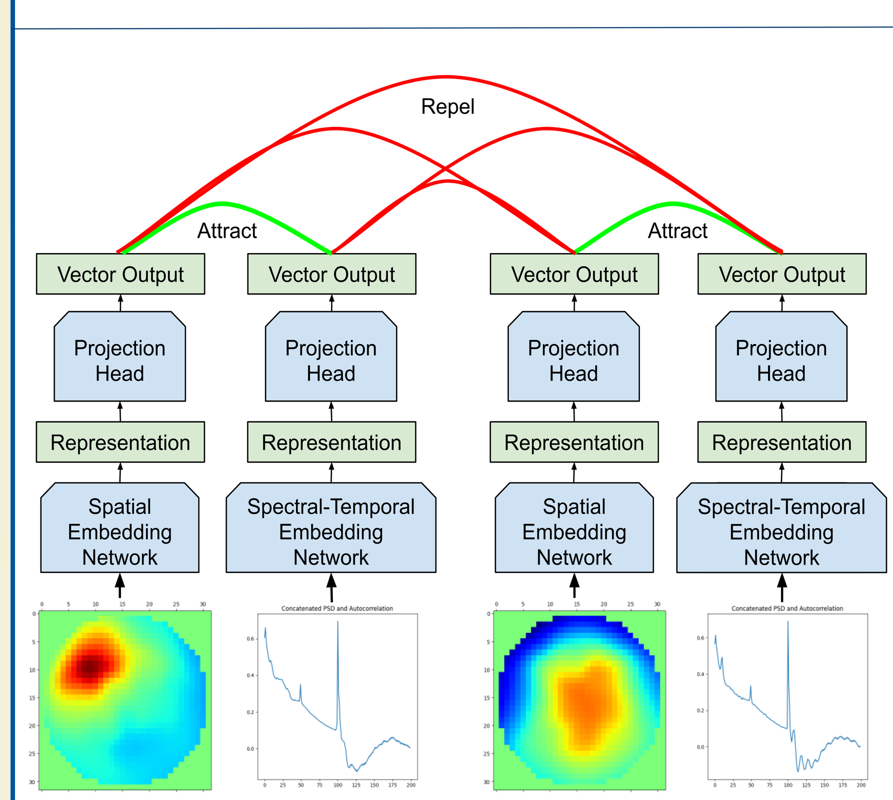

Figure 2: Multimodal Embedding figure example.

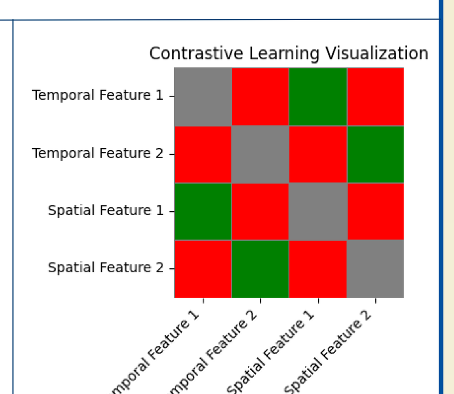

Figure 3: Contrastive learning matrix example.

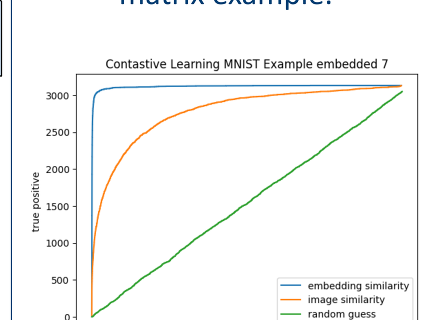

Figure 4: MNIST ROC Example.

What is the Goal?

The goal of this research is to learn how much spatial information in EEG ICA is embedded within the waveform. Our research tests this by using contrastive learning type machine learning. Our model finds there is spatial information and can predict location greater than chance.

