Decoding Music Representation in the Human Brain using EEG Data

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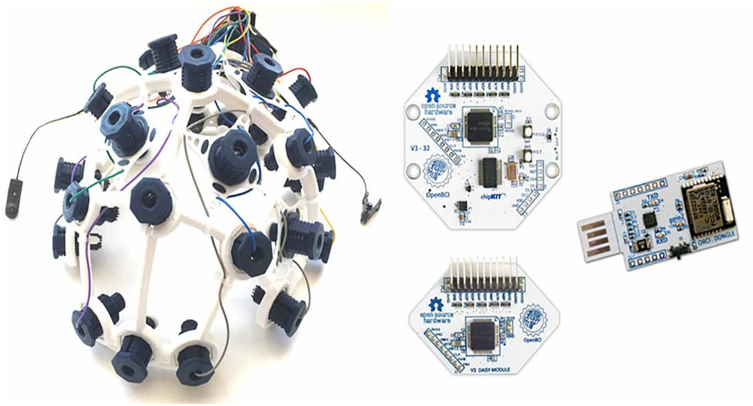
Why investigate EEG data?

- Prior research in Computational Linguistics
- Study language representations
- Augment features
- Young growing field in MIR
- Datasets: NMED-H, OpenMIIR etc.



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Goals

- Study the correlation between music features and EEG data
- Evaluate first steps to creating semantic audio feature vectors
- Exploratory analysis on a popular EEG music dataset

OpenMIIR Dataset

- 10 subjects listening to and imagining 12 short music fragments

  - each 7s-16s long

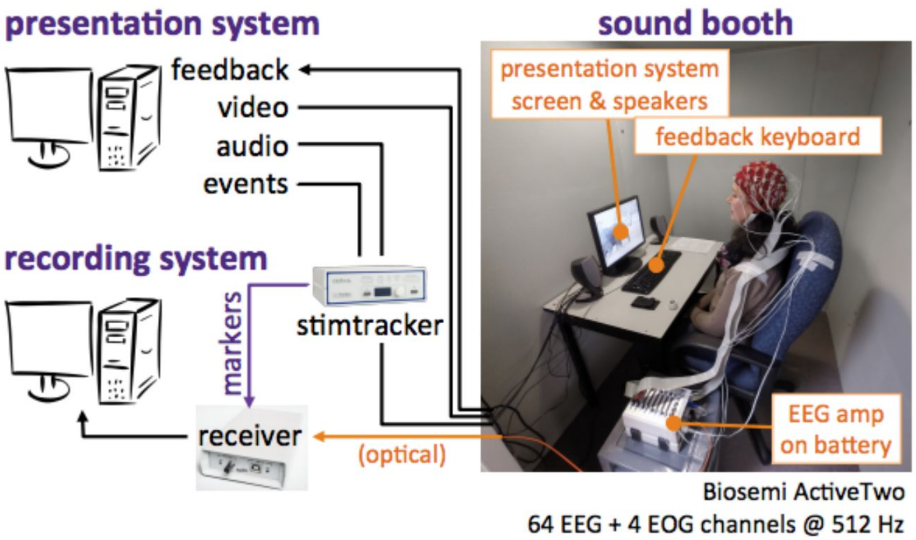
- Songs are from different genres, have varying tempos, some use vocals, etc
- There were 5 trials per participants with songs in random order
- 60 songs per participant (12 songs * 5 Trials)

OpenMIIR
public domain dataset of EEG recordings
for music imagery information retrieval

S Stober, 2015

Collection Methodology

1 Chim Chim Cheree (lyrics)
2 Take Me Out to the Ballgame (lyrics)
3 Jingle Bells (lyrics)
4 Mary Had a Little Lamb (lyrics)
5 Chim Chim Cheree
6 Take Me Out to the Ballgame
7 Jingle Bells
8 Mary Had a Little Lamb
9 Emperor Waltz
10 Hedwig's Theme (Harry Potter)
11 Imperial March (Star Wars Theme)
12 Eine Kleine Nachtmusik



