Decoding visual category information from scalp EEG data with logistic regression and support vector machine classifiers

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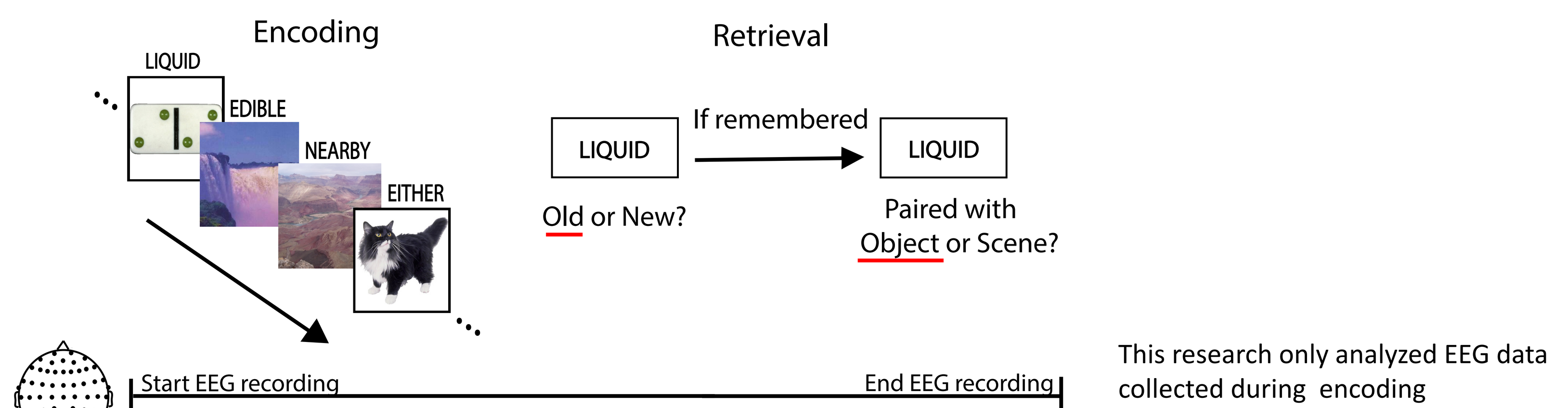
Introduction

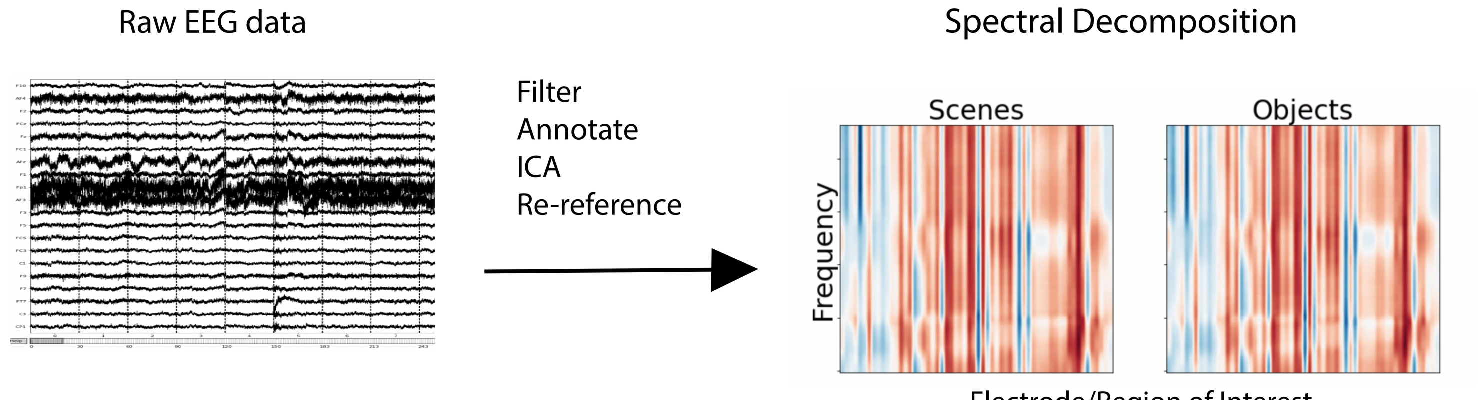
- fMRI studies have found that the brain represents categories of visual stimuli through distinct patterns of neural activity that are thought to be processed repeatedly over time to support learning and memory.
- Scalp EEG has much higher temporal resolution than fMRI, so we may be able to track these stimulus representations in the brain as they evolve over time.
- Some scalp EEG studies have attempted to classify aspects of visual experience (Stewart et al., 2014; Murphy et al., 2011; List et al., 2017), but it is not known how reliably visual stimulus categories can be decoded from scalp EEG data.
- Furthermore, we asked whether features present in the EEG data collected during encoding (spectral power at various times and frequencies) can be used to predict whether a subject is viewing an object or a scene.