Topographic Embedding Results

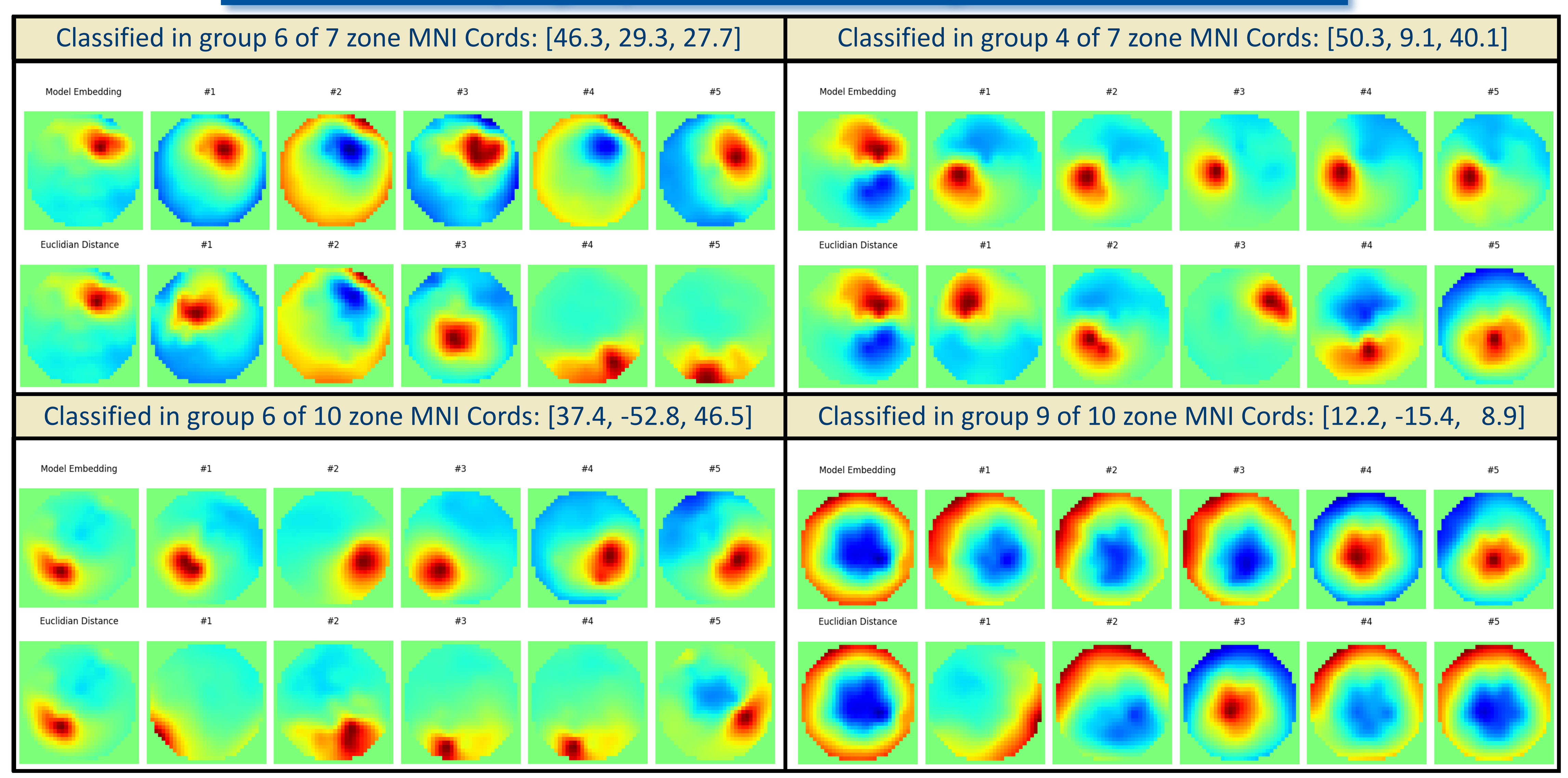

Figure 5: Four different topo-map comparisons. The first image in each row of the comparison is the true topo-map associated with the spectral-temporal features tested. The next 5 are the most closely embedded topo-maps. In the first row this is done by embedding the spectral-temporal features with the trained model and finding the most similar cosine embedding of all the training topographic maps. In the second row the most similar one is found by comparing the Euclidian distance of the test spectral-temporal features to all of the training spectral-temporal features, and then outputting the topo-maps associated with the closest spectral-temporal features. The second row approximates a modeless option for solving this task.