S Stober, 2015

EEG Data Preprocessing

- Remove bad channels
- Remove the ICA features
- Normalize the dataset

Prior work on the music EEG domain

- Correlate music features such as tempo, MFCC, zero crossings, CQT with brain data (NMED-H dataset) [1]
- S Stober trained an SVM to distinguish between 12 songs from the EEG data (18-27% accuracy with feature extraction) [2]
- Predicted tempo and rhythm perception from the EEG data [3]

[1] Cong, 2013
[2] S Stober, 2016
[3] S Stober, 2016

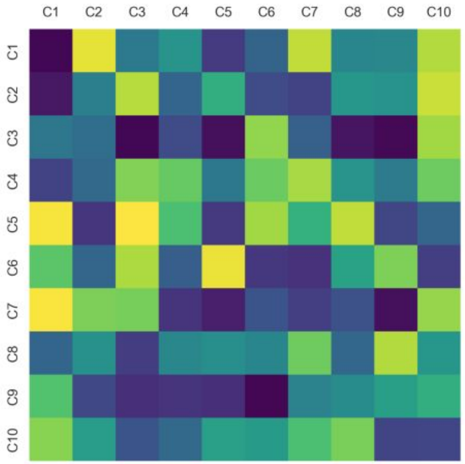
Creating audio vectors

- Inspired by “semantic word vectors” for computational linguistics
- Built audio vectors utilizing MFCCs, RMSE, spectral centroid, chroma STFT, spectral roll-off, tempogram, harmonic, and beat features
- Built vectors from tag-classification neural networks

Representational Similarity Analysis

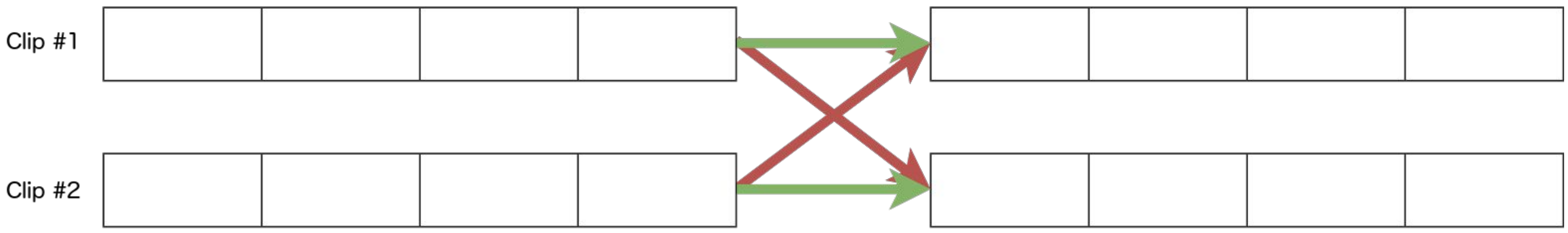
- Calculate a pairwise correlation matrix of EEG for the set of songs
- Calculate a pairwise correlation matrix of audio vectors for the set of songs

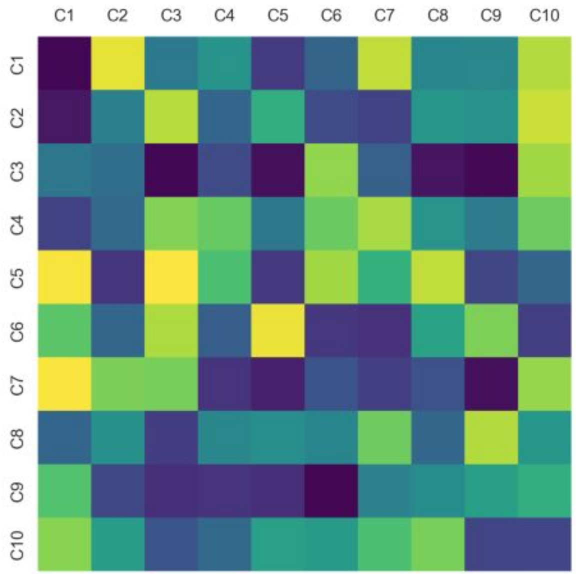
	Sing 1	Song 2	Song 3
Sing 1	1	0.2	0.8
Sing 2	0.2	1	0.3
Song 3	0.8	0.3	1