Methods

Collection of behavioral and EEG data



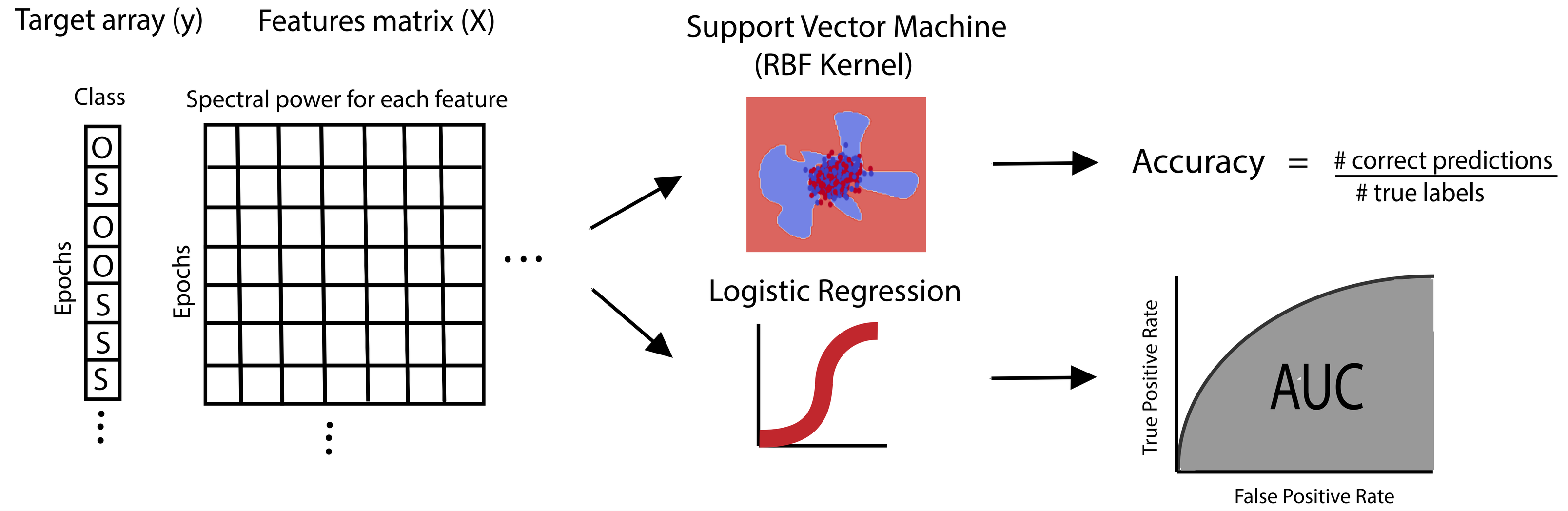
Post processing and spectral decomposition of EEG data



Univariate analysis

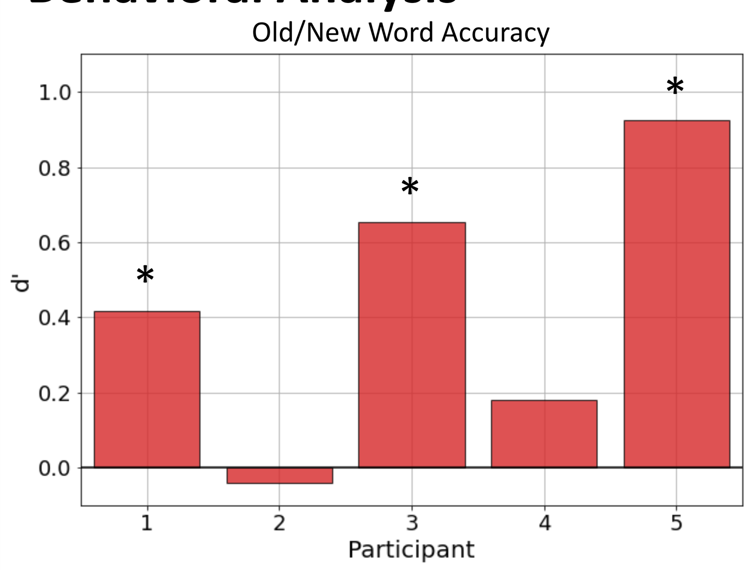
Frequency and time-frequency information produced by spectral decomposition → Calculate difference in spectral power between object and scene epochs

