Classifying EEG spectral features that predict subsequent memory performance across multiple sessions

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INTRODUCTION

- Prediction of subsequent memory using pre-stimulus electroencephalography (EEG) data has practical implications in cognitive science and brain-computer-interface (BCI) research.
- Prior research has demonstrated that it is possible to use machine learning to classify pre-stimulus EEG signals that predict whether a stimulus will be later remembered or forgotten.
- Feature selection is often performed by identifying features across frequency *x* time x location which correlate most labels, but this does not take into account variability between sessions.
  (This approach resulted in only chance test accuracy on the current data set)
- Approach presented here attempts to select features holistically by including space and time features and identifying key frequency bands for training and testing.

Research Question

Does classification of brain states that predict later memory within a session generalize to a novel dataset and predict memory performance in a different session?

EEG METHODS

- 32-channel EEG recorded during encoding
- Eye-blink artifacts corrected with ICA
- Artifact rejection by automatic/manual inspection
- Baselined -200 to 0ms before tone onset
- Re-referenced to average of L/R mastoid

MACHINE LEARNING CLASSIFICATION

- Classification via Support Vector Machine (SVM)
- Training via leave-1-out cross validation

FEATURE SPACE

- Spectral decomposition via spectrogram:
  - 42 frequency bands from 1-42 Hz
  - 4 non-overlapping 500msec time windows (2 pre-stimulus, 2 post-stimulus)
  - 12 scalp regions (spatial groups of electrodes)

FEATURE SELECTION

Session 1 Classification:

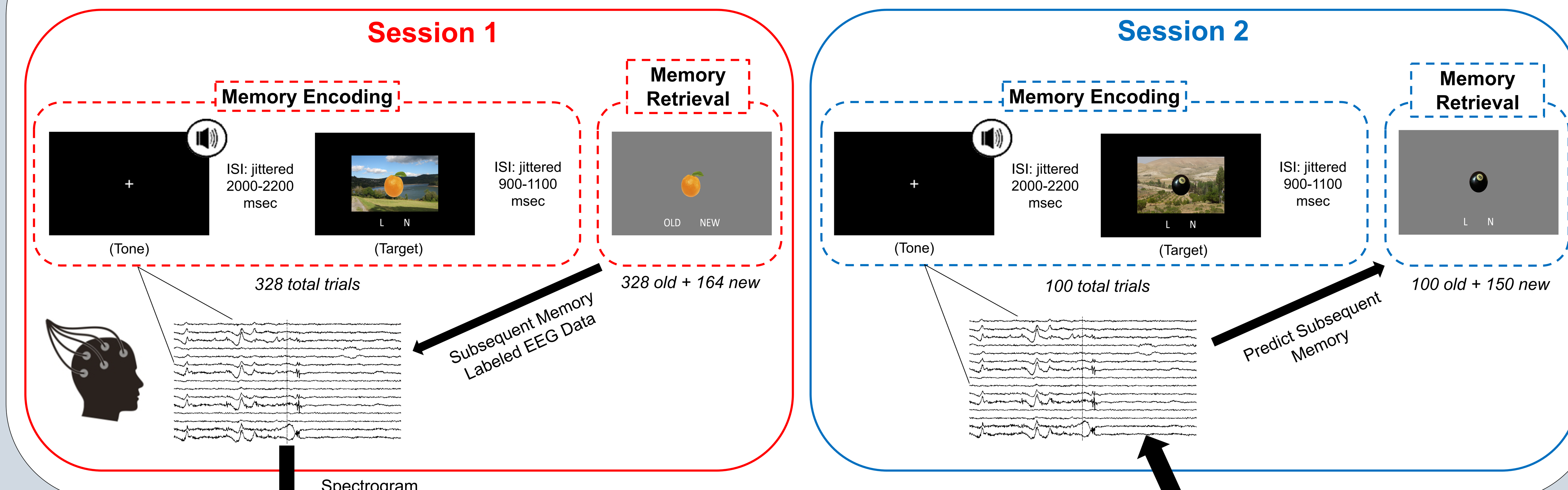
- For each participant, a series of classifiers are trained and tested on Session 1 data, each using the spectral power data of a specific frequency band
- Yields frequency bands rank ordered by test classification accuracy

Session 2 Classification:

- Optimal training set size determined by training classifiers on 1 thru 10 of top frequencies from Session 1
- Classifiers tested on Session 2 data

Overall method and model performance measured via mean test classification accuracy and number of participants yielding greater than chance