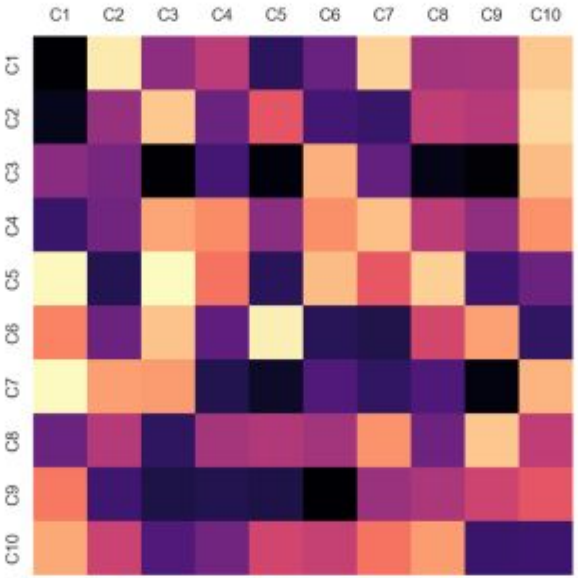


“2 vs 2” Correlation Test

- Simplify vector comparisons into binary classification task
- Used often in computational neurolinguistics
- “Leave two out” benchmark analysis




C1 C2 C3 C4 C5 C6 C7 C8 C9 C10
C1 C2 C3 C4 C5 C6 C7 C8 C9 C10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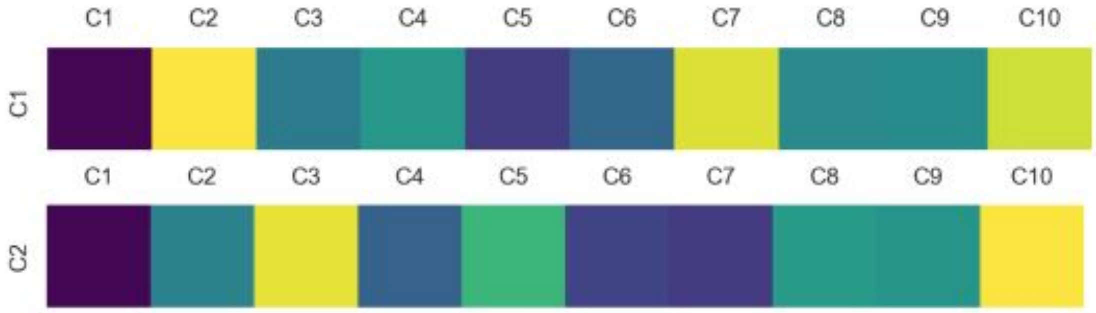