Training logistic regression and support vector machine classifiers and testing classifier performance

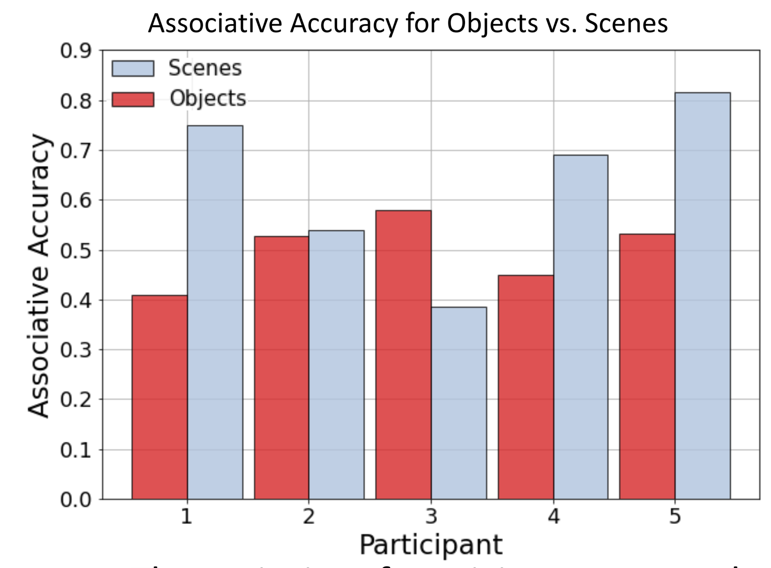


Results

Behavioral Analysis



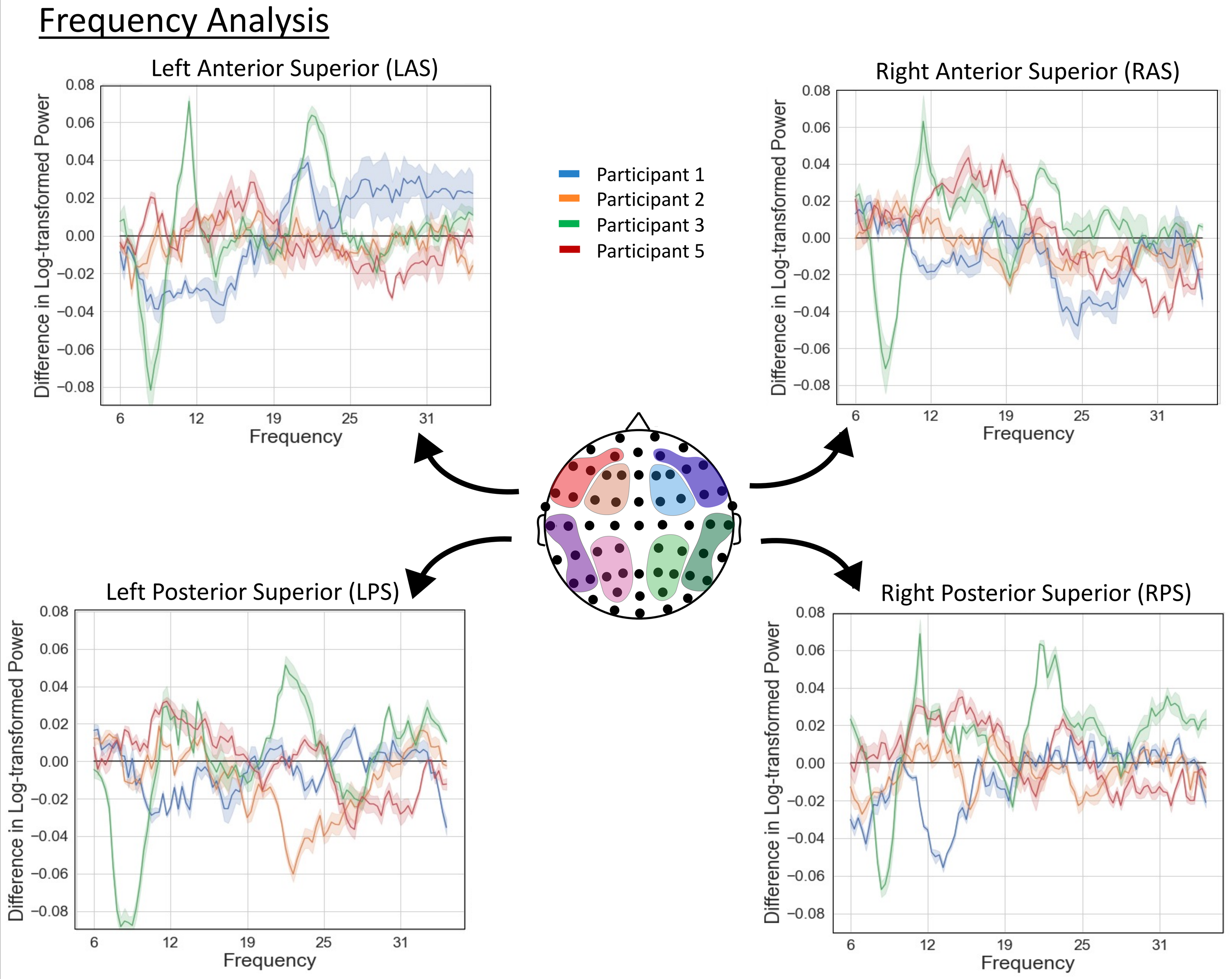
Subjects 1, 3, and 5 had statistically significant d' values (p=0.003, p=0.0002, p<0.0001).



