Group 1 Neuroscience Project

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1 Introduction

The aim of our project is to investigate the activity of neurons in the visual cortex in response to visual stimuli. The stimuli we consider are static gratings, which are shown to the subject (mouse) with three varying parameters. They are orientation, spatial frequency, and phase, with six, five, and four possible values, respectively. This gives us a total of 120 possible configurations. Note that each configuration is shown for 50 trials, for 250ms each.
We are interested in understanding how different combinations of parameters affect the neuronal response. Moreover, we are interested in seeing how responses to varying parameters differ between distinct areas of the visual cortex. The areas we consider are: primary visual cortex (VISp), anteromedial area (VISam), anterolateral area (VISal), rostrolateral area (VISrl), and ateromedial area (VISl).
Our project deals with neural encoding, which focuses on the mapping from stimulus to response, and catalogs how neurons respond to various stimuli. We have discussed the topic in class during the first part of the course, when we have also seen examples of tuning curves; see the presentation "Encoding I". We also took inspiration from this page from the Allen Institute.

2 Methods and Results

We have taken different approaches to investigate our research question. Mostly, as metric, we consider the average of the spike counts, for a given neuron, over the 50 trials, so disregarding the time at which spikes happened, and the trial-to-trial variability.
We also removed neurons showing unusual activation patterns, so cells that are always active and/or always inactive for all stimuli presentations (see the notebook for the details about the chosen thresholds).

2.1 Visualizing Neural Response

To start, for a randomly picked neuron, we plot its average spike count versus all possible combinations of parameters (Figure 1). For this particular neuron, we can see that all parameters are significant, and impact the response. This plot can be thought of as a 3D tuning curve, and in the next section, we discuss its statistical significance. It is important to note that the response for a given parameter (e.g. orientation) is not only rescaled when another parameter (e.g. phase) is changed, in the sense that the peak of the orientation tuning curve may be different for different phases.

2.2 Statistical Significance of Tuning Curves

As we can see from the plot (Figure 1), there seems to be a notable variance in spike counts as the parameters vary for a fixed neuron. We want to take a look at this hypothesis with statistics' formalism: more precisely, we are going to check whether each parameter has effectively an influence in triggering the spike count. To do so, we consider parameters independently, otherwise, the number of observations would only be 50, while we seek a larger number to perform a statistical test. Taking neurons individually, for a given class of parameter, we consider the tuning curve and perform a paired T-test to check whether the value at which the maximum spike count is obtained is significantly larger than the value at which the minimum is obtained. The results indicate a decent statistical significance: for orientation, more than $\frac{3}{4}$ neurons showed a p-value < 0.05, for