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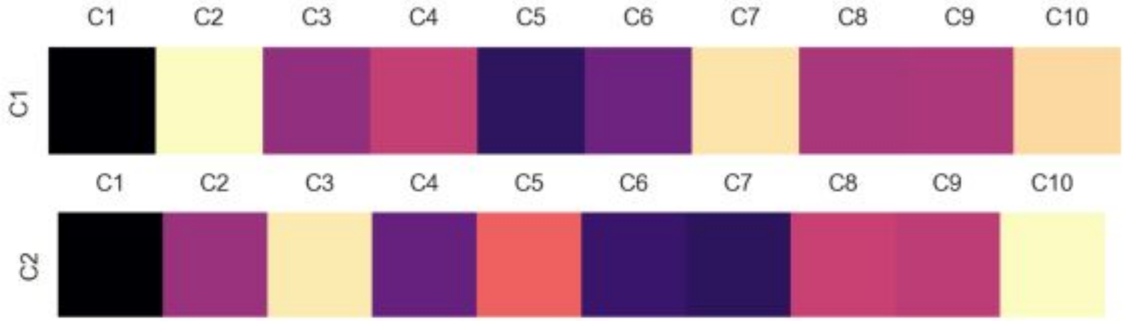
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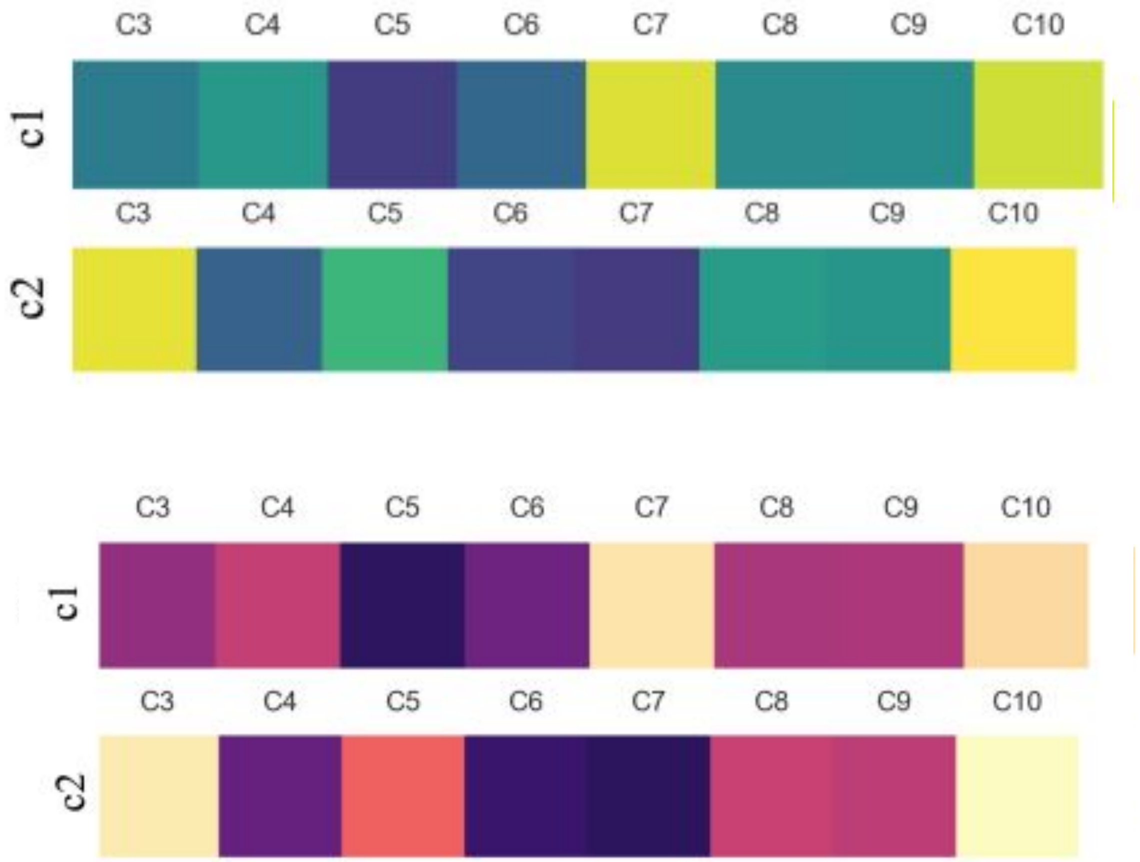
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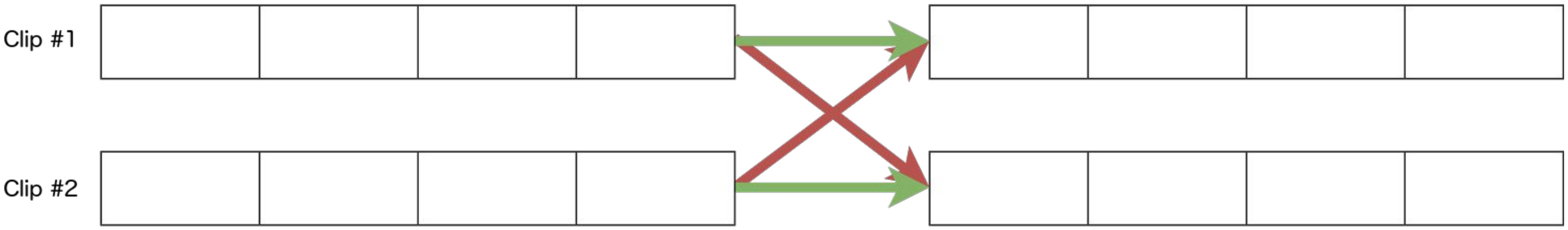
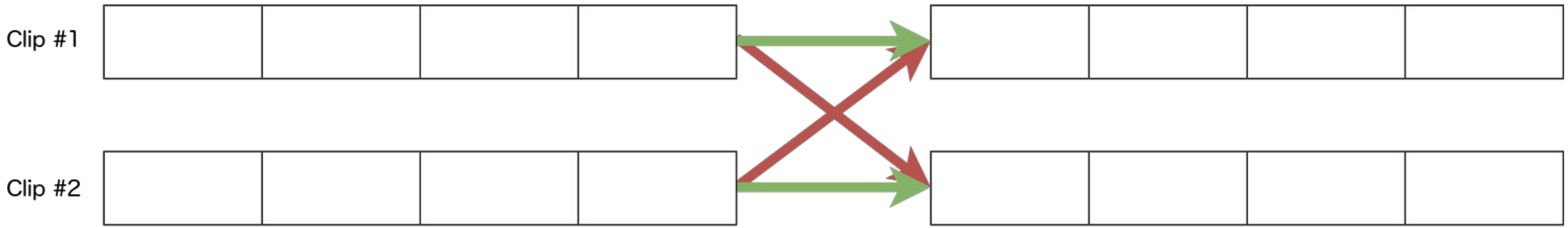

