

Classifying Idea Generation, Idea Evolution, and Idea Evaluation Tasks from EEG Signal

BCS512 Final Project Spring 2022

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Outline

- Dataset and Basis for the study
- Approach 1: Analysis based on prior work of Jia & Zeng
 - Feature extraction
 - Classification approaches
- Approach 2: CNNs for EEG Spectrogram Classification
 - Data generation
 - Classification Approaches
- Current results and work to be done

Basis for Study

Idea Generation, Evolution, and Evaluation

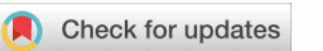
- A study by Jia & Zeng (2021)
- Loosely Controlled Experiment
 - Shown a stimulus
 - Rest with eyes closed for 3 minutes
 - Given up to 3 minutes to draw something from the stimulus and label it (Idea generation)
 - Given up to 3 minutes to draw something else from the stimulus that does not look similar to previous idea or a set of other images (Idea Evolution)
 - Given up to 3 minutes to describe the difficulty of idea generation and idea evolution (Idea Evaluation)

scientific reports

OPEN

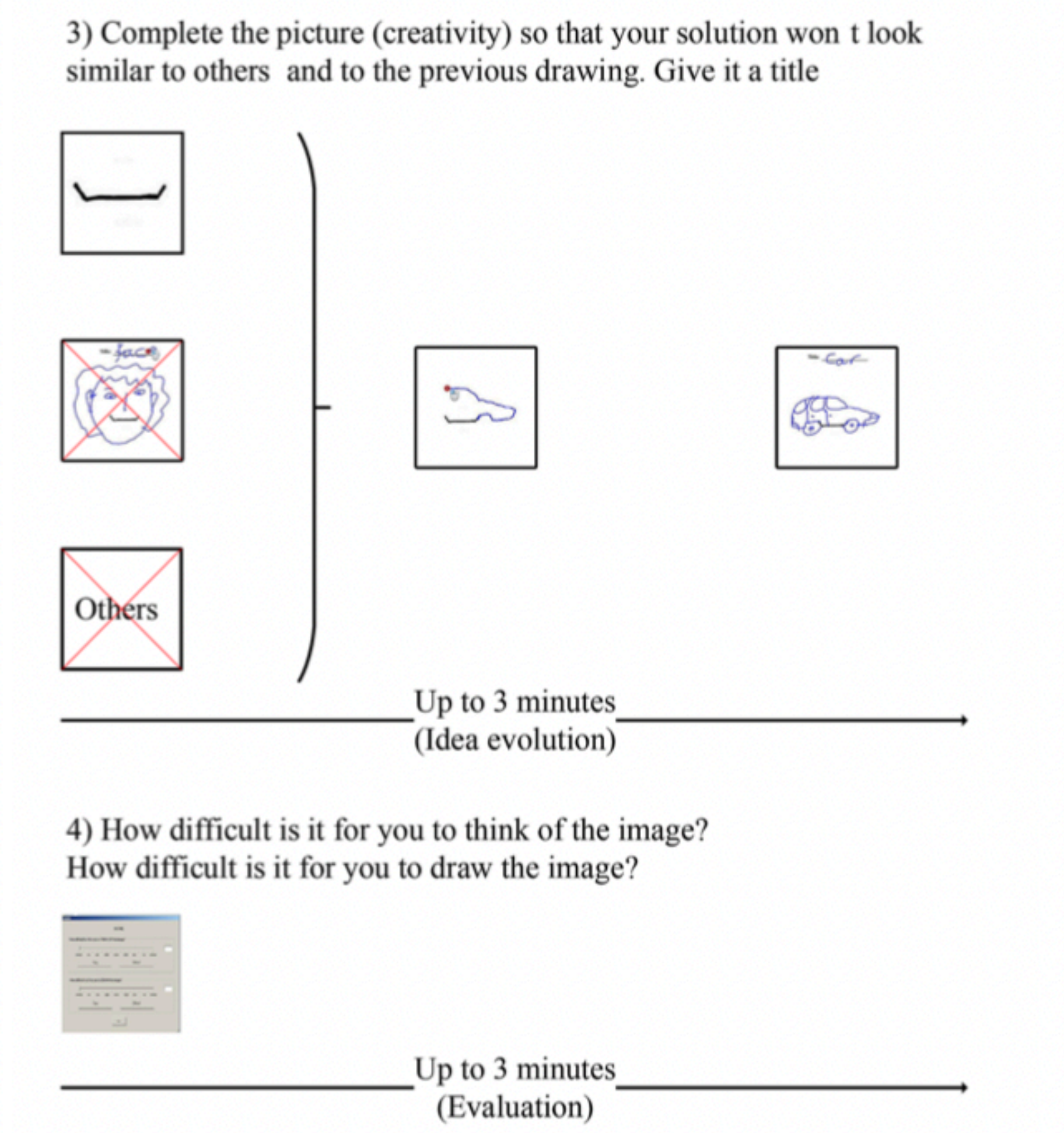
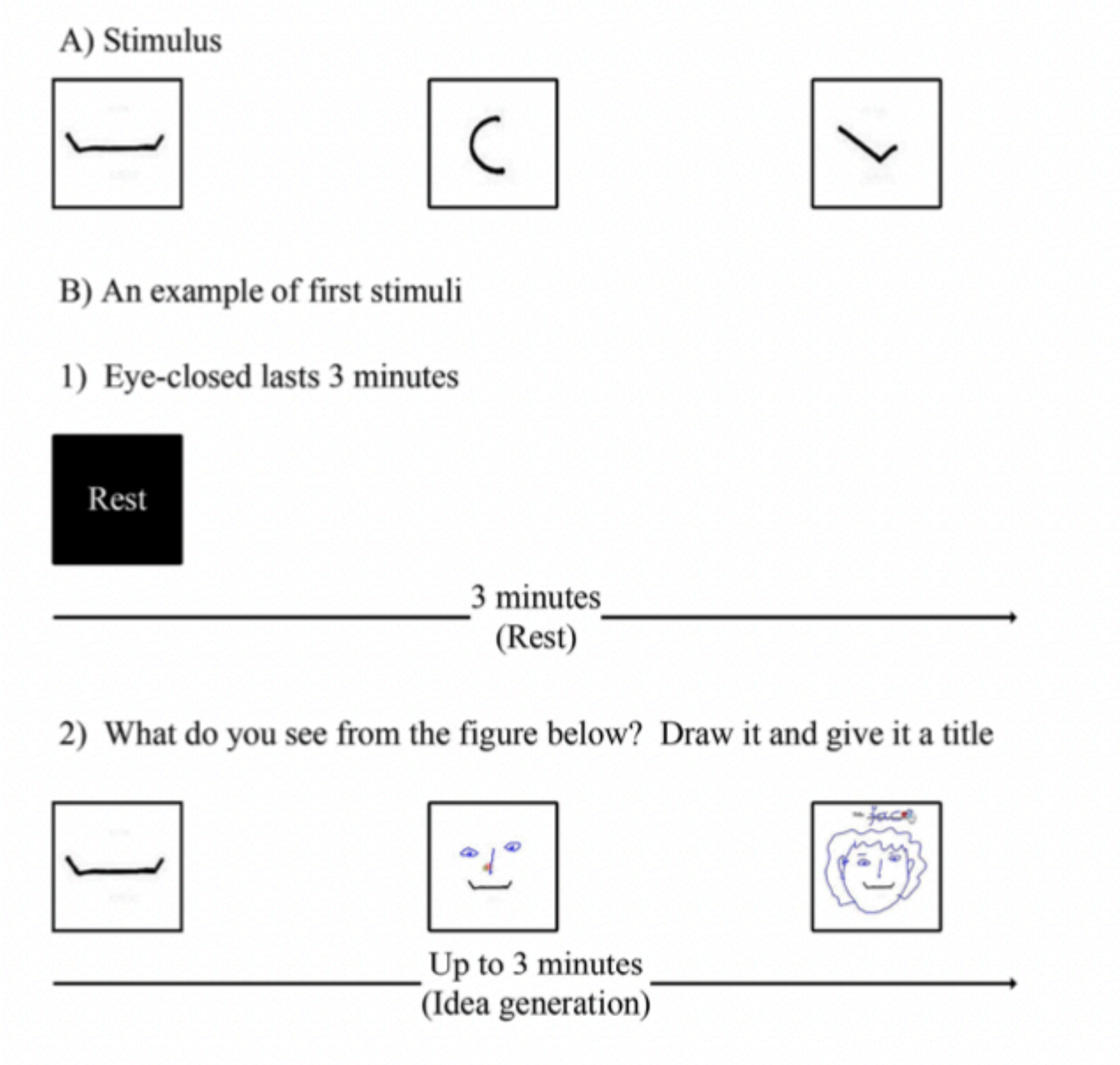
EEG signals respond differently to idea generation, idea evolution and evaluation in a loosely controlled creativity experiment

Wenjun Jia & Yong Zeng✉

 Check for updates

Basis for Study

Idea Generation, Evolution, and Evaluation



Takeaways from the Study

Idea Generation, Evolution, and Evaluation

- **Dataset**

- 63-channel raw EEG readings from 29 Subjects who completed the previously described experiment. Sampled at 300Hz
- Segmented by phase of the experiment (Idea Generation, Evolution, and Evaluation)

- **Statistical Analysis**

- Microstate duration and coverage was significantly different between the 3 creative modes of thinking
- Alpha power decreased significantly between rest and the three modes of thinking and between idea evolution and the other modes of thinking

Microstate Analysis

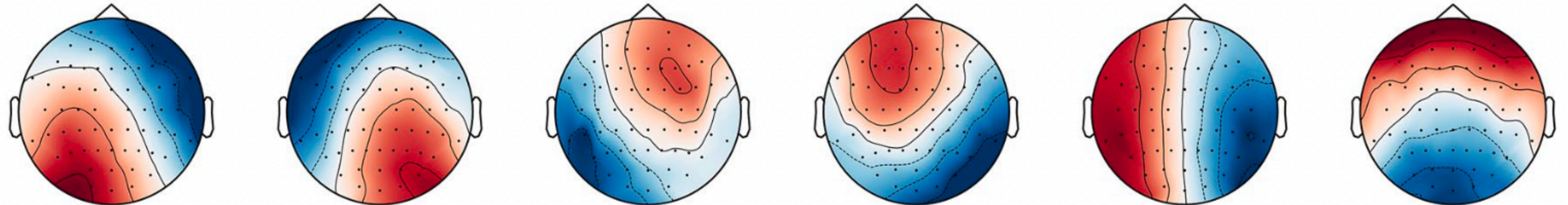
Extracting features based on previous study

- Microstates are short periods of stability in the scalp potential field
- Generated by the simultaneous activity of parts of large-scale networks:
 - “Researchers have proposed that these microstates represent the building blocks of the chain of spontaneous conscious mental processes” (Michel & Koenig 2017)