Model Performance Evaluation

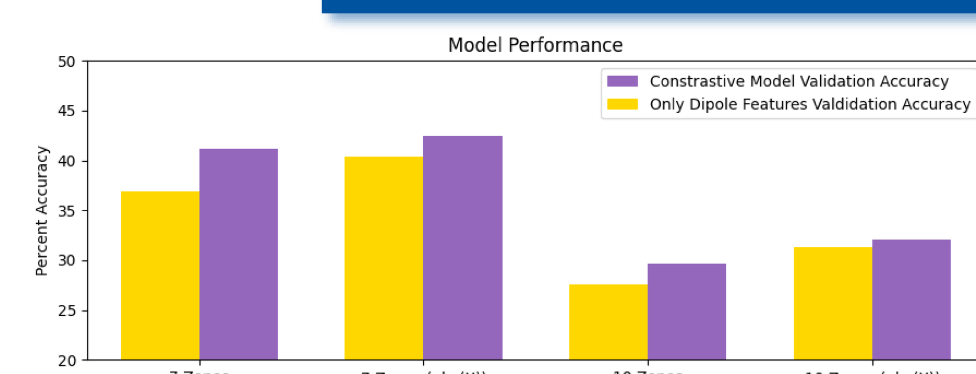

Figure 6: Dipole region classification performance with and without contrastive learning pre-training.

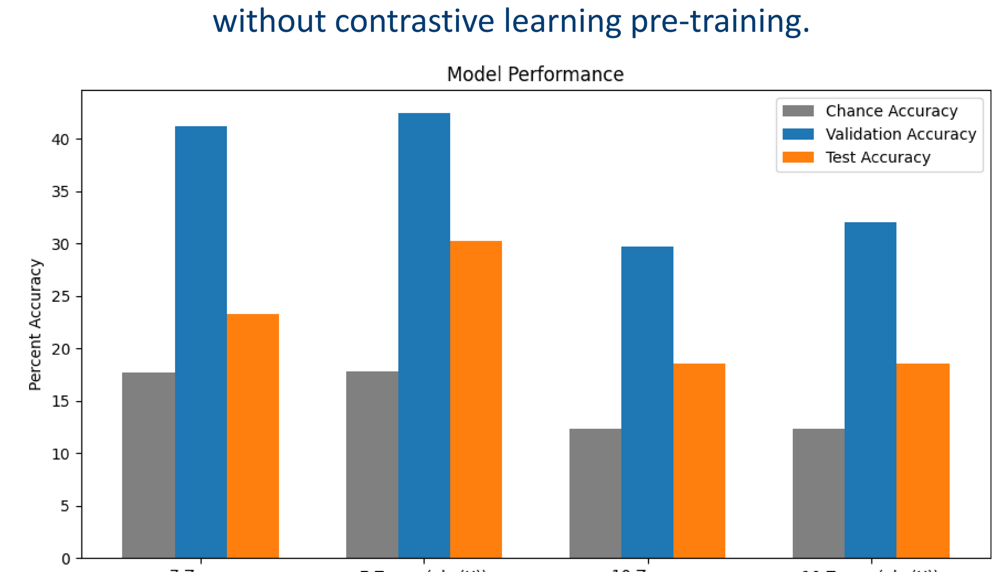

Figure 7: Dipole region classification in validation and test compared to chance.

