Decoding Visual Similarities of Stimuli through Neural Responses

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Abstract

This study explores the intricate relationship between neural responses in the visual cortex of mice and the visual characteristics of stimuli. Our research question is centered on whether similar neural responses correspond to similar visual attributes in the stimuli and, if so, what these characteristics entail. The study shows that in many cases, similar neuronal responses are indeed generated by images that have similar visual characteristics. It is emphasized that this phenomenon is not always visible, and the relationship between the image and the response remains very noisy. This is due to several factors, particularly noted in the study is that a strong factor is the dependence of the response not only on individual images but also on how they change over time, thus on the previously shown images. Possible techniques to test and other insights are reported in the conclusion.

1 Data and Research Question

The data for this study were obtained from *The Allen Brain Observatory* [1], which provides extensive neural response records from the visual cortex of mice. Our analysis focuses on data from a 110-day-old female mouse, encompassing responses from 825 distinct neural units.

We pose the following research question: *Can visual stimuli that elicit similar neural responses in mice also be characterized by shared visual features? If so, what are these defining characteristics?*

2 Data Preprocessing

Using the *Allen SDK*, we constructed a dataframe to analyze neural responses to visual stimuli. In this dataframe, each column represents a different neuron and each row corresponds to the neural response to a single image. The average firing rates for each neuron during a stimulus presentation are calculated as follows:

$$r_{\text{avg}} = \frac{\text{number of spikes during presentation}}{\text{duration of stimulus}} \tag{1}$$

To mitigate variations in neuron response due to repeated presentations of the same image, we averaged the responses across these presentations to reduce noise. Additionally, to enhance the performance of visualization and clustering algorithms, we applied a logarithmic transformation to the firing rates to reduce skewness, followed by the standardization of features.

3 Visualization

To gain insights into the properties of neural responses, we have utilized dimensionality reduction techniques. Specifically, Principal Component Analysis (PCA) has been employed to visualize these responses in three dimensions. Initially, we experimented with 2D visualization; however, the richness of the data is better captured in 3D. This approach is supported by an analysis of the cumulative explained variance from the PCA, which shows rapid diminishment when components are excluded. This indicates that a three-dimensional representation provides the most informative view of the data, providing a clearer understanding of the neural responses.

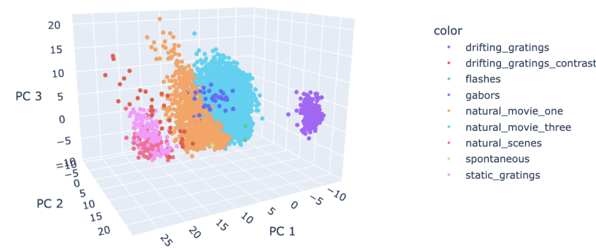

Figure 1: 3D Representation of Neural Responses using PCA.

4 Single Stimulus Analysis

From Figure 1, it is evident that responses to the same type of stimulus are similar. This observation enables focused analysis on specific types of stimuli. We have particularly concentrated on *Natural Movie One* and *Natural Scenes*.

4.1 Natural Movie

Analyzing the natural movie using PCA reveals no significant insights, possibly due to the complex structure of the data in the full-dimensional space. Consequently, we explored an alternative approach using UMAP (*Uniform Manifold Approximation and Projection*) [2]. Adjusting the `min_dist` parameter, which balances the preservation of local versus global structure yielded a plot (Figure 2) that illustrates responses distributed along a continuous line in chronological order. This pattern is expected, given the sequential nature of the movie scenes, which suggests that responses are influenced not only by the content of an image but also by the sequence in which they are presented.

Remark: Outside the scope of this research, we noted that sudden changes in the movie (e.g., a person running rapidly across the frame) correlate with an overall higher average firing rate across all neurons (Plot in the appendix).