Microstate Analysis

Extracting features based on previous study

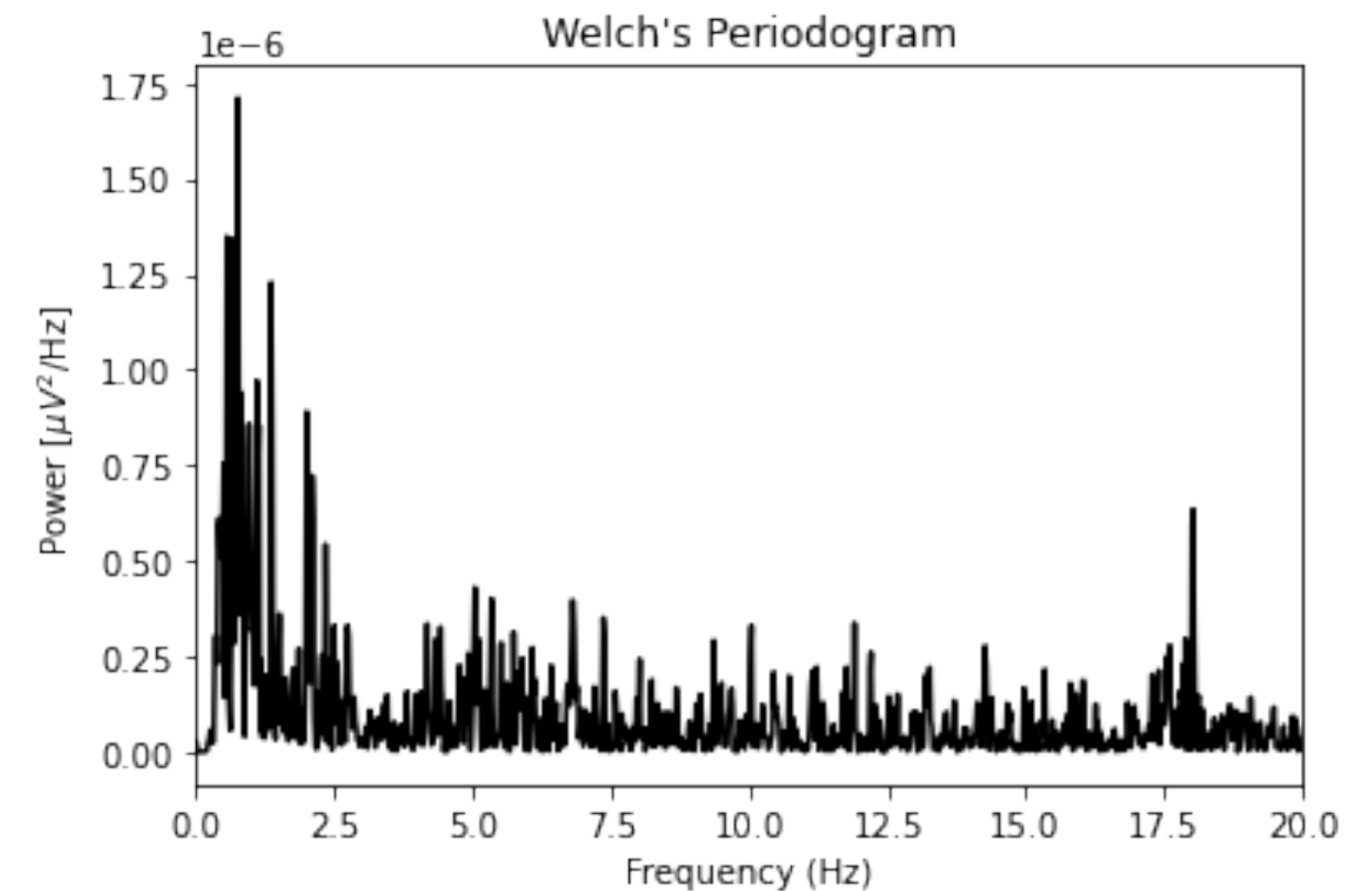
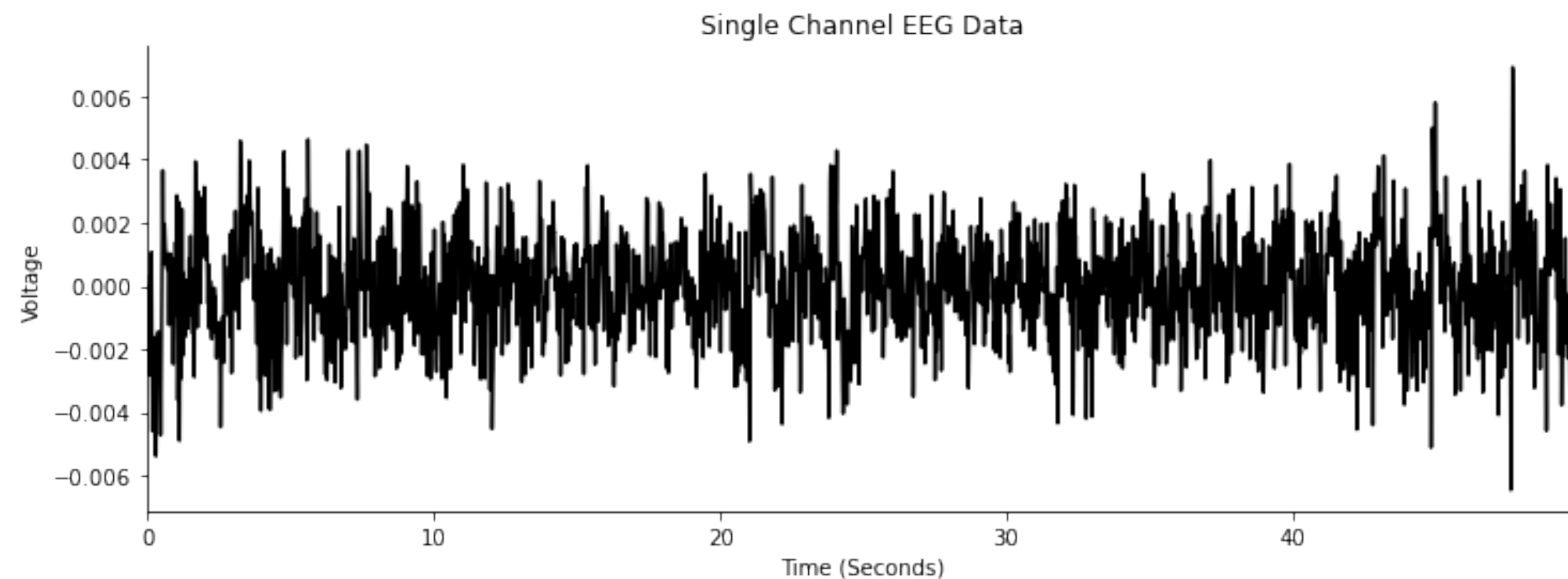
- Segment activity into 6 microstates
 - Extract the relative duration and percent coverage as features



Frequency Domain Analysis

Extracting features based on previous study

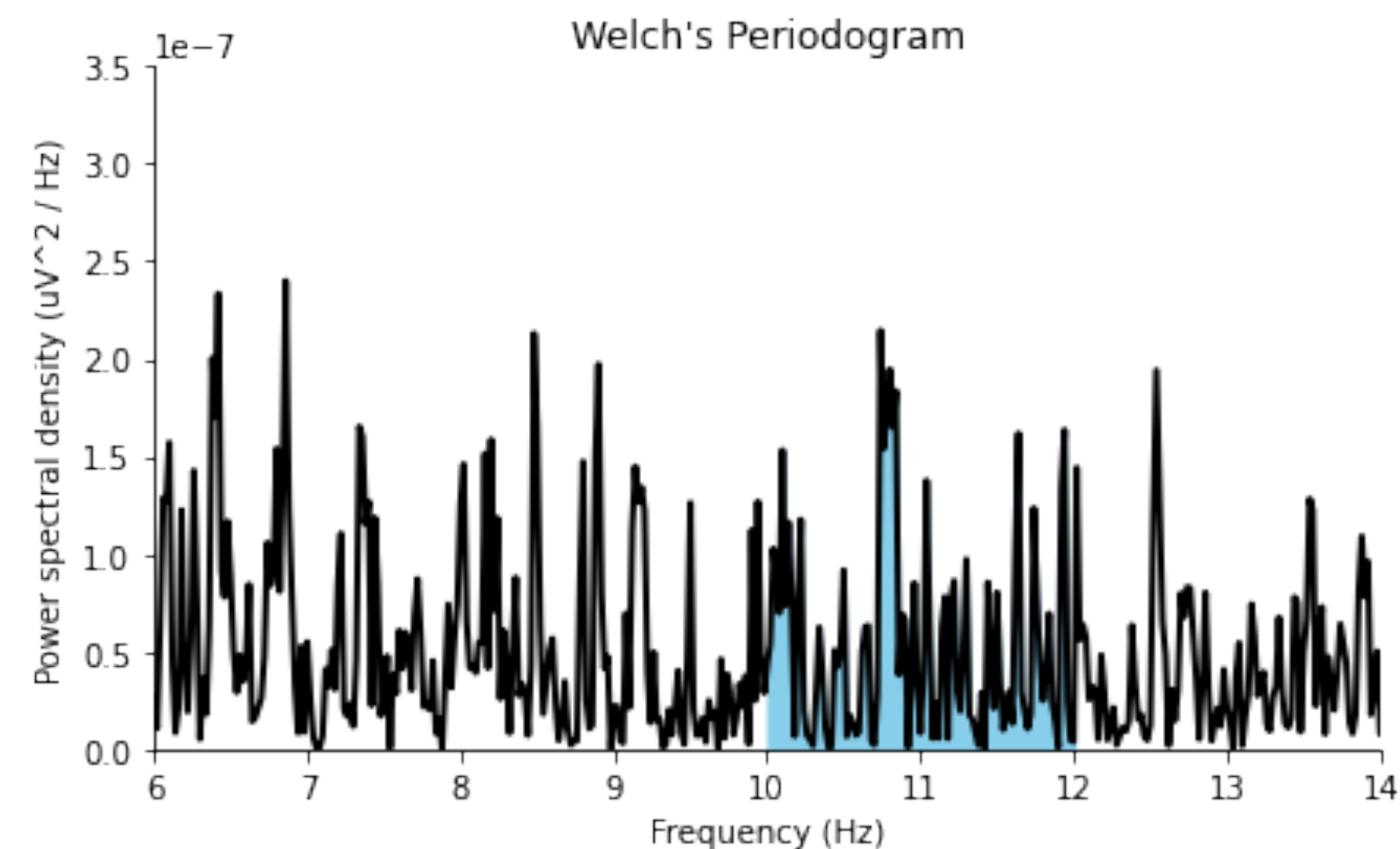
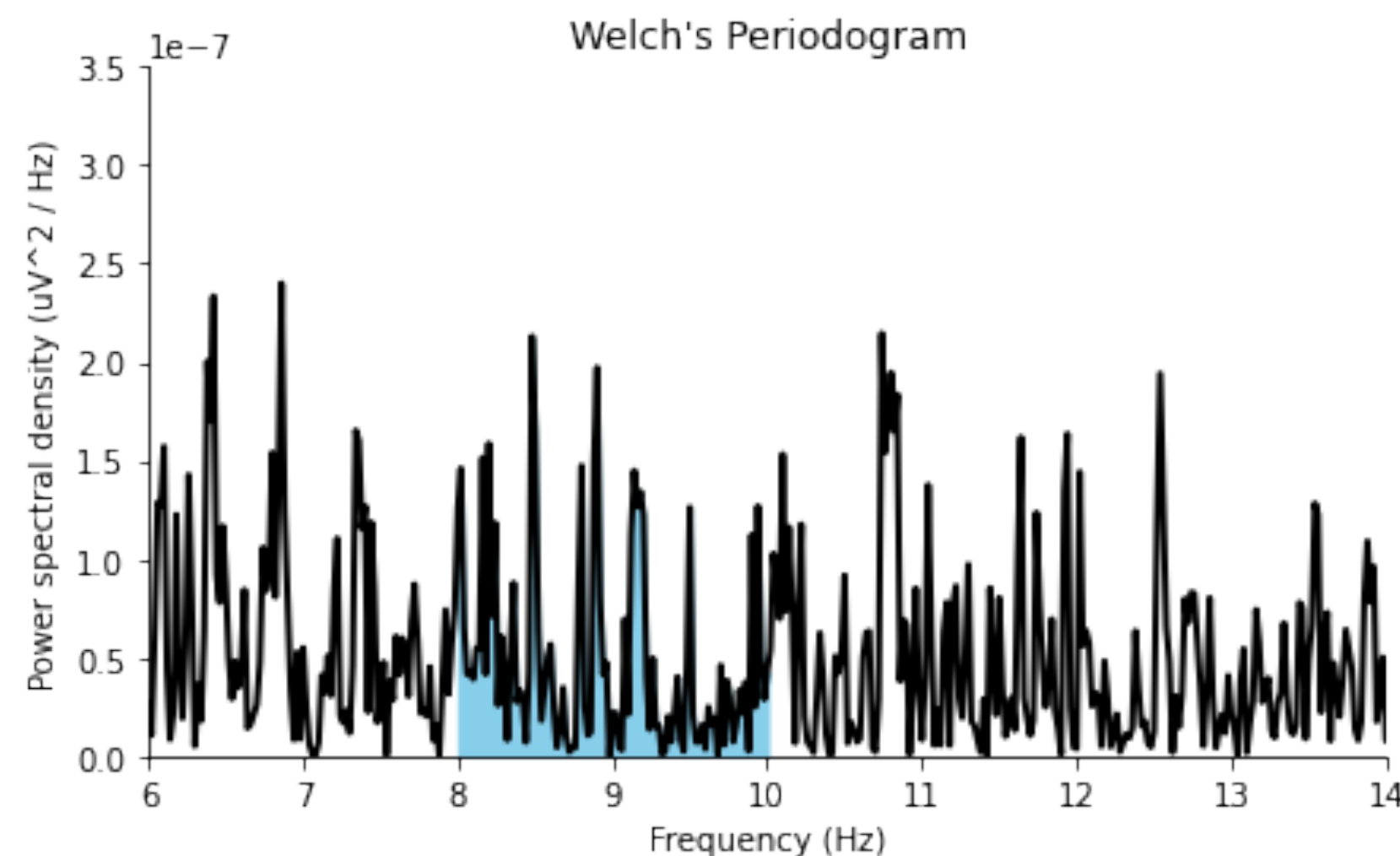
- Use Welch's method to estimate the power of the signal at different frequencies
- SciPy library in python



