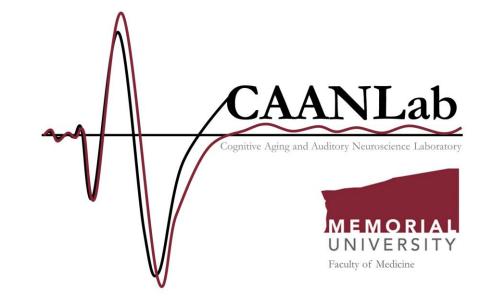
# Using Machine Learning to classify Timbre based on EEG Data



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# Objective



Explore how different timbral characteristics are encoded in EEG data



Current goal: Determine if a machine can discriminate between EEG data recorded when a participant is listening to different musical instruments



**Purpose**: For use in development of auditory prosthesis such as BCI-based hearing aids

Current music listening experience for hearing aid users less than ideal

#### Methods

### 10 participants



Age (SD)	Gender
27.4 (11.05)	7 Female 3 Male

#### **Experiment**



0.5-second A3 (F0: 220 Hz) tones of 4 different instrument timbres: Piano, Trombone, String and Clarinet, and Pure

Each instrument presented a total of 200 times

#### Data recording and pre-processing

EEG recorded from 70 electrodes



5 identical tones were presented in sets, and participants reported the instrument they heard after each set