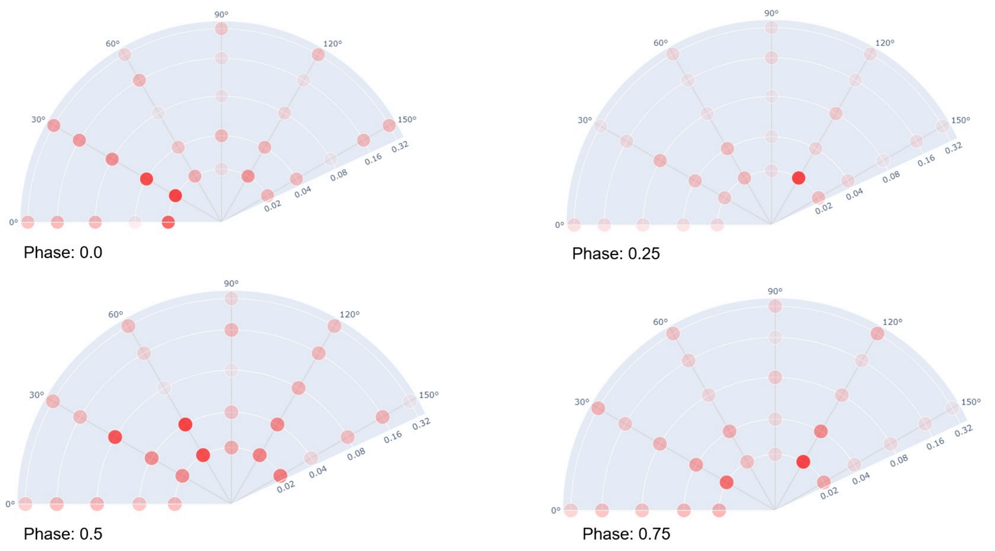

Figure 1: Average spike count versus parameters

spatial frequency more than $\frac{3}{4}$ neurons showed a p-value < 0.05, while for phase almost half the neurons showed a p-value < 0.05.

2.3 Exploratory Data Analysis

From this section on, we start to analyze neuronal activity by area, with the aim of observing activation patterns characterizing each region. Plotting the distribution of the spike count average for each parameter combination we observed that, given one region, the distribution is similar for all parameters. There is no parameter triplet for which the neurons in one brain section are all active, nor one for which all are inactive. By comparing distributions in distinct regions, we noticed that regularity depends on the region. The mean, 1st, and 3rd quantiles vary slightly between the areas, but the distributions maintain the same shape.
Next, we studied pairwise linear correlation between neurons by considering each region separately. Average pairwise linear correlation varies between the areas, with the maximum of 0.045 obtained for VISp and the minimum of 0.017 for VISrl. Standard deviation of correlation amounts to 0.100 in all regions. Overall, pairwise linear correlation results are weak.

2.4 Graphical analysis - Firing Rates

At this point, we selected neurons from various regions of the visual cortex to focus on visually identifying more similar activation patterns within neurons of the same region. By comparing the activations of randomly chosen neurons through firing rate plots, it seems that neurons of the same area exhibit quite similar behaviors, reaching similar peaks (Figure 2).

2.5 Classification

To quantify whether neurons in different areas respond differently to varying parameters, we try to perform classification. If we can predict the area of the brain one vector (i.e. 120D, with each component consisting of the average spike count for a given combination of parameters) belongs to, then it means that different areas of the brain respond differently. We used a simple, and a more complex classifier, Logistic Regression and XGBoost. To score our models, we performed 10-fold cross-validation over all neurons in the session. To understand if the performances of the classifiers are meaningful, we compared them with two other dummy classifiers, a stratified version (class is randomly drawn from a distribution resembling the one of the labels shown in the training data, without considering the input vector) and a uniform version (class is drawn from a uniform distribution). We can see (Figure 3, left) that the performance of the models is significantly better than the one of the two dummy classifiers.

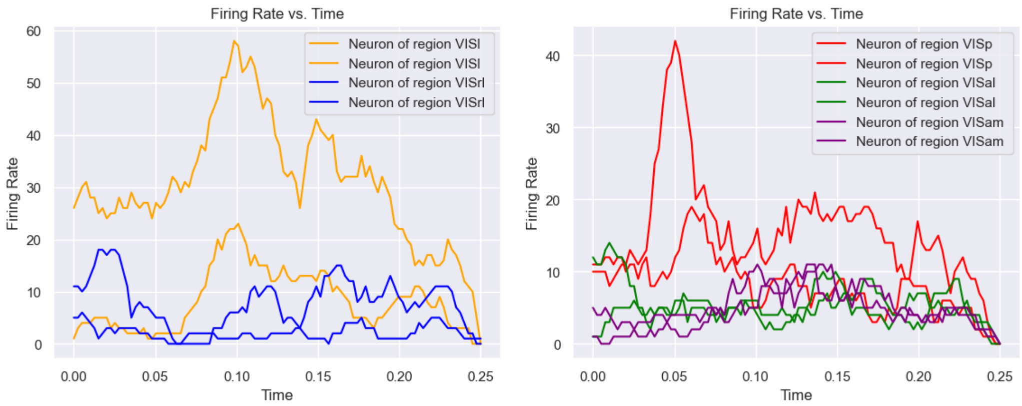

Figure 2: On the left: Firing rates of neurons of the areas VISl, and VISrl. On the right: Firing rates of neurons of the areas VISp, VISal and VISam.