Upper and Lower Alpha Power Changes

Extracting features based on previous study

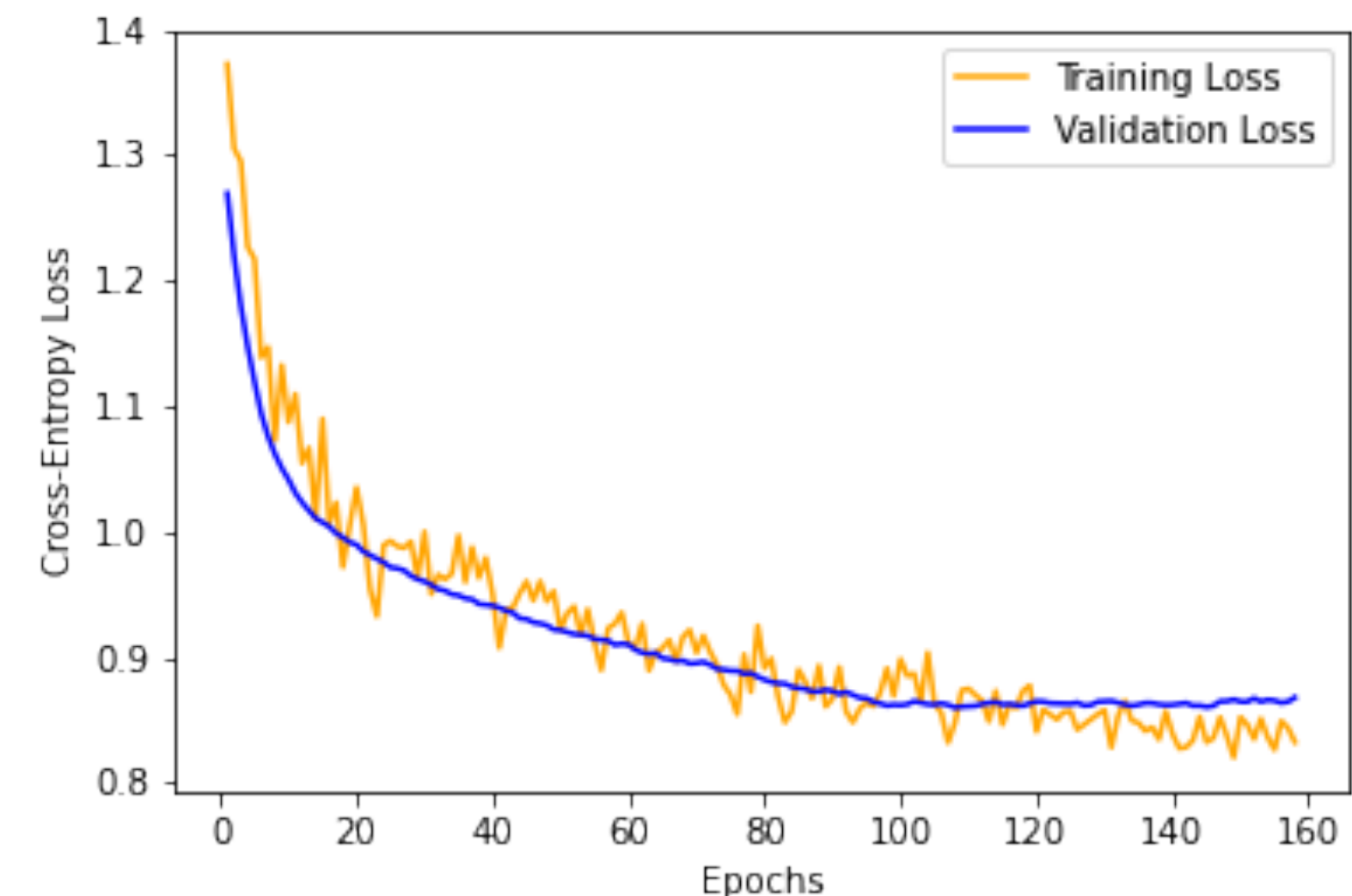
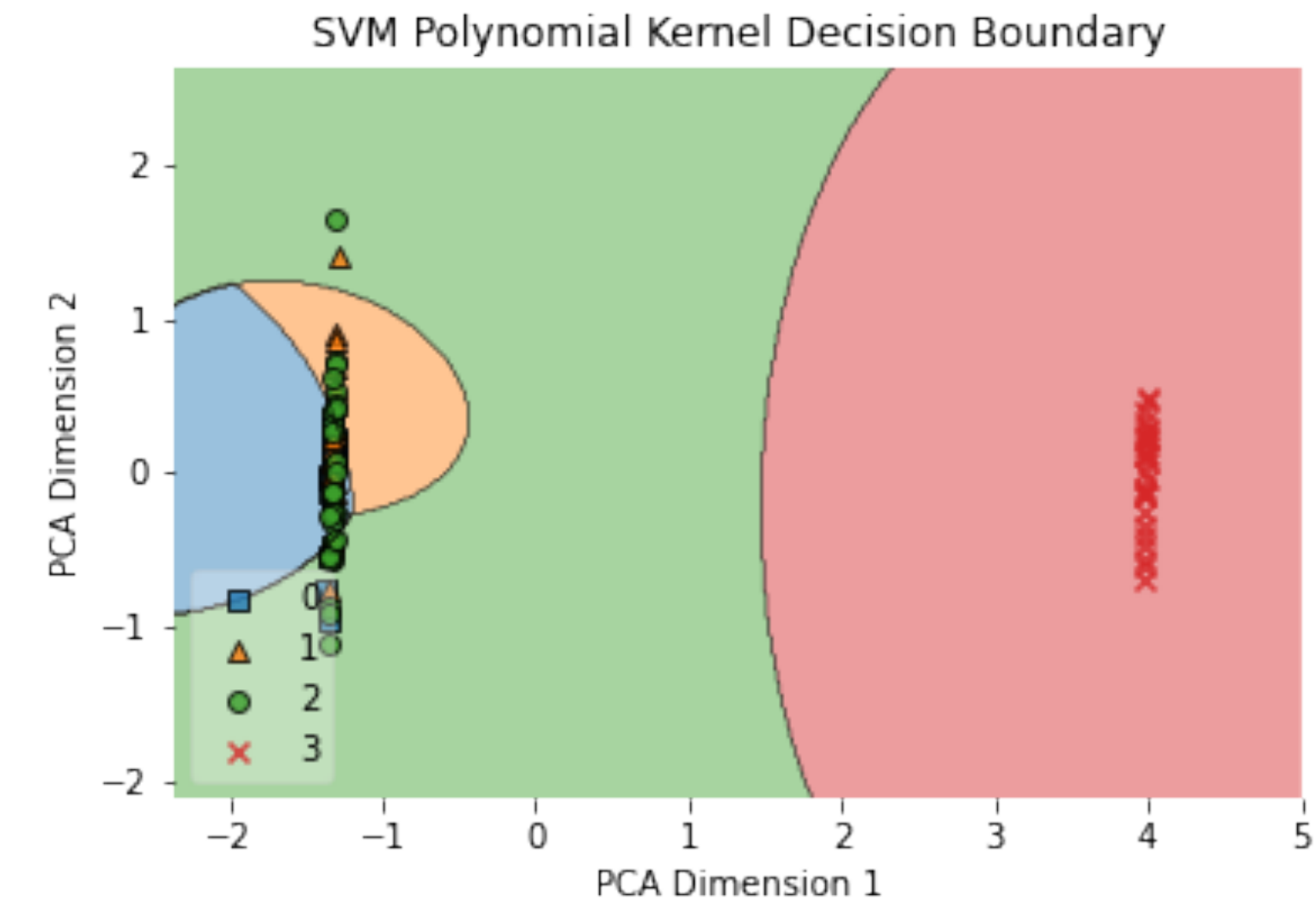
- Extract the power of the upper and lower alpha bands by estimating the area under this power spectrum
- Jia & Zeng found that idea evaluation was associated with increases in alpha power, but were not significantly different between idea generation and evolution



Modeling with Extracted Features

Can these features be used to build a classifier?