Clip #1
Clip #2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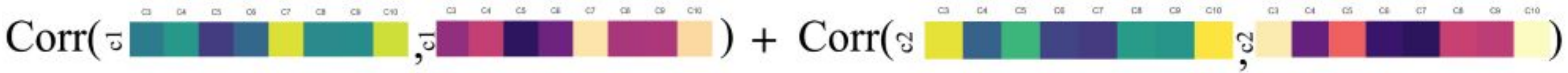
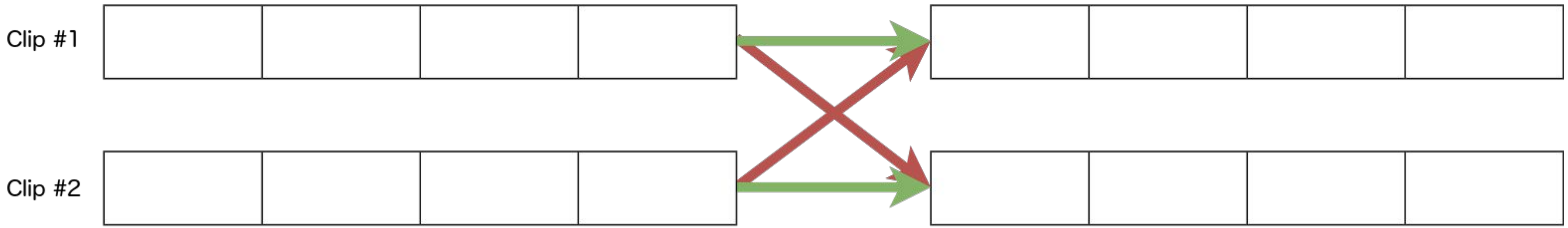
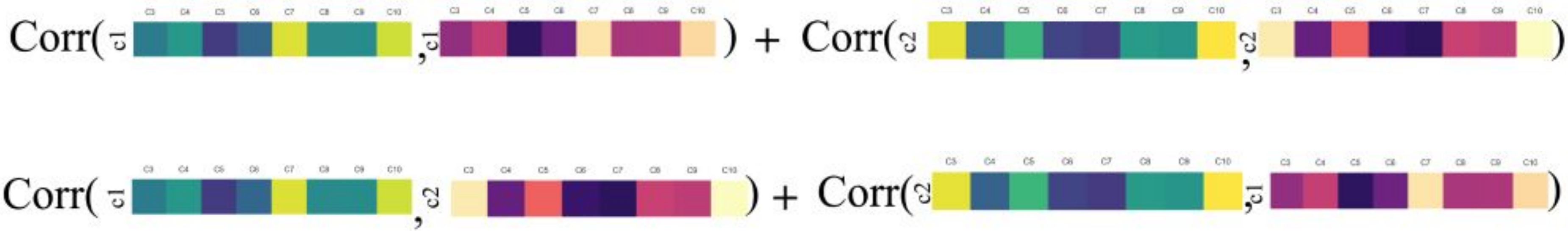