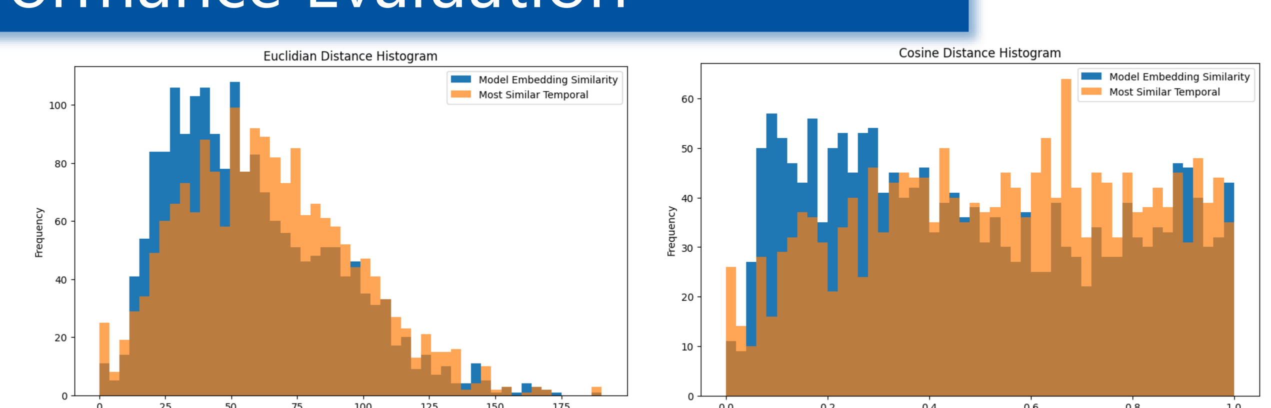

Figure 8: Graphs showing embedding performance by comparing distances associated with the top-5 topo-maps. (Left) Dipole location (Right) Topo-map distance

Actual Class / Predicted Class

A	0	1	2	3	4	5	6	
0	23	3	5	1	6	14	2	42.6%
1	3	21	0	8	3	6	9	42.0%
2	8	0	24	8	1	20	3	37.5%
3	1	1	5	24	3	5	2	58.5%
4	4	1	1	1	11	10	1	37.9%
5	11	4	21	10	11	20	1	25.6%
6	6	6	0	0	9	1	36	62.1%
	41.1%	58.3%	42.9%	46.2%	25.0%	26.3%	66.7%	

Actual Class / Predicted Class

B	0	1	2	3	4	5	6	
0	39	14	11	1	15	10	7	40.2%
1	7	16	3	1	3	2	3	45.7%
2	0	10	18	9	1	0	4	42.9%
3	2	4	16	34	4	1	7	50.0%
4	24	9	0	1	23	15	12	27.4%
5	1	1	0	3	4	10	2	47.6%
6	3	4	0	3	7	2	8	29.6%
	51.3%	27.6%	37.5%	65.4%	40.4%	25.0%	18.6%	

Figure 9: Confusion matrices showing performance of dipole region classification model. Matrix A combines left and right hemispheres. Matrix B is the full brain.

How to Evaluate Model?

- Evaluation of embedding space is challenging
- Topo-map can be decomposed into dipole [4]
  - The dipole is in Montreal Neurological Institute (MNI) space
  - The MNI space is a standard brain coordinate system
- Turning brain dipoles into classification task
  - Dipoles in the dataset's points can be k-means clustered
- Different k-means clustered types:
  - Full-brain mapped clusters
    - Groups of 7 and 10
  - Brains with right and left hemispheres combined
    - Groups of 7 and 10