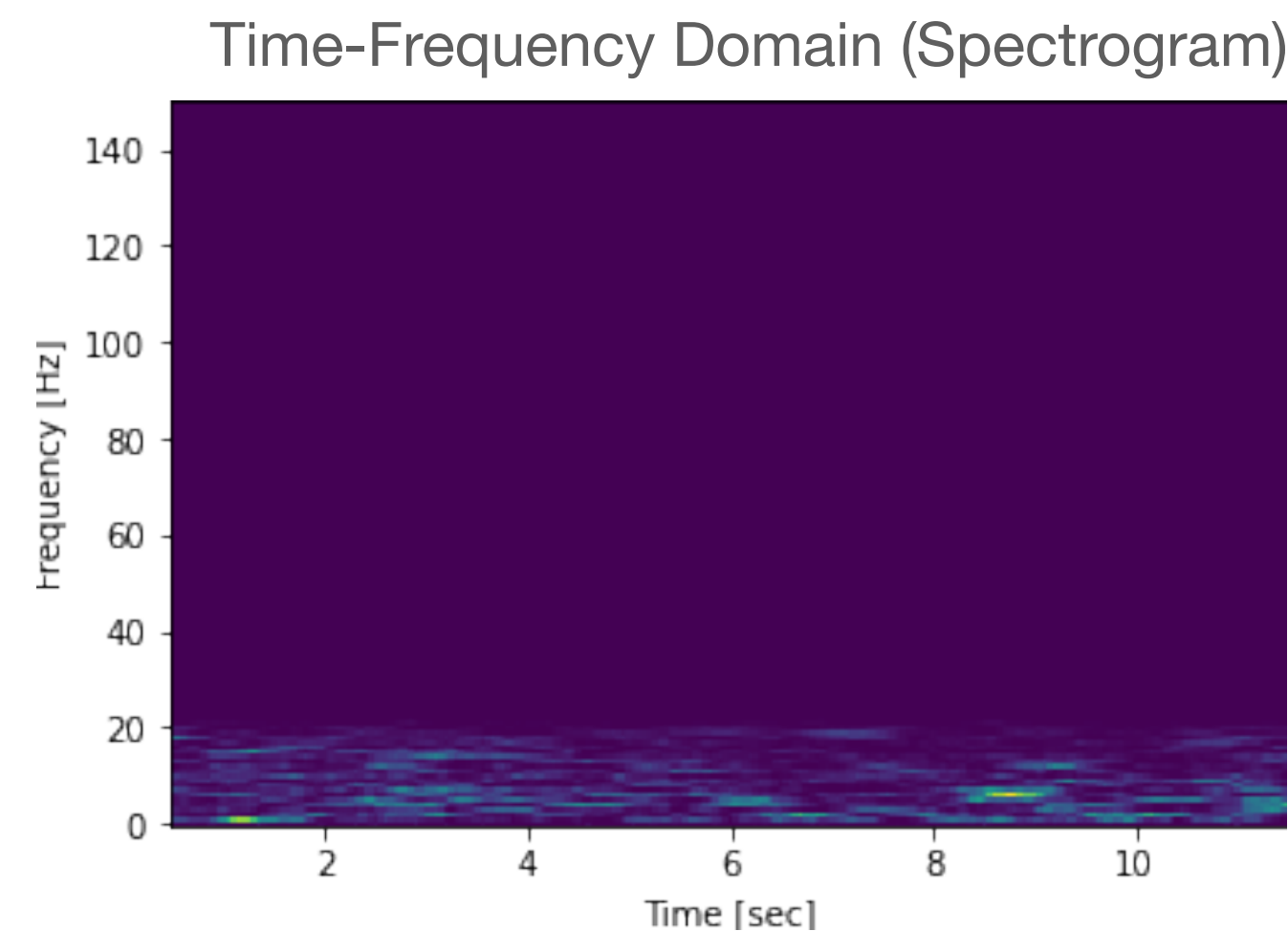
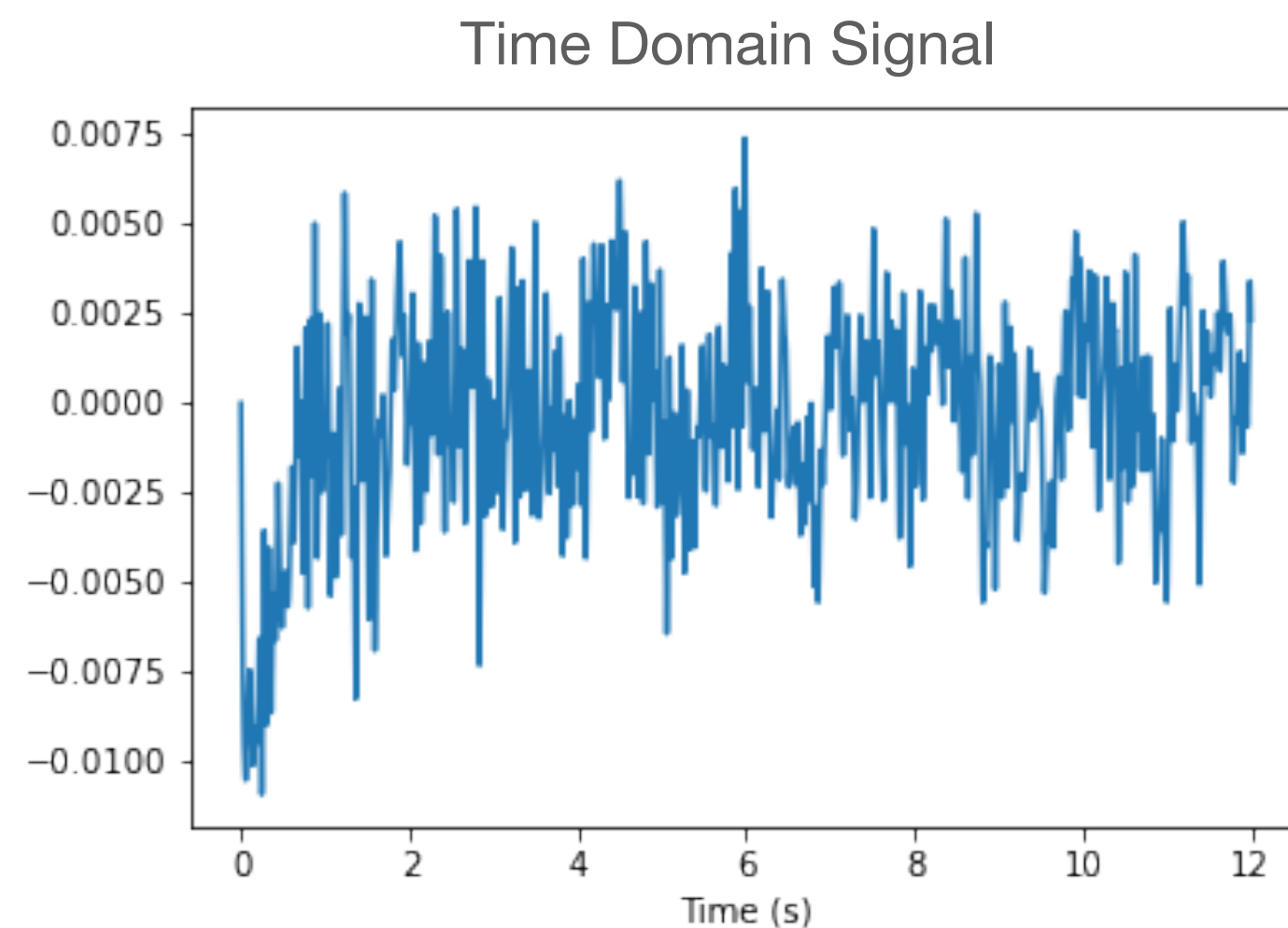
- **Support Vector Machines**
 - Polynomial kernel function
 - 64% Test Accuracy
- **Feed Forward Neural Network**
 - 67.65% Test Accuracy
- Accuracy here is inflated because the rest state is extremely easy to classify - around 55% test accuracy between modes of thinking without rest state
- Creative modes of thinking do not seem to be easily separable using these features alone
 - This would make sense if micro state analysis was effective at identifying resting state and differences in alpha power were not significant across modes of thinking



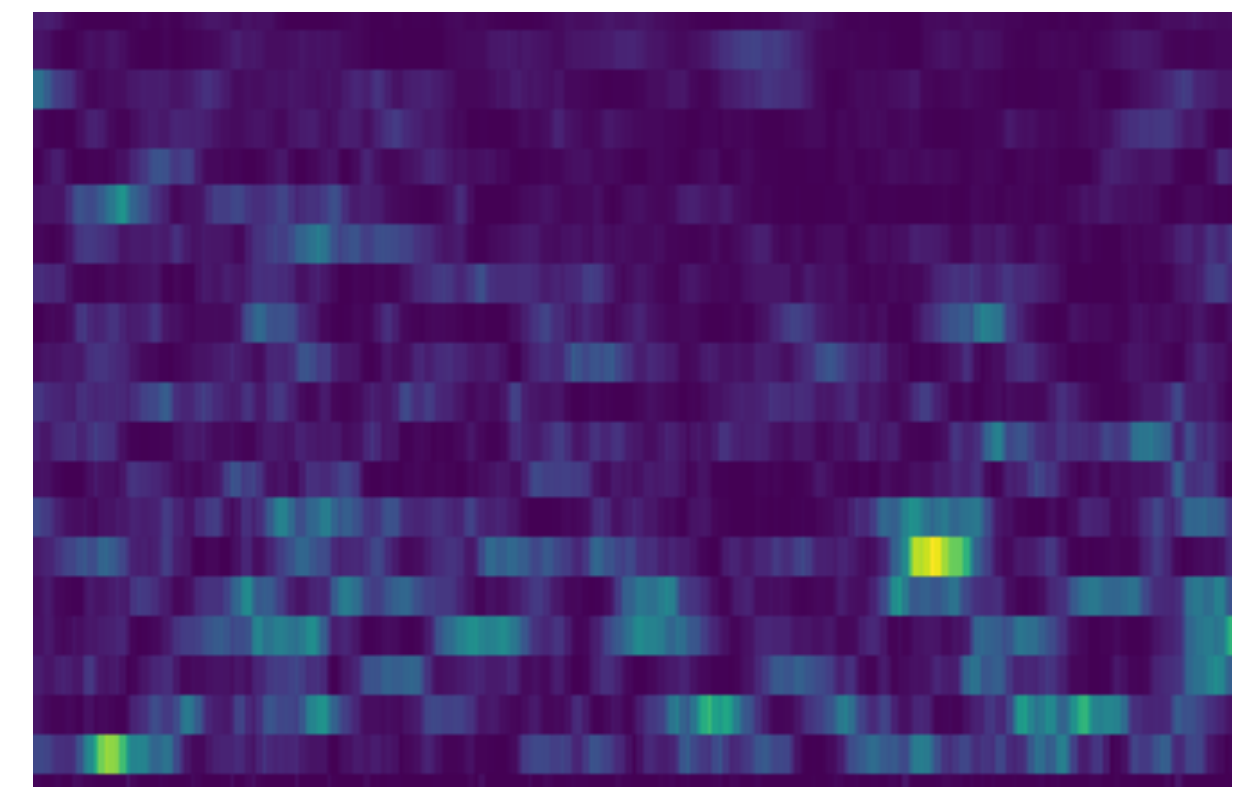
Time-Frequency Analysis

EEG Spectrogram Analysis

- Can use short-time Fourier transform to create spectrograms
- Spectrograms show the change in power of the frequency components of a signal over time
- **Concept:** Chop the signal into 10-second segments, generate spectrograms, and reframe the problem as an image classification problem with these spectrograms



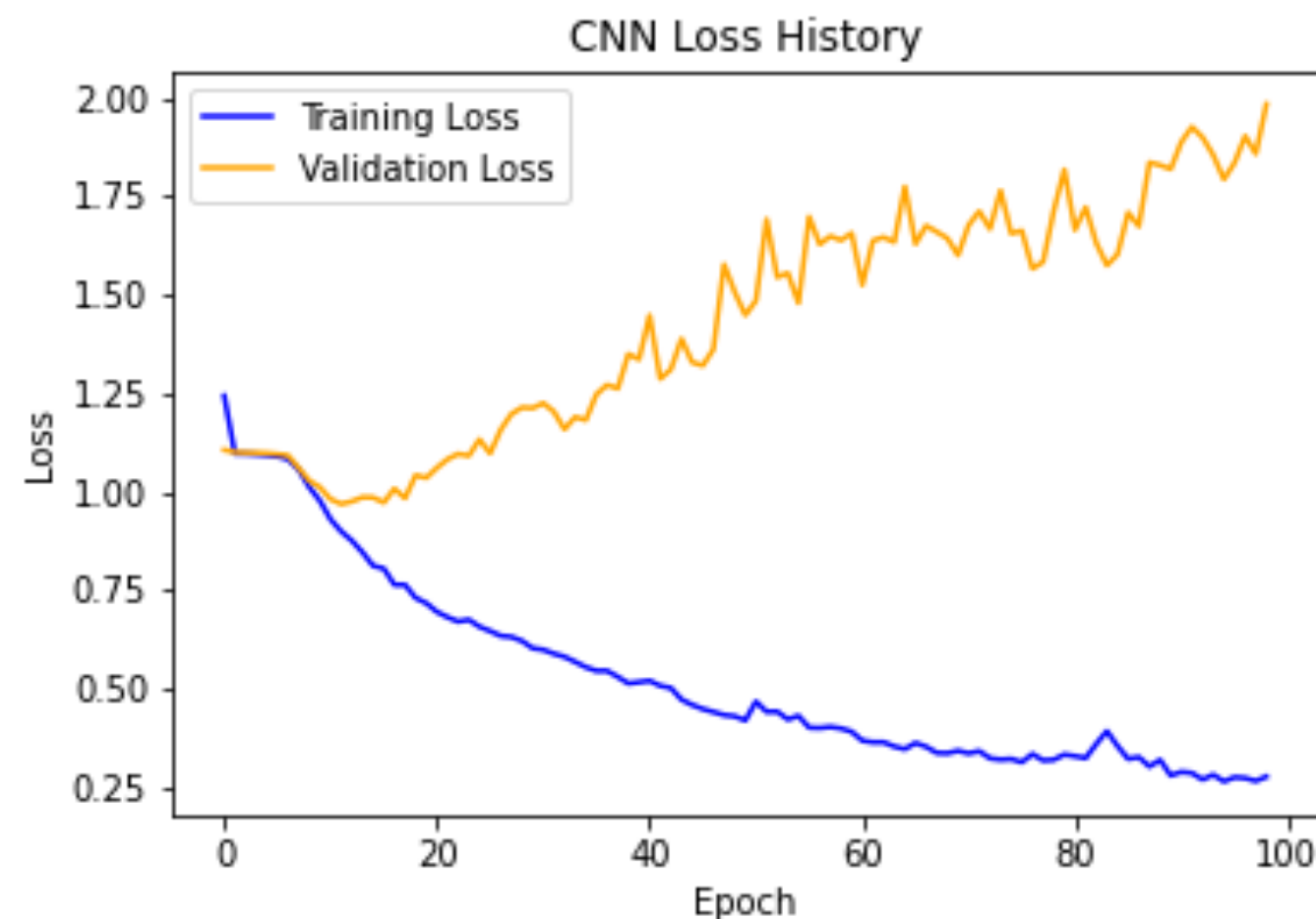
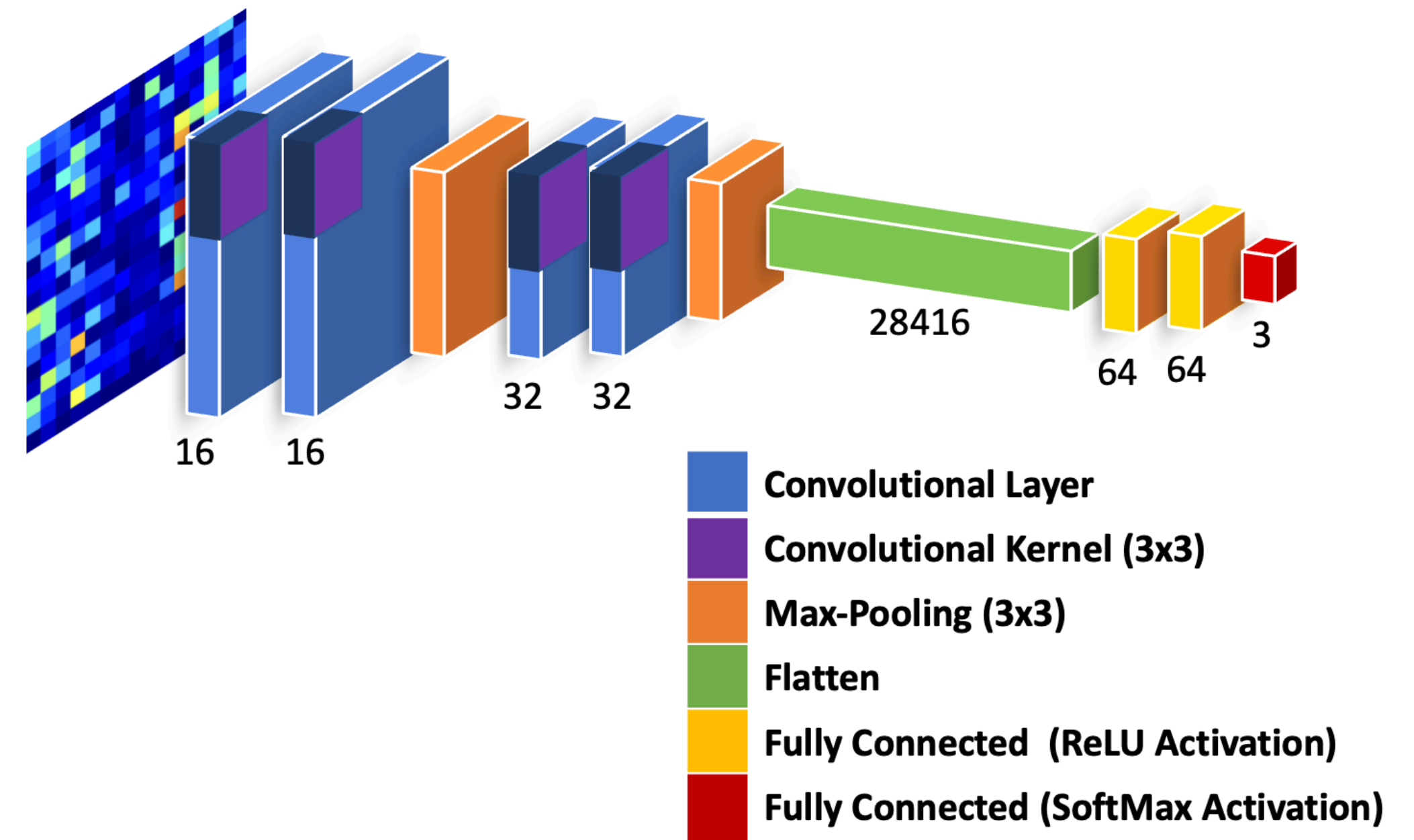
Input to CNN? Filtered Frequency <20Hz,
Removed Axes