High pass filter of 0.1Hz

Artifact removal using ICA

Epochs segmented from -1s to 2s

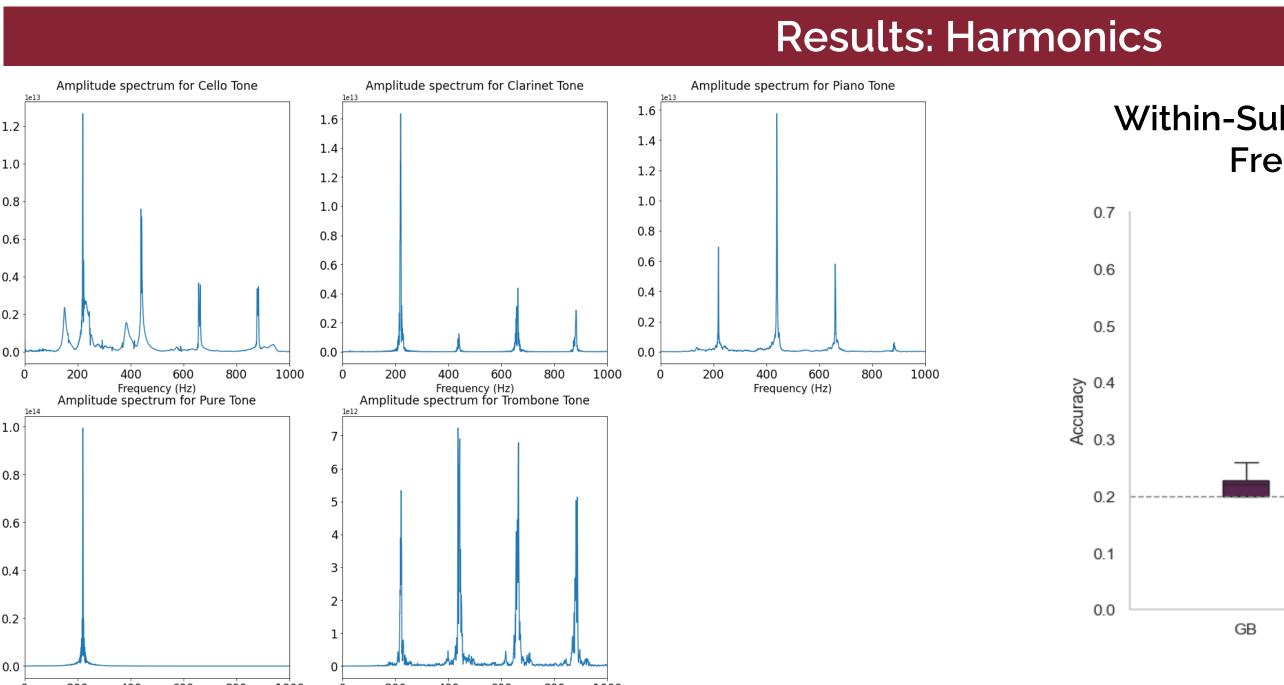


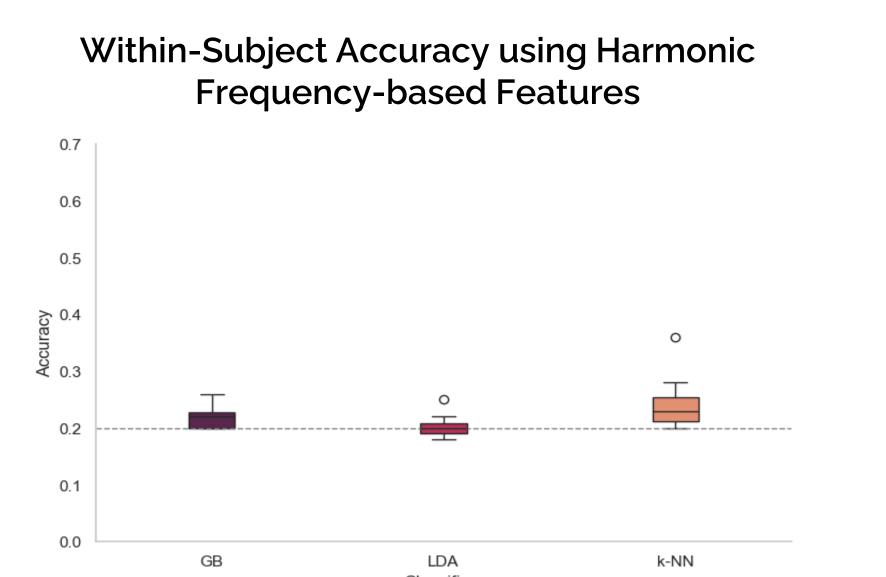
#### Classification

Tested three classifiers: LDA, GB, k-NN