Corr(c1 , c1) + Corr(c2 , c2)


Clip #1
Clip #2


Corr(
c1
,c1
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c2
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Corr(
c1
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) + Corr(
c2
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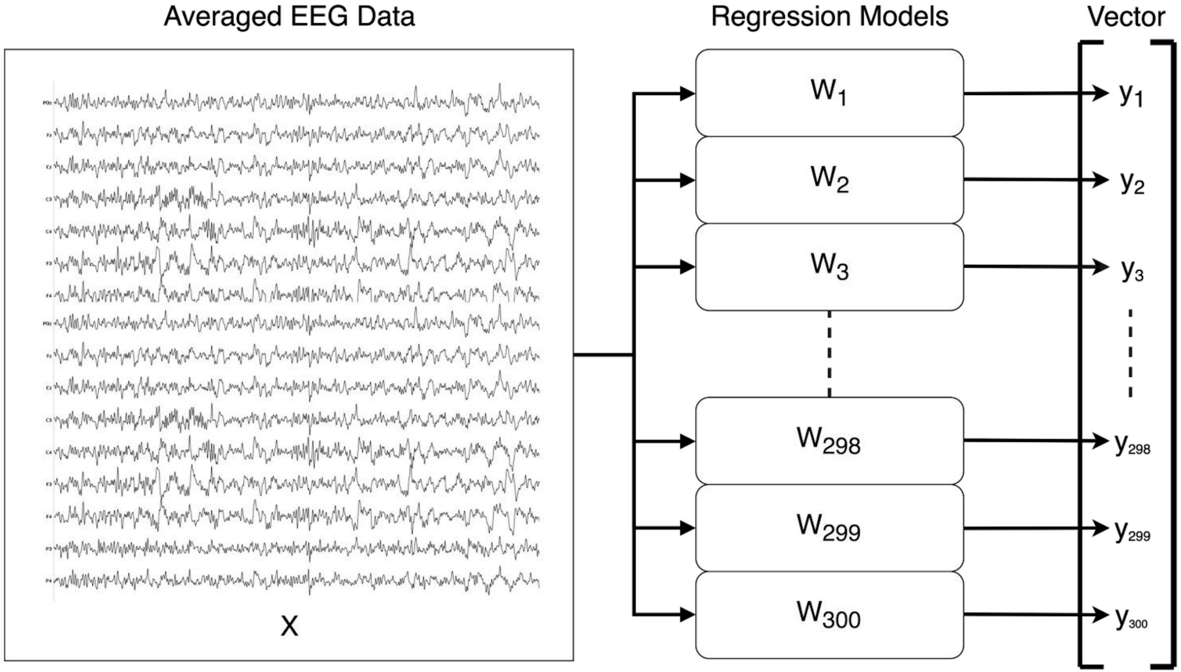
)