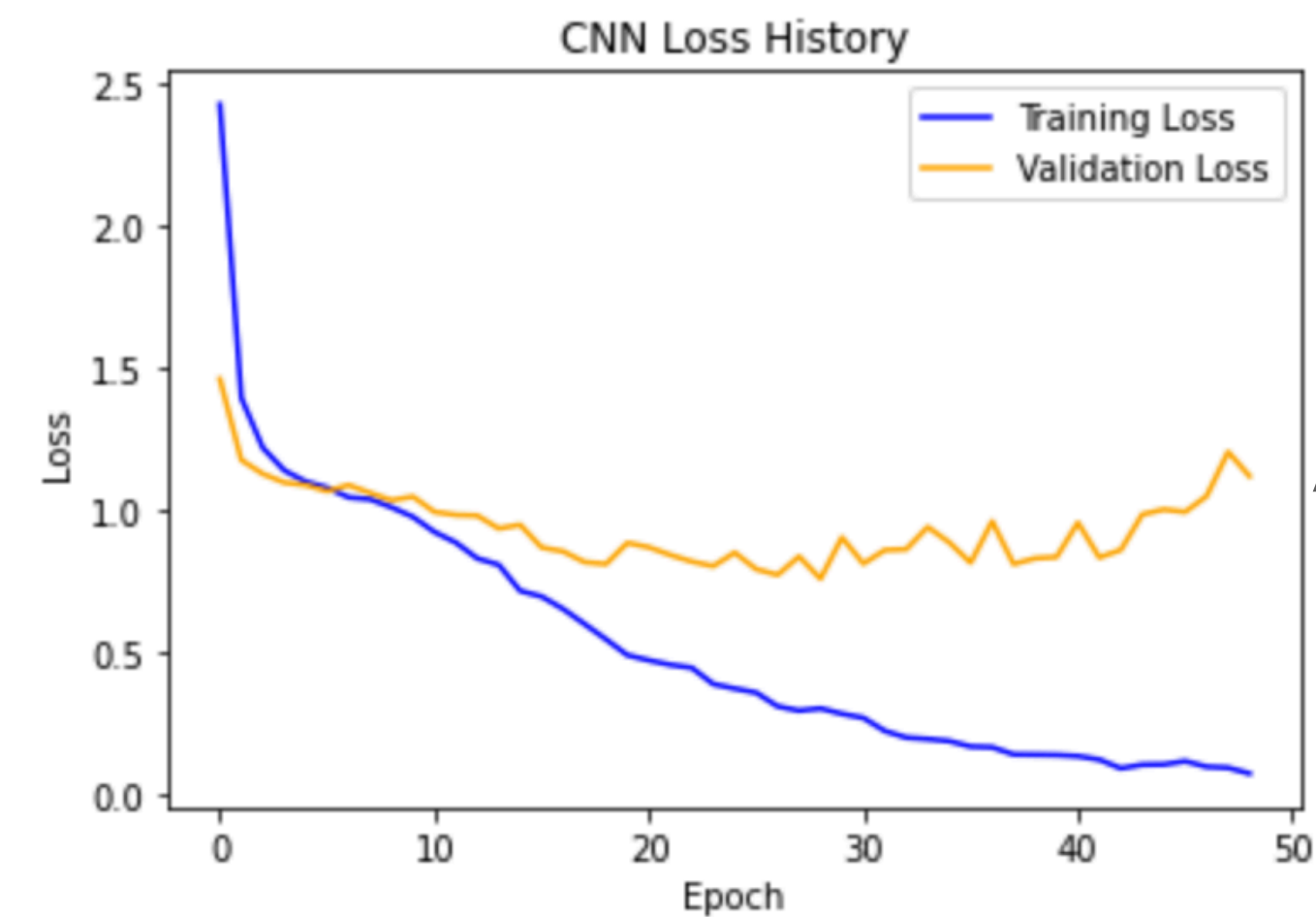
Convolutional Neural Networks for EEG Spectrograms

Approach and Adjustments

- 2 VGG Blocks
- Heavy Data Augmentation (nonintuitive?)
 - Vertical and horizontal flip
 - Vertical and horizontal shift
- Oversampling minority class
 - Loosely controlled experiment - different amount of time for different tasks



Without Data Augmentation

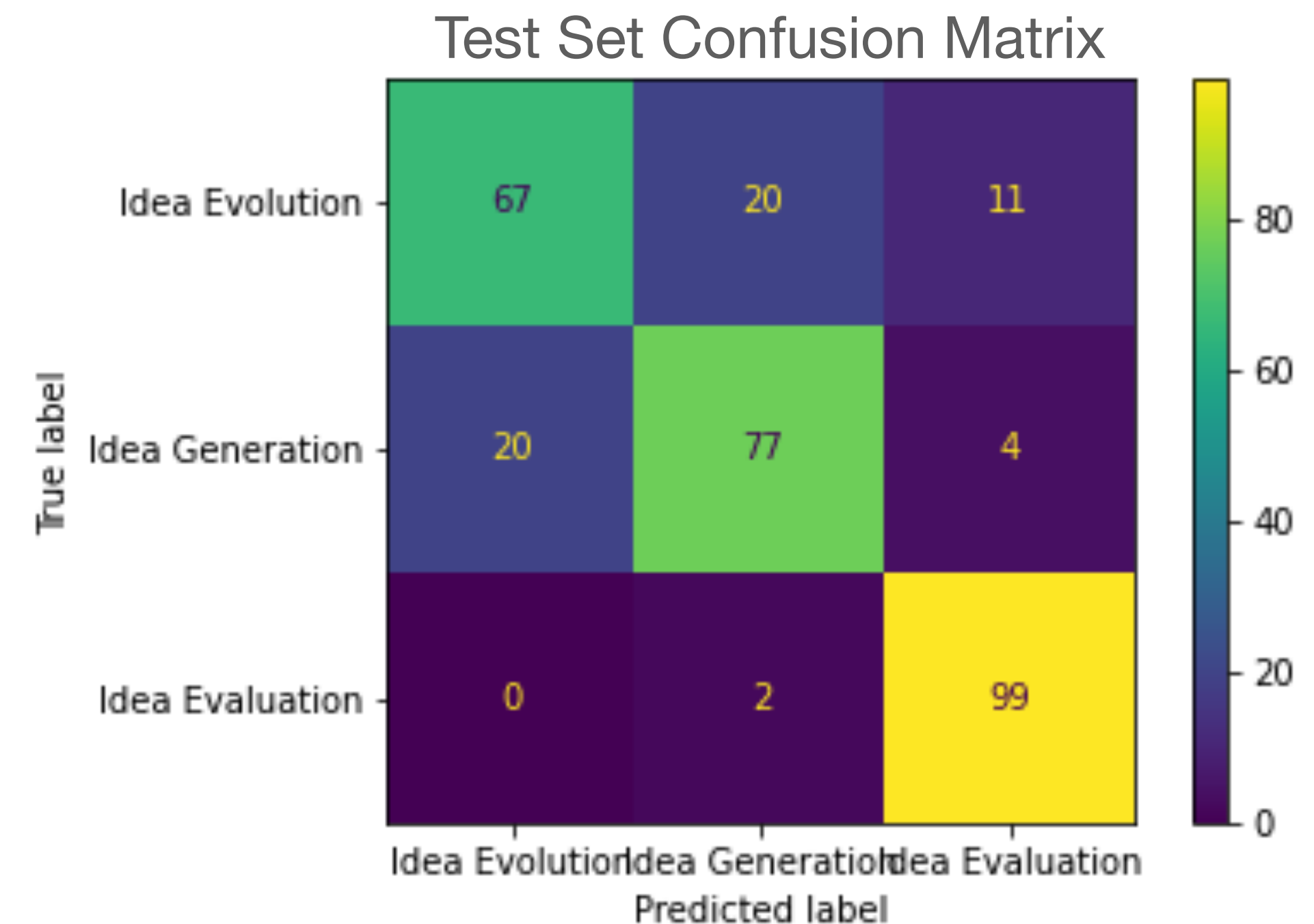
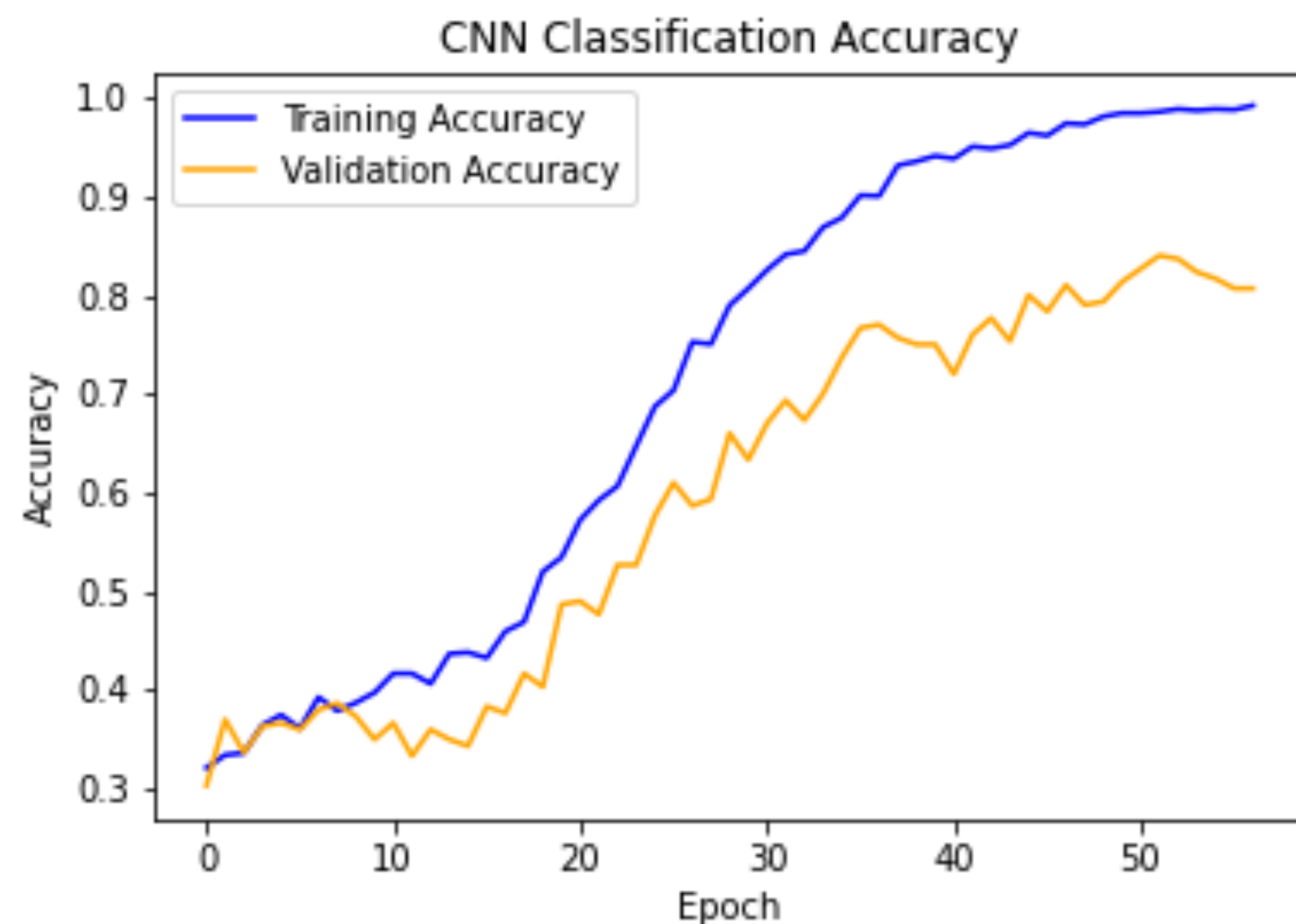