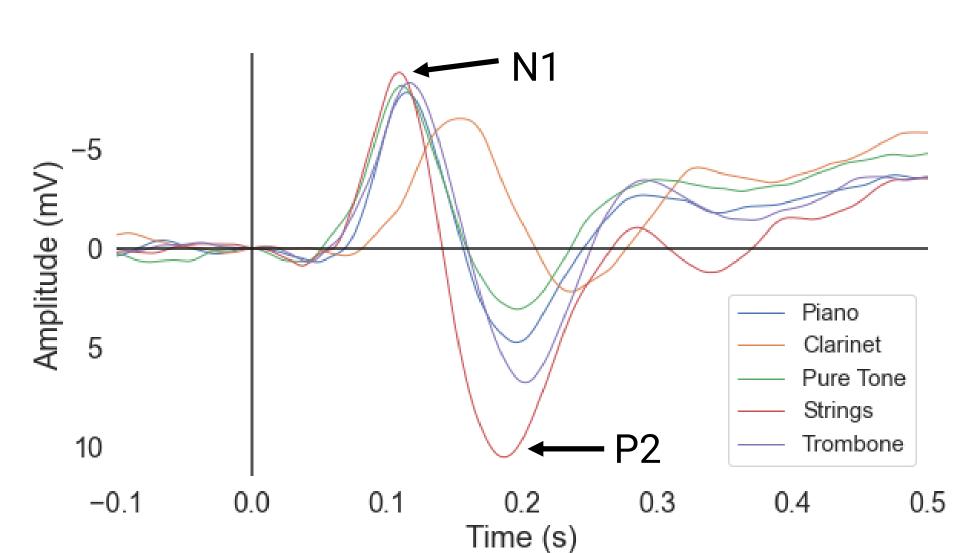


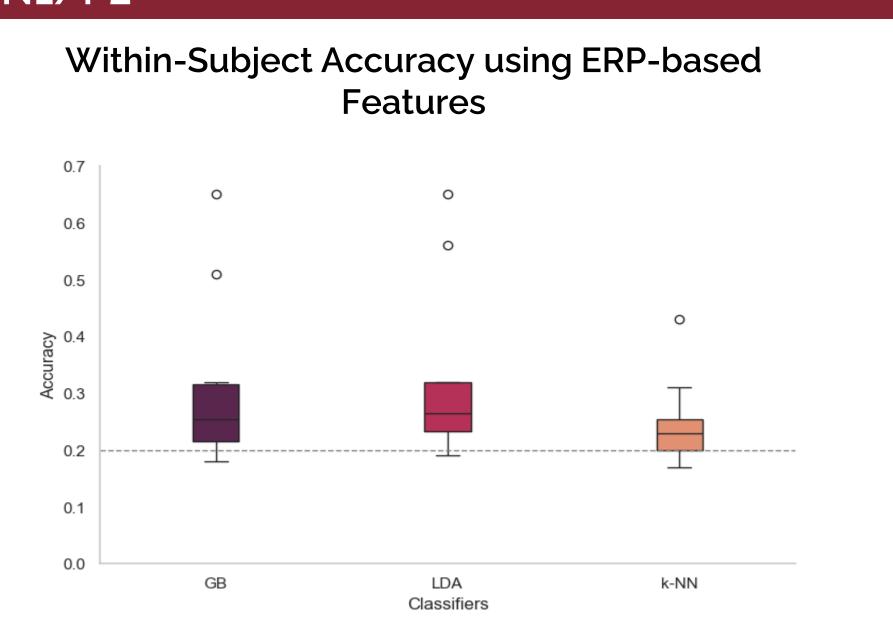




#### Results: ERP-N1/P2

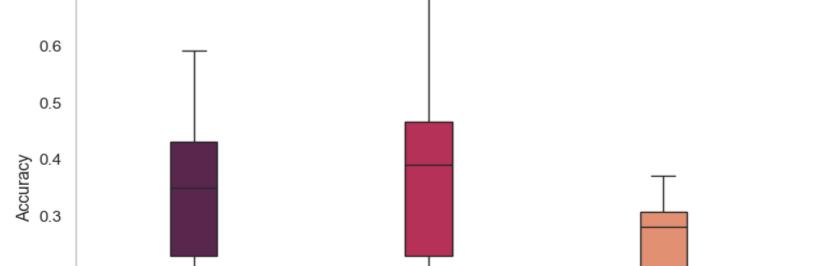
**Grand Average ERPs across Participants** 