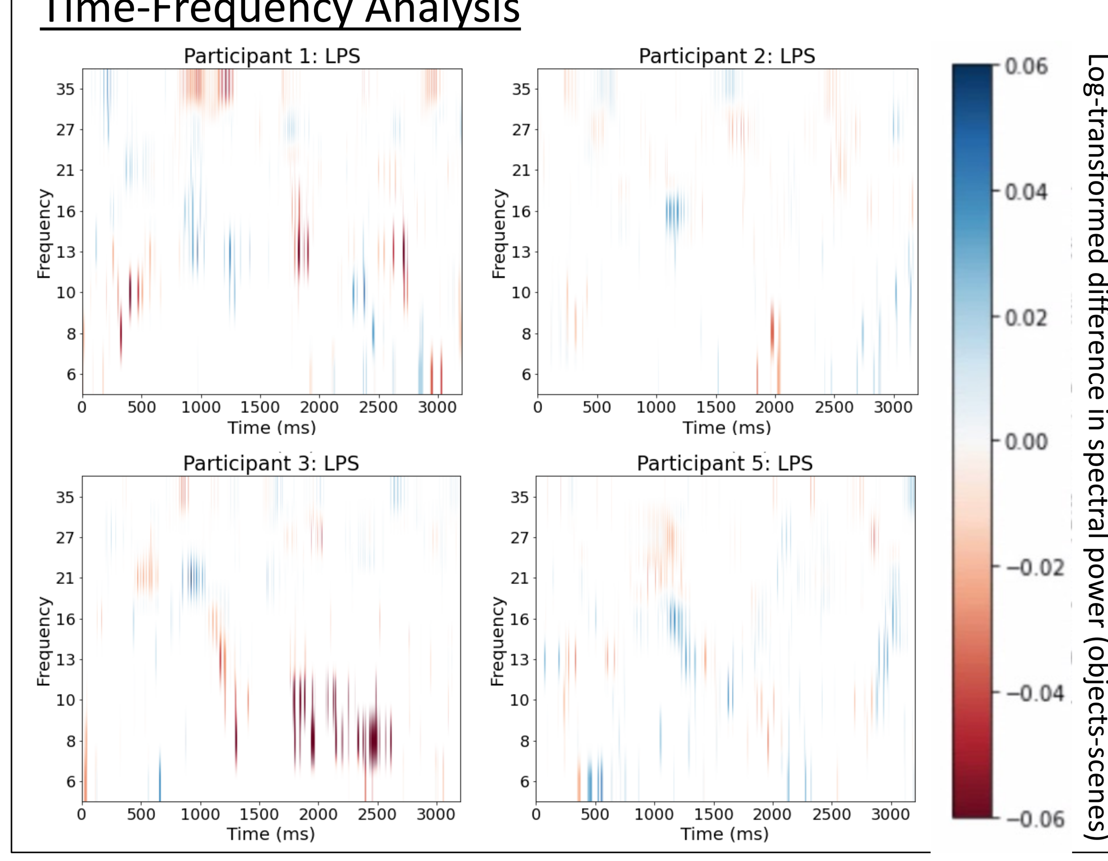
The majority of participants correctly remembered more scenes that objects.