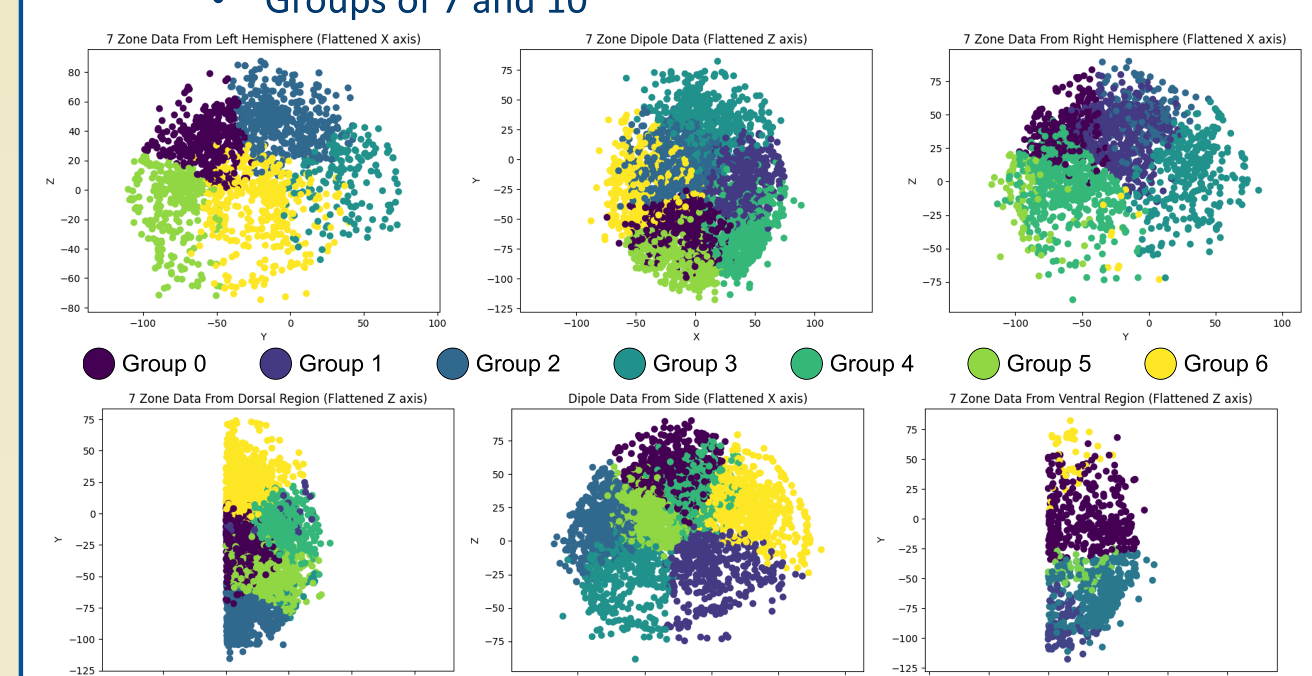

Figure 10: Plots of the 7 zones used for dipole fit evaluation. The top 3 are for full brain dipole fits while the bottom 3 have combined hemispheres.

Future Research

- Spatial prediction from temporal features is possible
- Using the time signal instead of PSD and autocorrelation function
- Using a functional brain atlas instead of k-means groups
- Including dipole moment instead of just position
- Future applications:
  - Flagging suspect brain activity in patients
  - Quickly confirming locations during surgery
  - Classifying ICs with temporal data

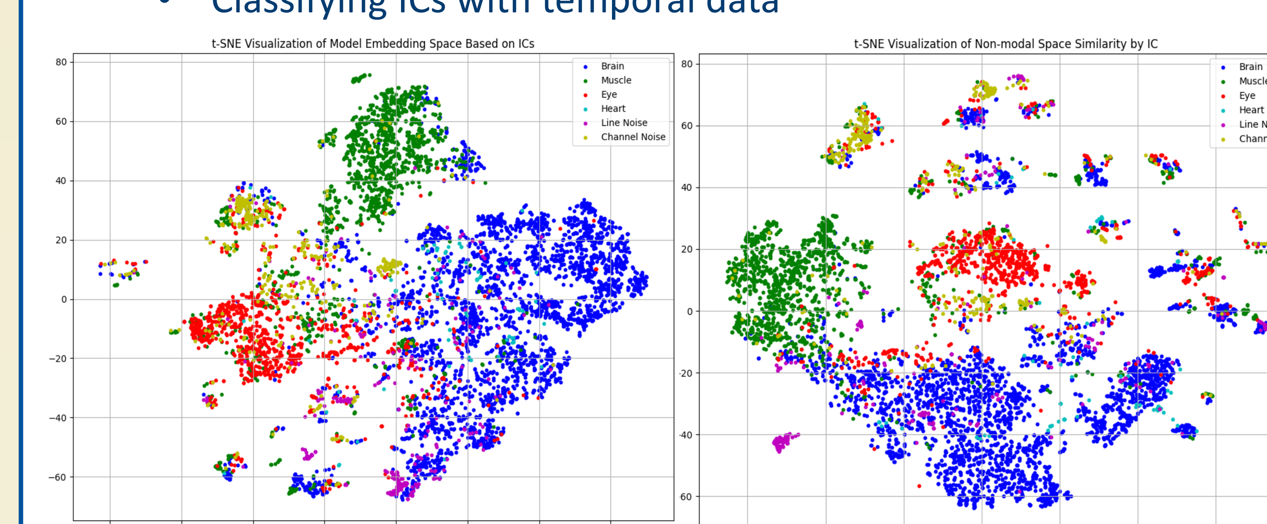

Figure 11: t-SNE Visualization of embeddings based on Ics.

Acknowledgements and References

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