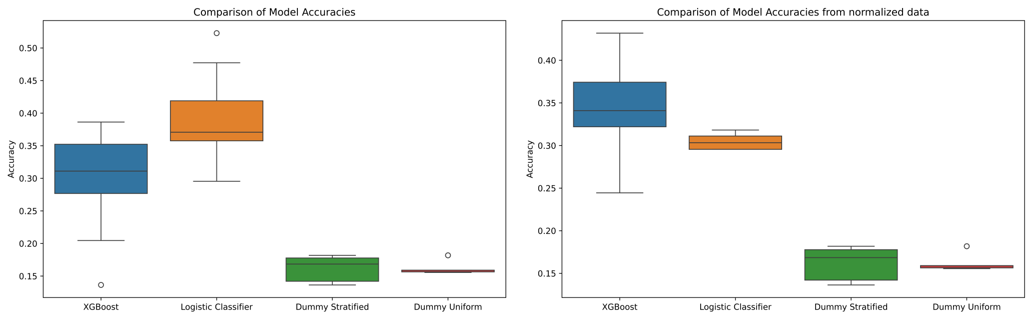

Figure 3: Comparison of models' accuracy. Left: Non-normalized data. Right: Normalized data

It is possible that classification is mainly driven by the average activation of a neuron, rather than its actual response to different stimuli, so that the models are performing because neurons in one area have a higher mean activation. To understand if this is the case, we divided each vector by its sum, so that the only information stored is the strength of the response to a given parameters combination compared to the other combinations. The models are still performing (Figure 3, right), so we can confirm that there is some relation between the area a neuron is in, and the response to different parameters.

2.6 Response by Area

After having seen the relevance of how the neuron's response does indeed depend on the area and the type of stimulus, it is of interest to see whether such a relationship could also be seen visually. Specifically, by fixing one parameter from either phase, orientation, and spatial frequency there were interesting patterns which could be produced for whole visual cortex areas in response to the variation of the other two. Most notably, for VISal there is no apparent sensibility to varying orientation and phase but the neurons in the area respond quite differently to spatial frequency (Figure 4).

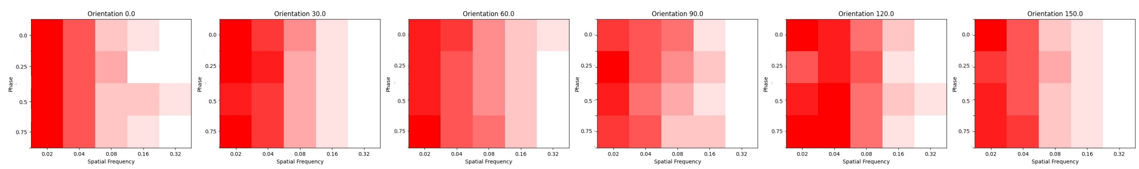

Figure 4: Visualisation of how VISal average nueron spike count changes with distinct orientation values (value in the title increasing in each graph from left to right) and phase (y-axis) vs spatial frequency (x-axis)

3 Discussion

From Section 2.2, we can conclude that most neurons have different spike count averages for different values of a parameter. This is true in particular for orientation and spatial frequency, and up to a certain degree for the phase.
In Section 2.5, we have been able to determine that the area of the visual cortex in which a neuron is located can influence the strength of its responses to different combination of parameters. We do not have a strong signal, as the accuracy of the classifiers is better than random guessing, but still smaller than 50%. To deepen the study, one could build a more solid classifier, or try to develop a mechanistic model. However, it seems not trivial to spot general rules for correlating neurons in one area: it is more complex than linear pairwise correlation, and spike counts of neurons in the same area differ a lot, particularly in terms of the activation scale: some neurons produce way more spikes than others. A promising direction of research may lie in analyzing the firing rates, indeed, observing firing rates of neurons for a specific parameter triplet, we can visually spot similarities for neurons in the same area.