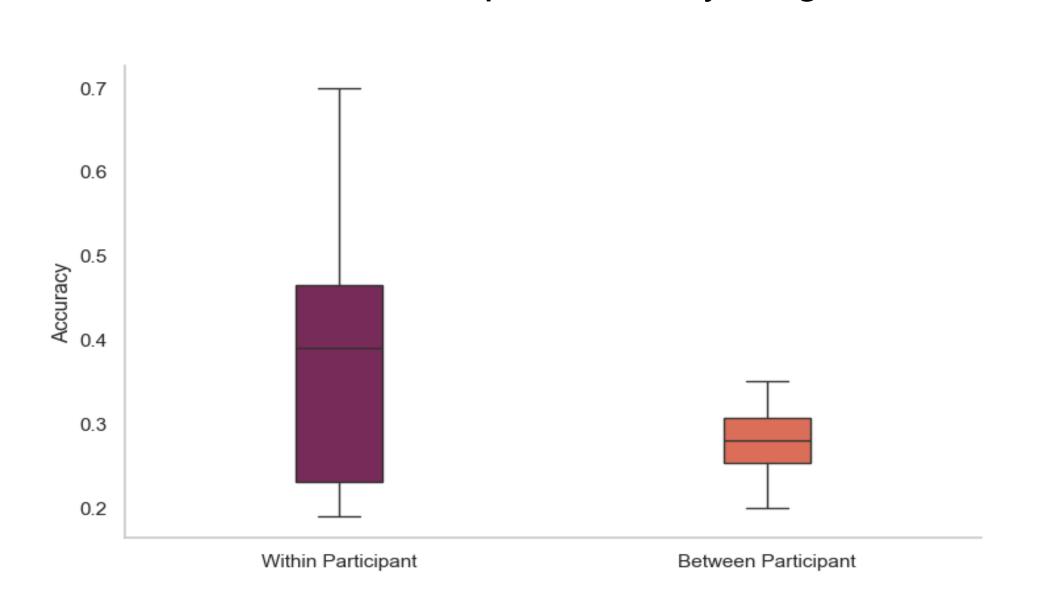
#### Results: Raw EEG

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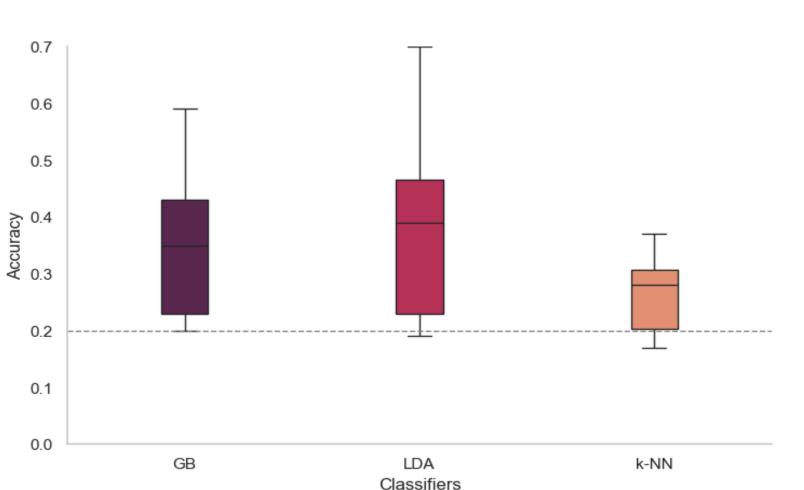


### Results: Within-vs Between Participant

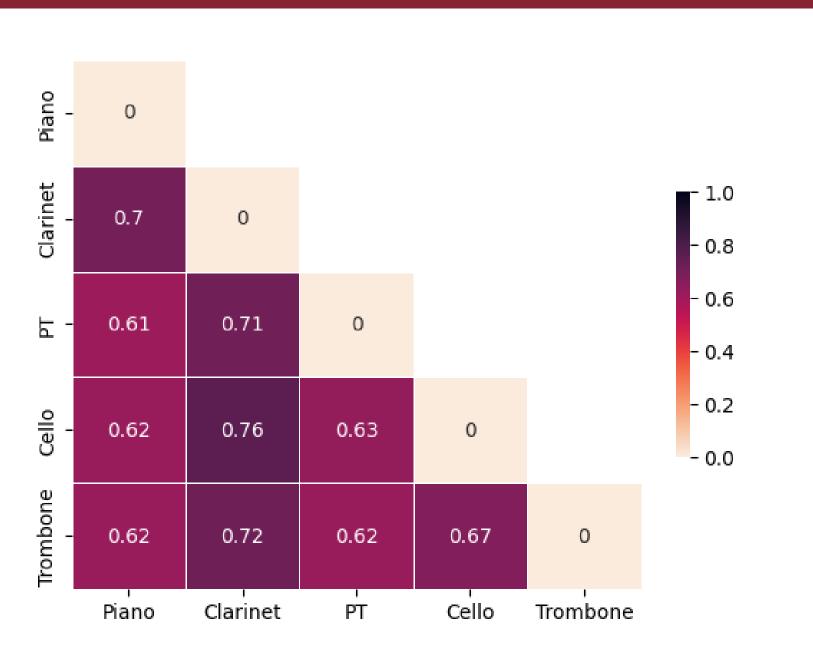
# Within vs Between-Participant Accuracy using Raw EEG



# Within-Subject Accuracy using Raw EEG



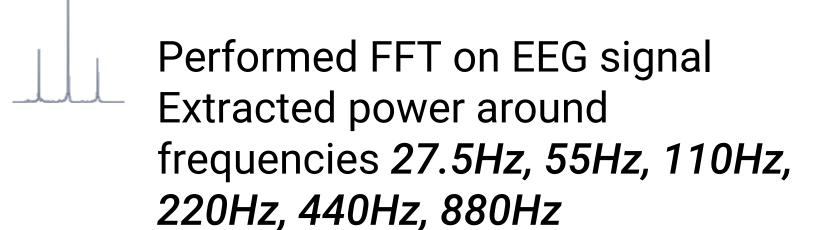
#### Results: Pairwise Classification



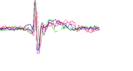
#### Methods

Within-Subject models trained on following features individually:

> Spectral information around harmonic frequencies of audio tone:







Used mean and peak amplitude and latency of N1 and P2



## Raw EEG

Raw EEG input without any feature extraction

#### PCA used for feature reduction

Between-Participant classification performed with **Raw EEG** 

#### Discussion

- Classifier performed above chance
- Features related to harmonic frequencies did not seem to contribute to classifier performance as much compared to raw EEG and ERP-Based features
- Performance of within-participant model > between-participant model
- More complex models could possibly lead to higher accuracy rates
- ► Pairwise classification indicates **Clarinet** and **Cello** are the most easily discriminated