With Data Augmentation

Convolutional Neural Networks for EEG Spectrograms

Examining results of CNN image classification problem

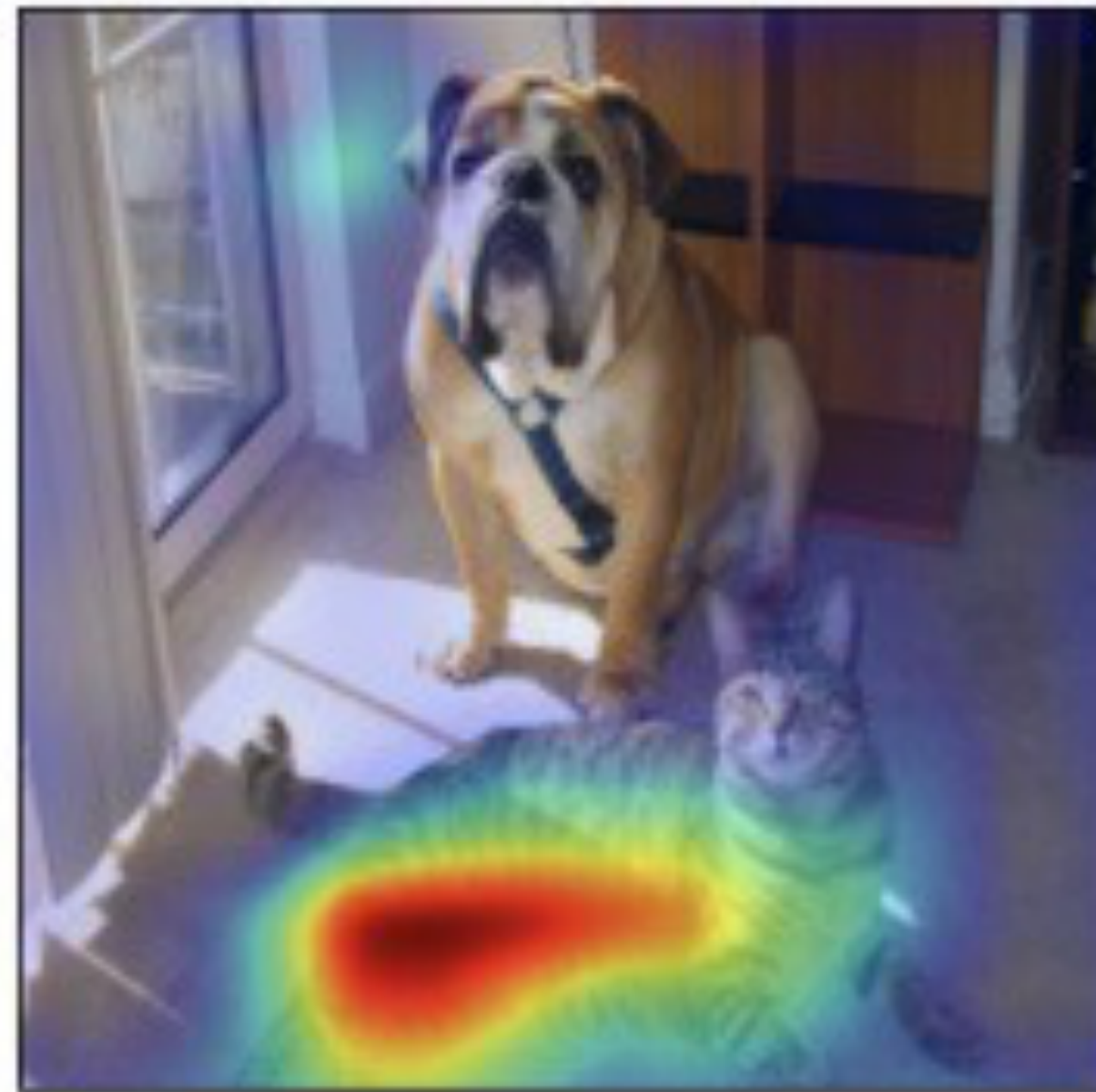
- 82.33% accuracy on unseen holdout test
- The three creative modes of thinking seem to be separable based on the features generated by the CNN and results seem to generalize well to unseen data



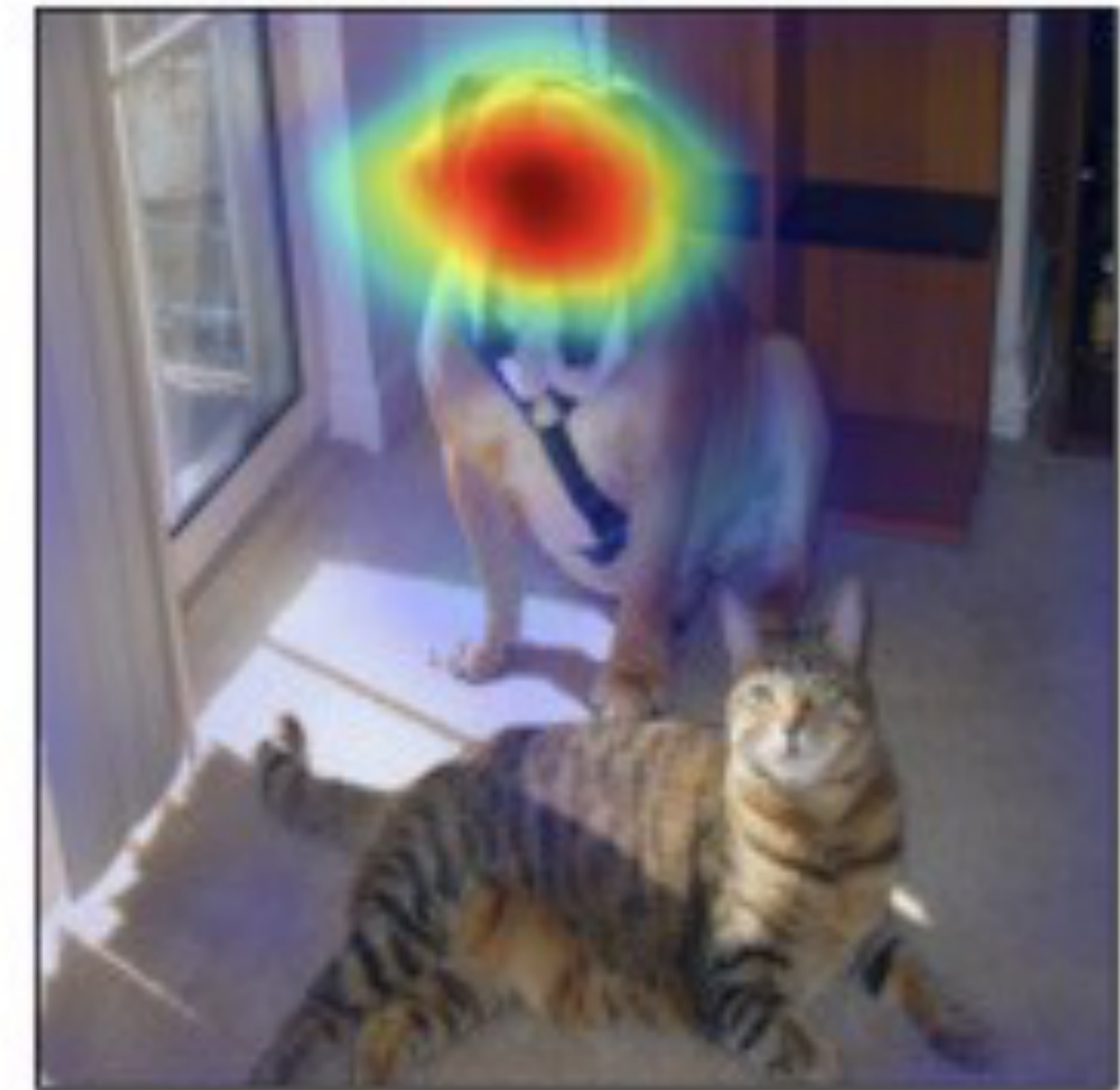
Gradient-weighted Class Activation Mapping (GradCAM)

Visualizing what the model is “looking” at

Grad-CAM for “Cat”



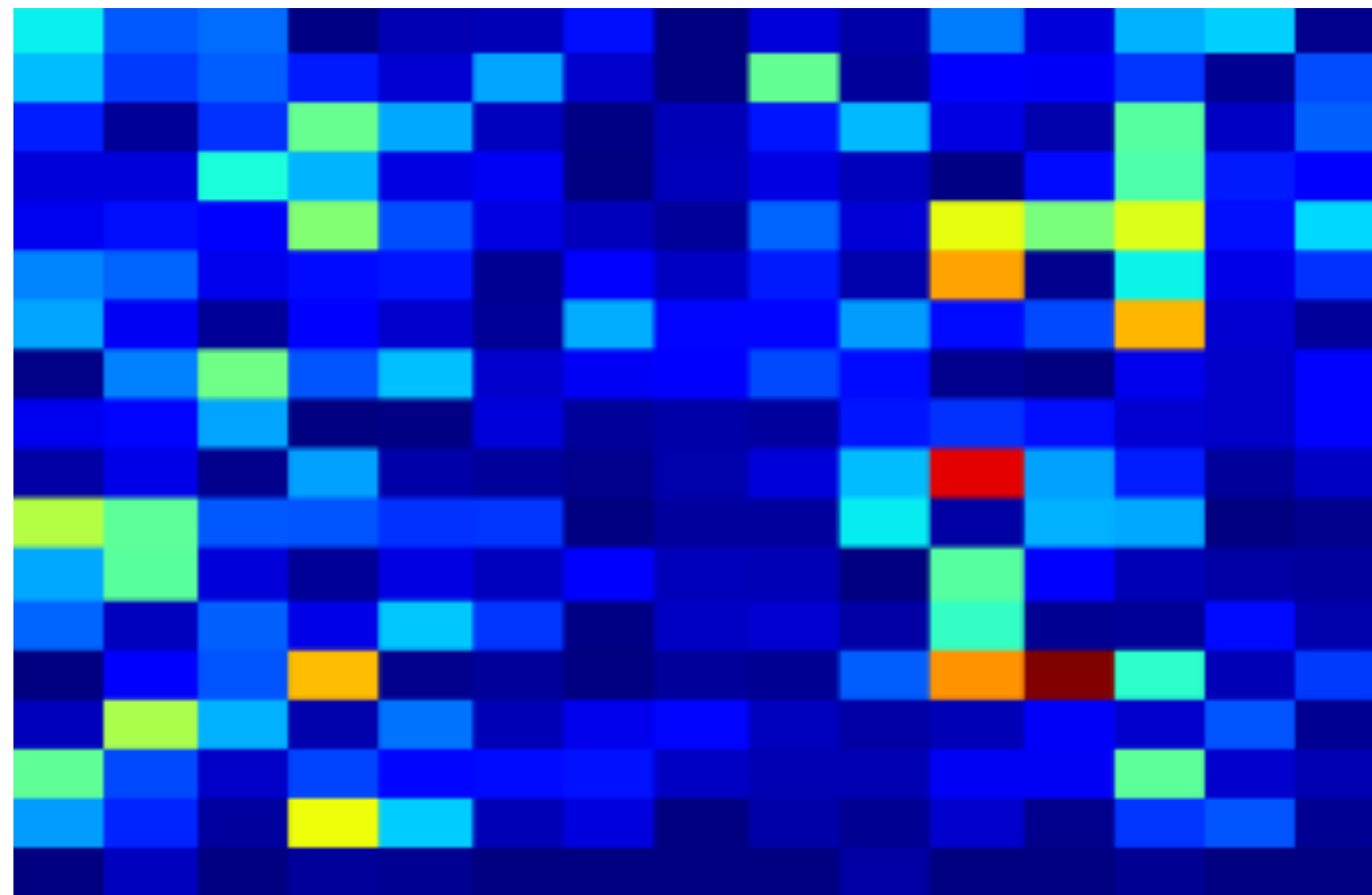
Grad-CAM for “Dog”