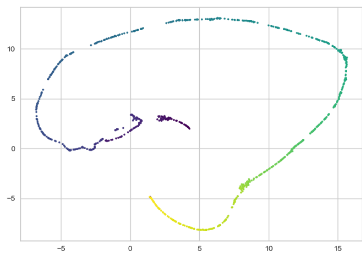

Figure 2: 2D Representation of Responses to *Natural Movie One*. The colors indicate the frames in the movie.

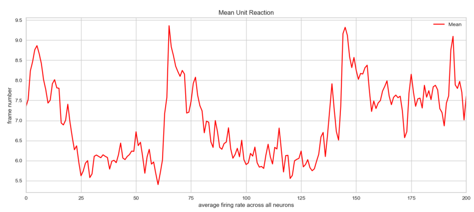

Figure 3: Mean unit firing rate. The peaks correspond to frames where a man passes fast in front of the camera.

4.2 Natural Scenes

Using UMAP for dimensionality reduction of the natural scenes data, we obtained the plot shown in Figure 4, where colors represent cluster labels assigned by HDBSCAN. Notably, compact clusters emerged, and a close inspection of the images within the same cluster revealed discernible visual similarities; typically high-level features or recurrent patterns and textures. Despite variations in algorithm parameters and data preprocessing techniques, some of the clusters remained consistent, suggesting a genuine basis for their formation. The most intriguing findings are presented in Figure 5.

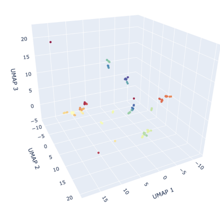

Figure 4: 3D Representation of Responses to *Natural Scenes*. The color indicates the cluster label assigned by HDBSCAN.

Figure 5: Each row represents a different cluster.

5 Testing Across Sessions

Through repeated trials of the aforementioned procedures across multiple sessions, utilizing male mice of varying ages, the results have demonstrated remarkable consistency. However, further research should include fine-tuning of the parameters for each session. Taking into account the inherent variability and noise present in neural responses, both in the case of natural scenes and natural movie analysis, the recurrence of the results across distinct experimental conditions underscores that the way mice respond to the stimuli in this research is not significantly influenced by age-related variations or session-specific factors. For brevity, we report in the appendix only the plots obtained for one different session.

6 Conclusions

Our results affirmatively suggest that certain visual patterns such as specific orientations, contrasts, and textures are likely to elicit similar neural responses, providing insights into the visual features that neurons may be encoding. Furthermore, our analysis of the natural movie reveals that neural responses are influenced not only by the static content of images, but also by the dynamic relationships between consecutive images and their evolution in time. It is important to note that our study was conducted on a relatively small dataset. Future research should aim to validate these findings with a larger dataset to enhance the robustness and generalizability of the results. Additionally, deep learning models such as VGG16, could be used to overcome the issue of defining image similarity. Convolutional networks like VGG16 analyze images by breaking them down into complex patterns and features. By comparing these patterns and features, the model can determine similarities between images, providing a robust method for defining image similarity. Lastly, further investigation into how neurons respond to sequences of images with strong causal relationships, as in the case of the movie, could provide deeper understanding of the temporal aspects of visual perception.

References

[1] **Allen Brain Atlas - Data Portal**, *https://observatory.brain-map.org/visualcoding/*

[2] **Leland McInnes, John Healy, James Melville** (2020) "UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction" *arXiv:1802.03426 [stat.ML]*

Appendix

Figure 6: Comparison of mean unit firing rate of different sessions.

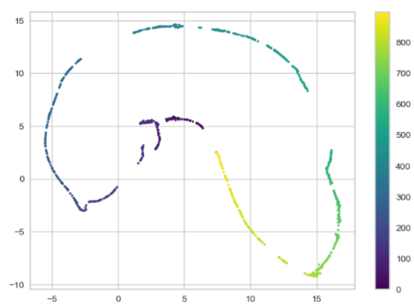

Figure 7: 2D Representation of Response to Natural Movie One of another session.

Figure 8: Sample cluster of a session.