## Regional Band Oscillations Orchestrate Human Conscious Content – Analysis of the Cogitate Datasets (batch #2)

Christina Yi Jin[1]

1. Research Center for Frontier Fundamental Studies, Zhejiang Lab, 311100 Hangzhou, China

### Abstract

The current analysis aims to validate the findings of Cogitate dataset batch #1 on dataset batch #2. The current data preparation and neural decoder design followed the same protocol as batch #1. Furthermore, we used the same features that have been regarded as informative in decoding conscious content in batch #1 to train the neural decoder of batch #2. The current results show a generally efficient decoding performance, indicating the generalizability of the neural features across datasets.

## Results

The current analysis aims at validating the results that we achieved with Cogitate dataset batch #1 on dataset batch #2. In order to realize the goal, we performed the same data preparation steps (Report 1 Fig. 1b) on batch #2, including the FLUX pipeline for clean MEG and data segmentations and temporal-frequency analysis to transform the time domain data into the time-frequency domain. Three individual datasets were removed during this process because two of them have missing runs (CA158, CB049) and one has a split run data that does not match the event file (CB003). Next, instead of re-computing the PC loadings with the new dataset, we used the PCA fits that we obtained with batch #1 to decompose the data of batch #2 and concatenate the top 3 PCs from each frequency to form the spatial/frequency (S/F) feature, same as what is done with batch #1. The reason for doing so is that it allows us to validate if the features we found with batch #1 can be generalized to batch #2. The neural decoder is the same design as for batch #1 (Report 1 Fig. 1a). Furthermore, we involved the same 57 S/F features that have been regarded as informative in training neural decoders with batch #1 (Report 1 Fig. 2). A successful generalization across datasets can be indicated when the decoders trained with features found in batch #1 also perform well on batch #2.

As shown in Fig. 3, the performance of neural decoders based on batch #2 generally surpasses the chance level = 0.333, except that one decoder (CB030) has biased detection against the target class. Furthermore, the statistical comparisons using independent t-tests and Bayes Factors (BF) show that the modeling performance between batch #1 and batch #2 is not significantly different, indicating a well-generalization of the S/F features across datasets.

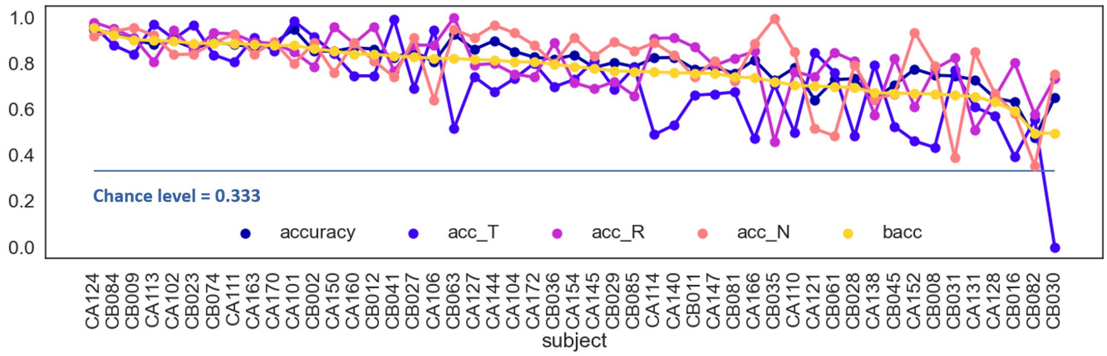


**Fig 3. Performance of the neural decoders of batch #2 dataset.**

Performance is sorted by the balanced accuracy (bacc). accurcy=overall accuracy, acc_T=accuracy in detecting targets, acc_R=accuracy in detecting relevant non-targets, acc-N=accuracy in detecting irrelevant non-targets.

**Table 1. Performance summary and comparisons between batches.**

| Metric | Batch #1 | Batch #2 | t | *p* | BF10 |
|---|---|---|---|---|---|
| Accuracy | 0.80±0.08 | 0.80±0.10 | -0.12 | 0.91 | 0.217 |
| Accuracy: targets | 0.71±0.13 | 0.71±0.19 | 0.09 | 0.93 | 0.216 |
| Accuracy: Relevant Non-Targets | 0.77±0.11 | 0.81±0.12 | -1.53 | 0.13 | 0.606 |
| Accuracy: Irrelevant Non-Targets | 0.84±0.11 | 0.81±0.15 | 1.39 | 0.17 | 0.504 |
| Balanced Accuracy | 0.78±0.07 | 0.77±0.10 | 0.05 | 0.96 | 0.216 |

## Discussion

In conclusion, the current results validate the findings that we achieved with batch #1 that the S/F features can well predict conscious content in a visual discrimination task even with a different dataset. The interpretation of the S/F features is band-specific. Recall that in the pre-registration, the alpha and lower/middle beta bands have a dominant neural activity at the parietal region, largely supporting the Integrative Information Theory (IIT), and delta and theta bands with dominant neural activity at the bilateral frontal regions might support the Global Neuronal Workspace Theory (GNWT). In other words, both theories might indicate a crucial process during the consciousness activity, only the paths of information flow might be organized by different neural oscillations.

## Methods

The data preparation pipeline was the same as what was performed on batch #1. Instead of re-computing the PC loadings on batch #2, we directly used the PC loadings that were computed with batch #1 data. When training the classifiers, the feature selection was also skipped – we directly used the 57 S/F features that were selected in Batch #1. We made these two changes to keep the features consistent between batches. More importantly, it allows us to verify the generalizability of features across datasets. The other parts of training neural decoders remained the same as batch #1.

## Open Code Statement

Code for analysis is openly available on https://github.com/christina109/Cogitate_data_challenge.