Spectral power during encoding: objects vs. scenes

Frequency Analysis



Time-Frequency Analysis



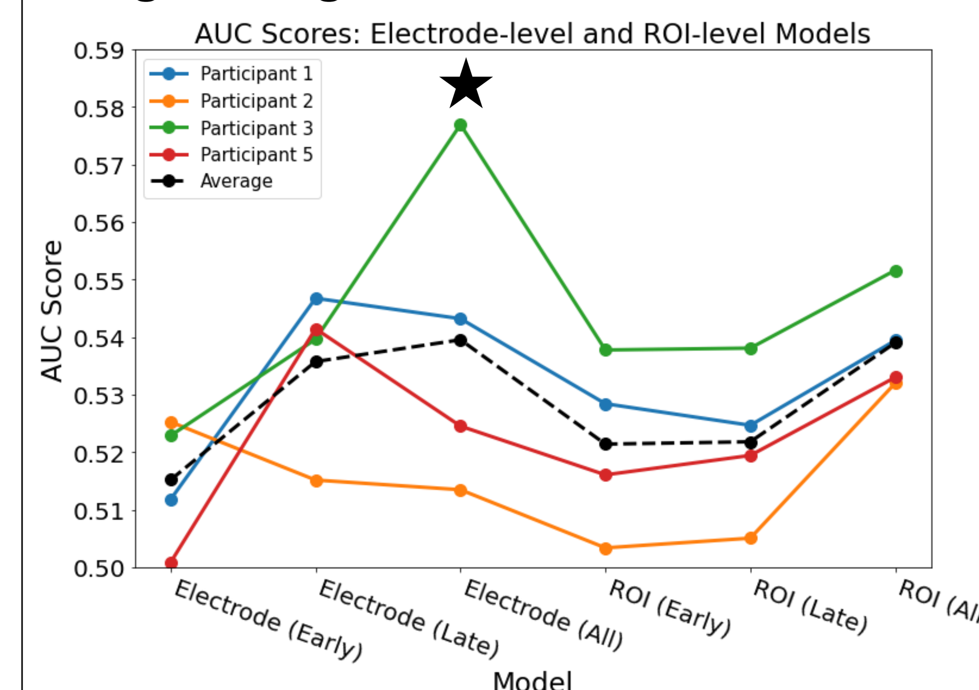
Using FDR analysis, we found no statistically significant differences in spectral power between object and scene epochs

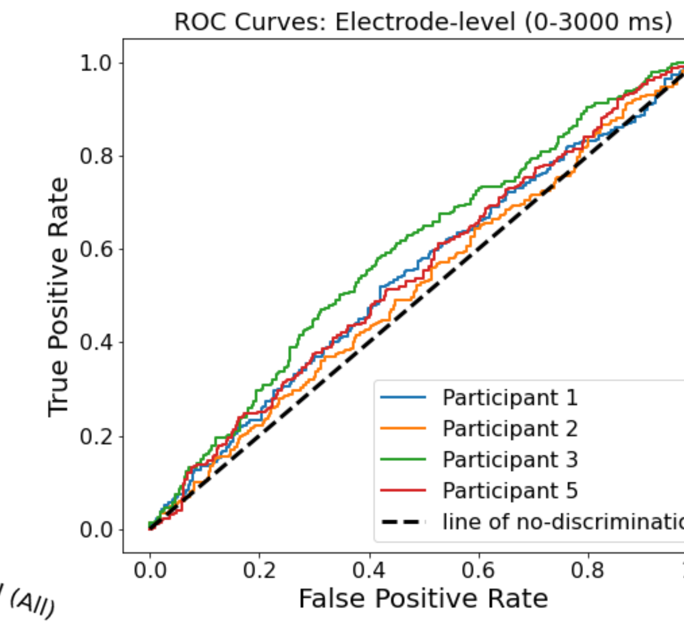
Logistic regression and support vector machine classifier