Linear Models Approach

- Machine learning model - set of linear ridge regressors

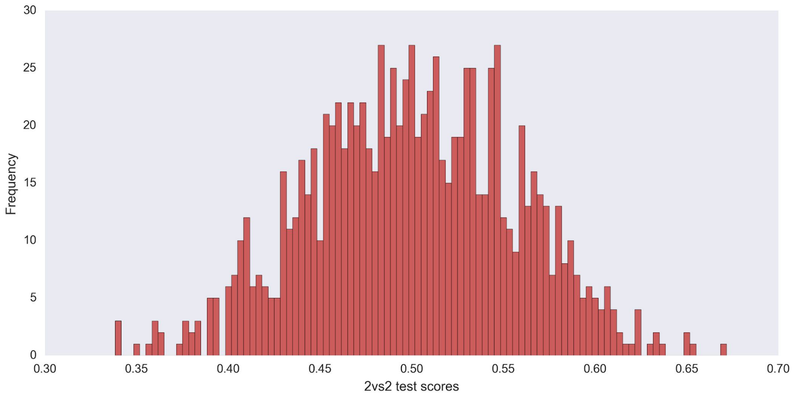


Correlation Results

- We've explored various features for correlating with the brain data
  - MFCC coefficients, tempo, beat features, chroma, mel spectrogram features....
- We've detected evidence of correlation!

MFCCs: **0.62** Tempogram: **0.63**

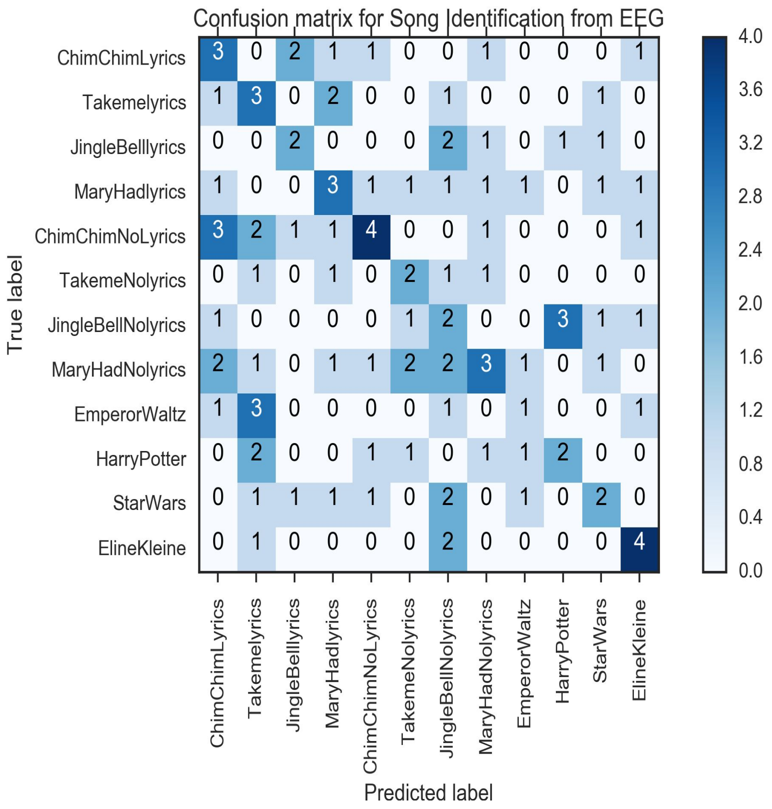
- However, more thorough testing and permutation tests are needed to confirm these results



Performing Song Identification

- Searching for correlation is a good opportunity to explore the dataset!
- We improved on the original song identification via logistic regression

Model	Accuracy
SVM (Raw)	18%
SVM (SCE)	27%
LogReg (Raw)	**29%**



Why might correlation be hard to find?

- This is a difficult task with very high noise
- There is a lot of data, and there is little data!
- Trials captured over multiple recordings
- Much of the data is mixed classes
- The “semantic song space” is small
- The “semantic song space” is narrow

The Perfect Experiment™

- Standardized track length
- Full 64 sensor recording
- Larger spread of audio genres
- Single-session recording
- Larger number of audio tracks
- Larger number of participants

Future Work

- Exploring regularization improvements
- Exploring combination of subject data
- Continuing iteration on audio feature vectors
- Further improvements / classifications on dataset
- Perform the Perfect Experiment™?

Summary

- Designed and built an experiment methodology for applying techniques from computational neurolinguistics to a new and exciting audio-EEG dataset
- Found evidence of correlation between the EEG activity of participants listening to songs and the features which we extracted from those songs
- However, this dataset has a number of limitations for this task!
- Improved over previous work on this dataset, using a greatly simplified model

Questions?