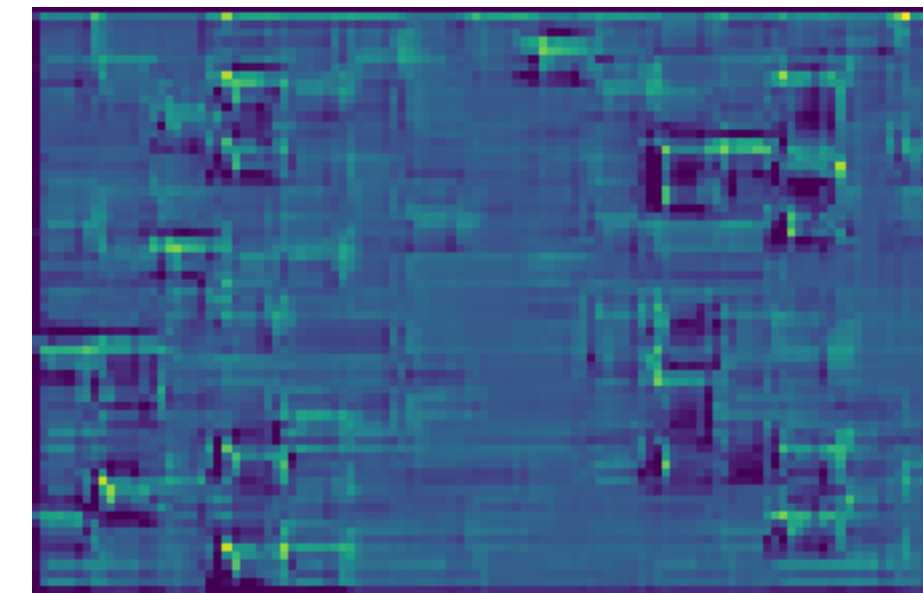
Gradient-weighted Class Activation Mapping (GradCAM)

Visualizing what the model is “looking” at

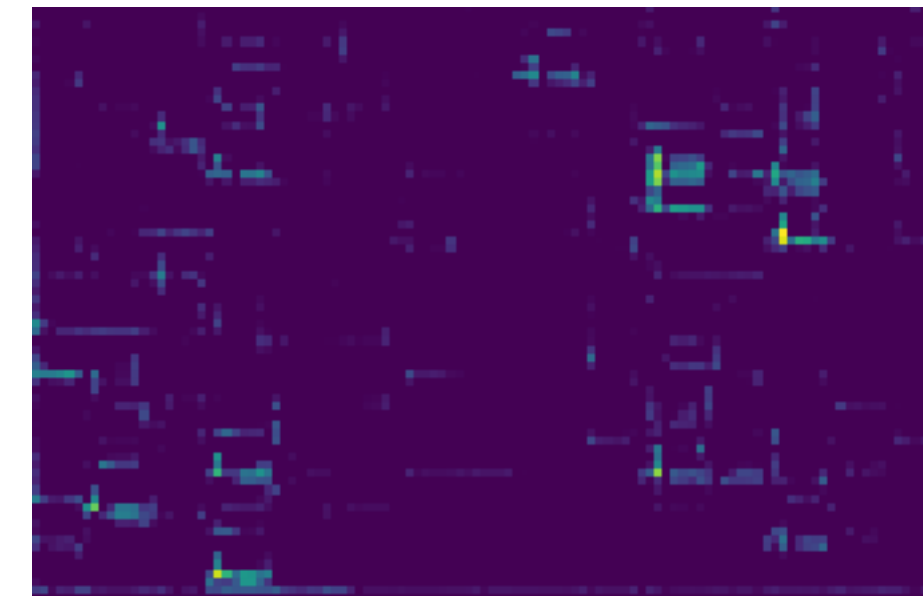
Input Spectrogram
Label = Idea Evolution



Class Activation Maps
Of Final Convolutional Layer



Idea Evolution (Predicted Class)



Idea Generation

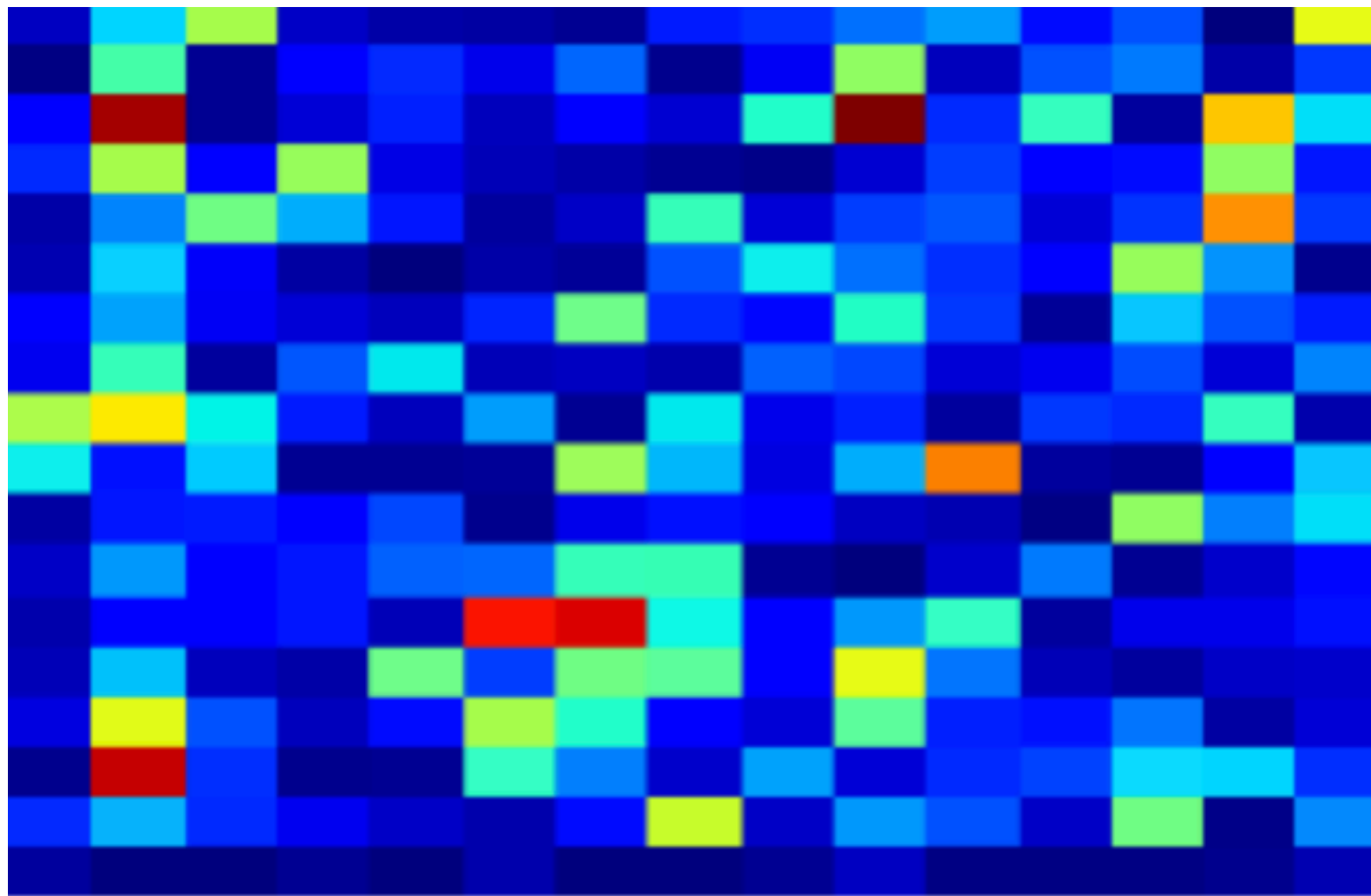


Idea Evaluation

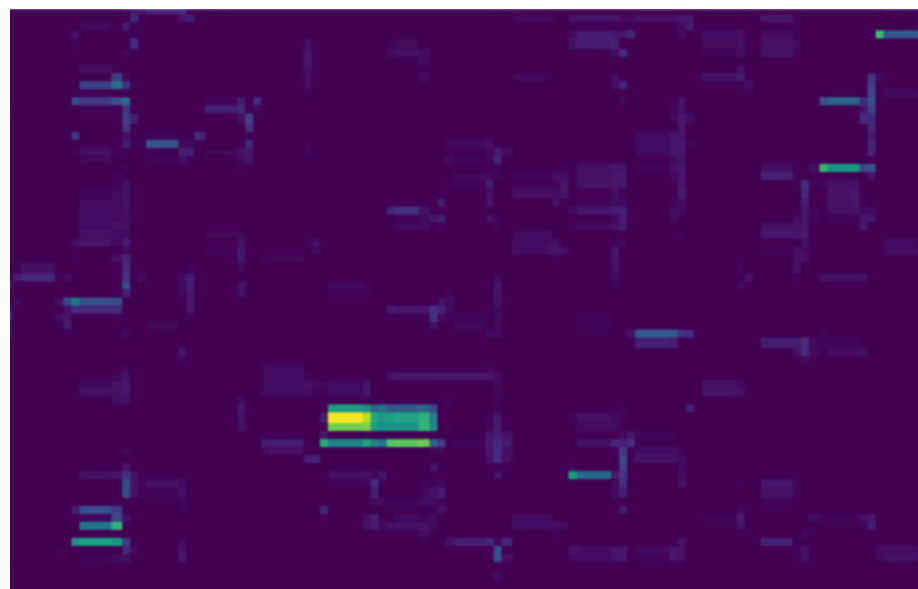
Gradient-weighted Class Activation Mapping (GradCAM)

Visualizing what the model is “looking” at

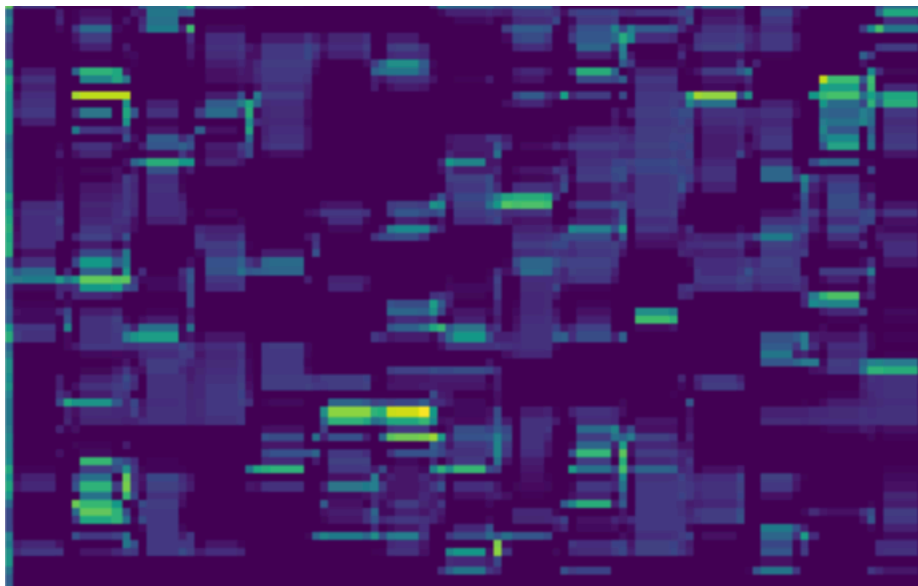
Input Spectrogram
Label = Idea Generation