METHODS



Feature space

(42) Frequency Bands
x
(4) Time Windows
x
(12) Electrode Regions

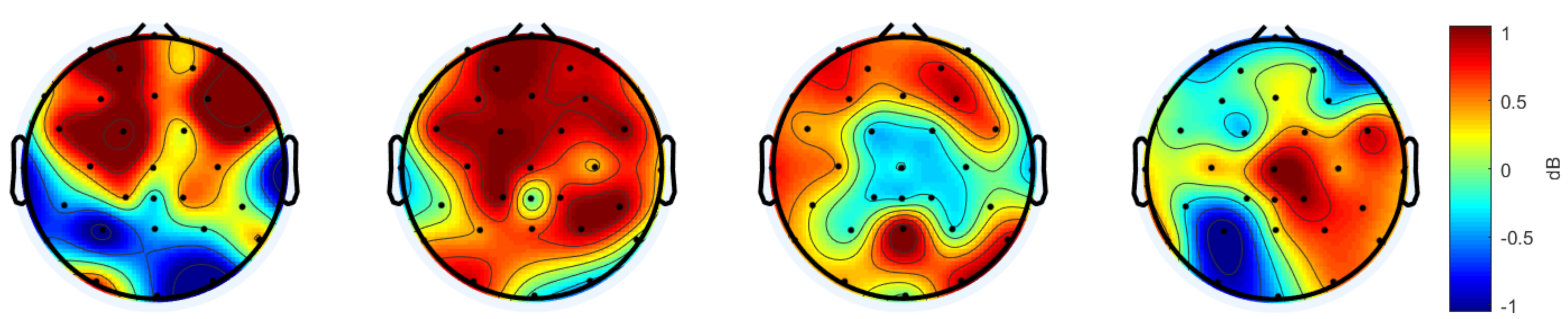
→ Train and test SVM classifier on single frequency data from Session 1 using leave-1-out cross-validation

→ Identify top frequencies yielding highest test classification accuracy

→ Train SVMs on data from 1 thru 10 of the top frequencies

→ Test on Session 2 data

Spectral Power Topoplot
(Mean Hit Power – Mean Miss Power)
Participant 1, Frequency band #1



-1100 to -600 ms | *-600 to -100 ms* | *100 to 600 ms* | *600 to 1100 ms*

Test Classification Accuracy on Session 2 Data

Finding optimal number of frequency bands to include in training data

Balance between under-fitting and over-fitting

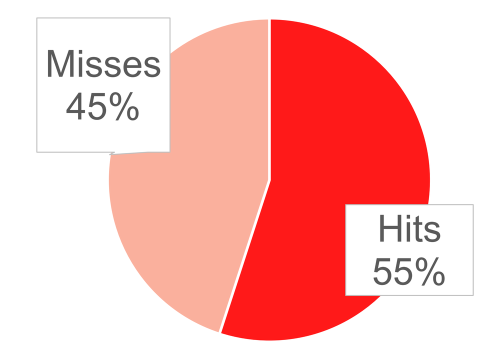
Number of Frequencies in Training	Participant 1	2	3	4	5	6	7	Mean	Greater than chance	# > 50% (1–7)
Top 1	79%	44%	61%	44%	65%	65%	37%	56%	4/7	
Top 2	84%	45%	39%	62%	62%	60%	34%	55%	4/7	
Top 3	83%	45%	29%	64%	64%	60%	37%	54%	4/7	
Top 4	83%	54%	46%	60%	71%	60%	35%	58%	5/7	
Top 5	81%	55%	46%	59%	71%	58%	35%	58%	5/7	
Top 6	**83%**	**55%**	**54%**	**60%**	**68%**	**61%**	**35%**	**59%**	**6/7**	
Top 7	81%	51%	50%	60%	66%	65%	34%	58%	5/7	
Top 8	80%	49%	46%	62%	64%	63%	27%	56%	4/7	
Top 9	85%	51%	39%	62%	78%	51%	31%	57%	5/7	
Top 10	83%	51%	39%	62%	76%	51%	30%	56%	5/7	

PARTICIPANTS

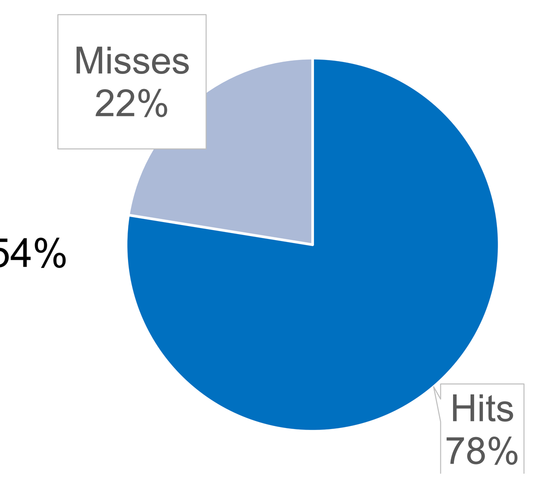
- 7 young adults (2 male)
- Mean education = 14.7 yrs
- Mean age = 22.30 yrs
- All right handed

BEHAVIORAL RESULTS

Memory Recognition



Session 1 Hit Rate
Mean Hit Rate = 55.03%
SD = 13.97



Session 2 Hit Rate
Mean Hit Rate = 77.54%
SD = 16.47

CONCLUSIONS

- The subject-specific models optimized for Session 1 were then tested on Session 2 datasets, yielding greater-than-chance classification accuracy for 6-out-7 participants with a mean classification accuracy of 59% across all participants.
- The feature selection approach presented yielded greater test classification accuracy performance than the typical method of selecting top correlated features.
- These results suggest that individualized, frequency-based feature selection can provide useful input for EEG classification model design that generalizes to novel datasets (Session 2) and predicts memory performance across time.

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