Results

Logistic Regression Classifier

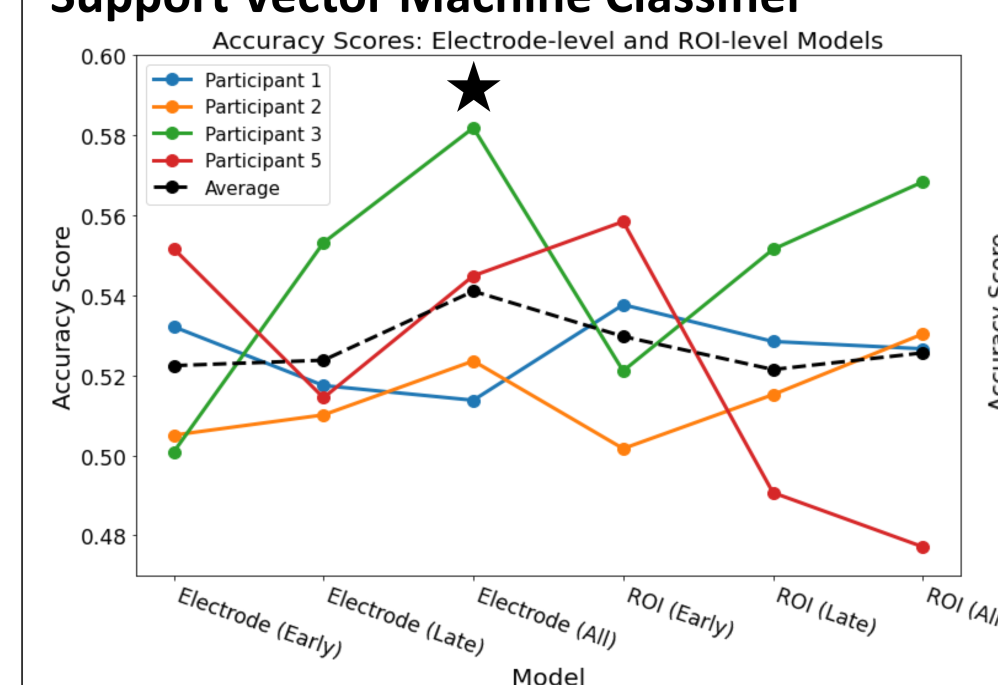
★ = largest average AUC score

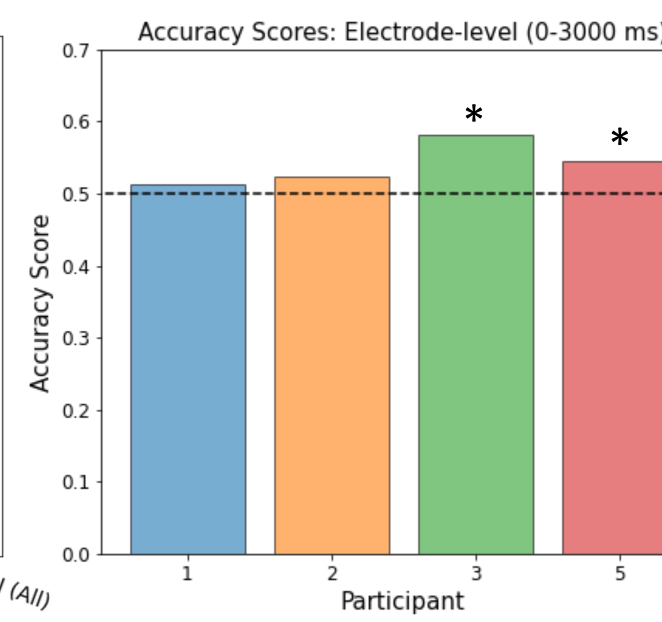




The electrode-level LR classifier predicted class labels significantly better than chance for participant 1 (p=0.046) and participant 3 (p=0.002).

Support Vector Machine Classifier





The electrode-level SVM classifier predicted class labels significantly better than chance for participant 3 (p<0.001) and participant 5 (p=0.033).

** P-values were calculated using permutation testing.

Conclusions & Future Work

- The logistic regression classifier applied to EEG data from participants 1 and 3 predicted visual stimulus class significantly better than chance and the support vector machine classifier applied to EEG data from participants 3 and 5 predicted visual stimulus class significantly better than chance.
- The superior performance of electrode-level models may be due to a larger number of features. Additionally, the ROI-level models used 38 electrodes while the electrode-level model used 60.
- Further analysis of this data could include examination of classifier weights for different features.
- We could also improve the model by collecting more data and training the classifier across subjects. We could then use the classifier to decode other time periods such as retrieval.

References

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