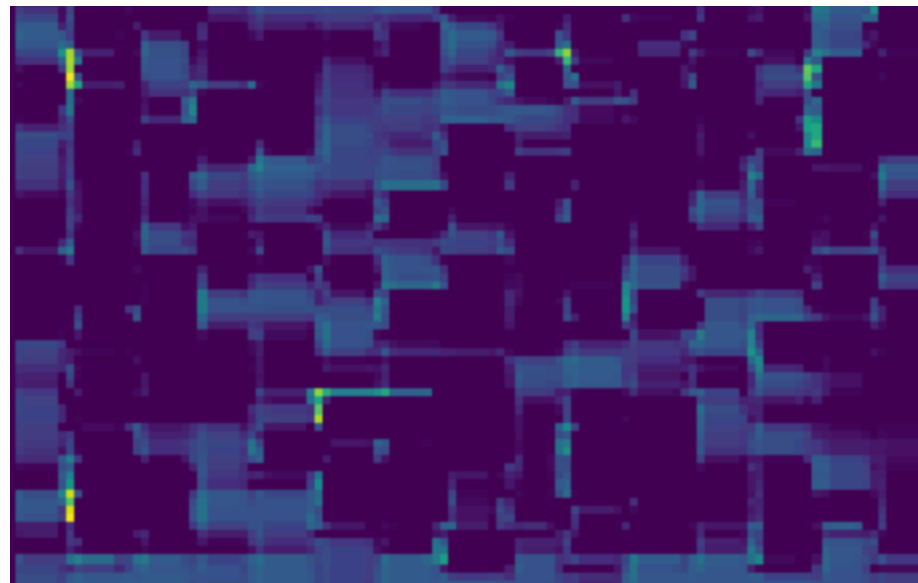
Class Activation Maps
Of Final Convolutional Layer



Idea Evolution



Idea Generation (Predicted Class)

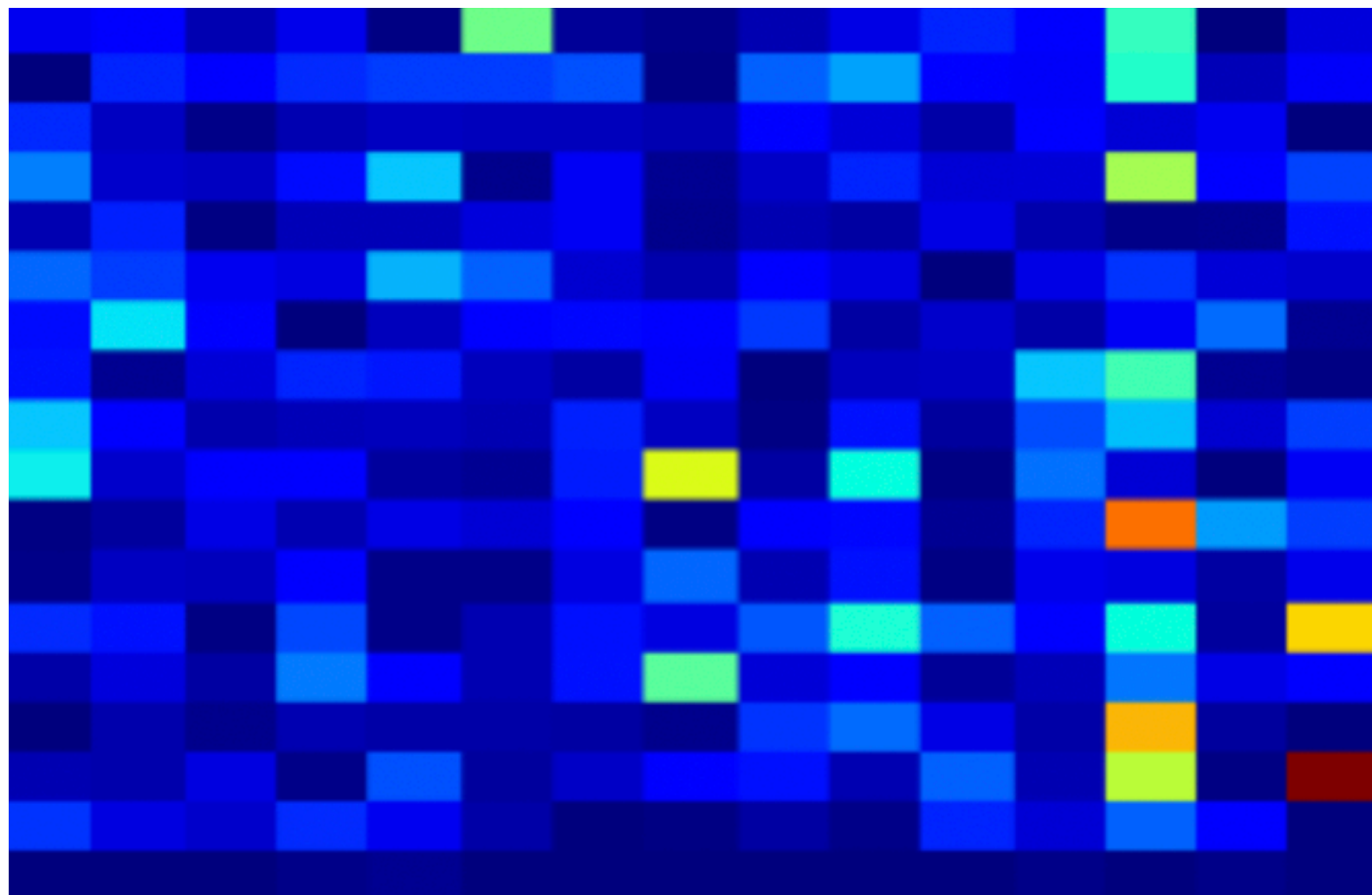


Idea Evaluation

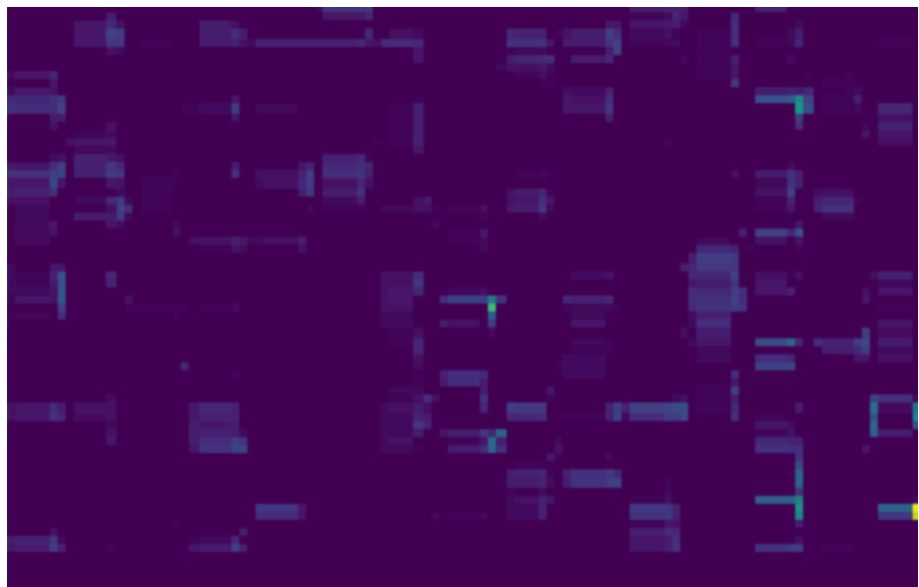
Gradient-weighted Class Activation Mapping (GradCAM)

Visualizing what the model is “looking” at

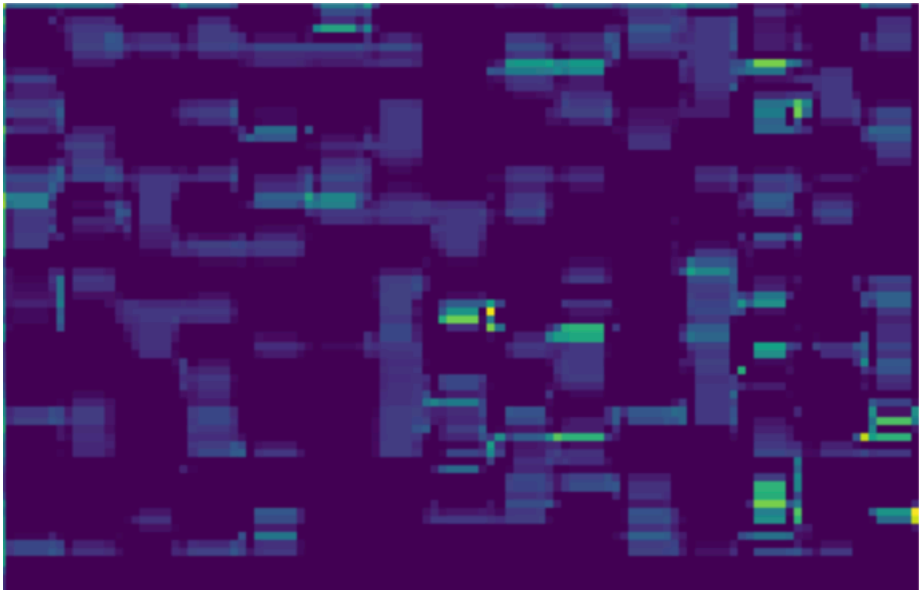
Input Spectrogram
Label = Idea Evaluation



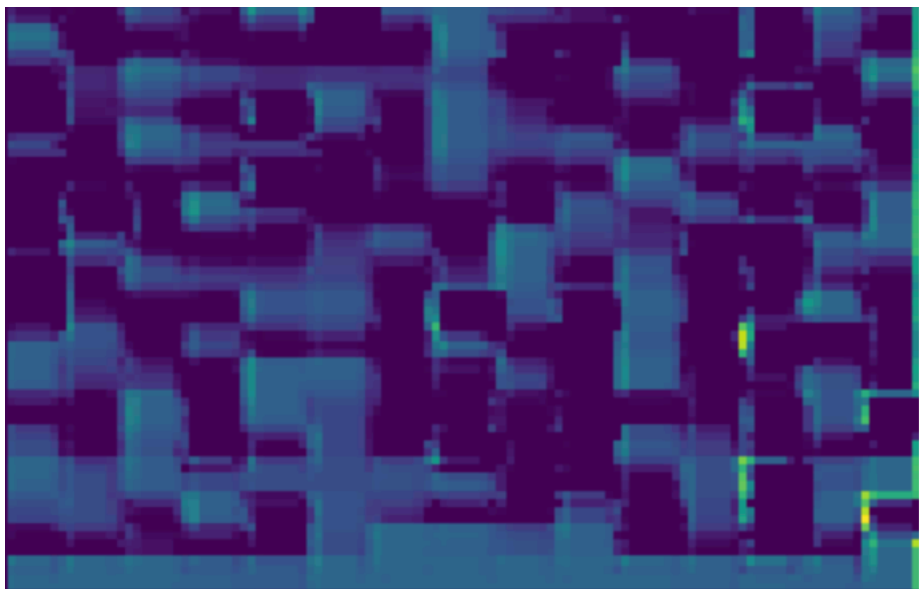
Class Activation Maps
Of Final Convolutional Layer



Idea Evolution



Idea Generation



Idea Evaluation (Predicted Class)

Conclusion

- With the features suggested by the Jia & Zeng study alone, we were not able to effectively classify the three creative modes of thinking
 - However, we were able to easily identify when subjects were in rest state
- Using Convolutional Neural Networks on short-period (10 second) EEG Spectrograms seemed to be a very effective method for classifying what stage of the creative process a subject was in
 - Reached 82.33% Accuracy on test dataset with 300 unseen observations