Sensing Senses

Correlations Between Image Features and Neural Spikes

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What types of images excite the brain? By correlating features of images with neural spikes, we can begin to answer this question. Several potential features for images, along with a method of determining statistically significant correlations are provided. They are used against an existing experimental data set, determining the most relevant features for that study. Potential flaws and tests for accuracy of these correlations are also discussed.

1 Experimental Data

The data set we will use to test our method comes from David Sheinberg's lab at Brown University. During the deriving experiment, a sensor was placed in a test subject's inferior temporal cortex. Images of various, individual objects were displayed on a screen within the subject's sight while its neural activity was recorded. As this area of the brain is known to be associated with object recognition, we expect different objects to elicit different spike rates.

The experiment was ran over three days, with two test subjects. We do not know if the sensor's location moved between days, nor do we know the subject's familiarity with the displayed objects. We chose to proceed with only one day's results, as spanning days and/or subjects may not provide comparable data. The second day's dataset was chosen as it has the most data points.

2 Finding Features

Effectively, we begin this study with a collection of neural spikes and the images that were on screen when those spikes occurred. To determine which features of these images are most relevant to the spike rate, we will need to decompose the images into their component features. This task is challenging, however, as images can be described (i.e. converted into features) in a limitless number of ways – a picture is worth a thousand words, alone. Our chosen set of potential features will therefore directly limit which correlations we can derive.

Recognizing that we cannot be complete, we will start with the simplest features and slowly expand in to the sophisticated. The most obvious attributes of an image, at least a digitized image, are the red, green, blue, and transparent ("alpha") values for each pixel. To convert these individual values into something which applies to the entire image, we will calculate the *average* red, green, blue, and alpha values for the image as a whole. Though simple, one of these will prove to be one of the most statistically significant correlations.

The colors we perceive are combinations of these values, however. The color "yellow" may lead to more neural activity than red, green, or blue alone. We should therefore combine our primary colors through addition, multiplication, and divisions of their average hues. Here, great caution is warranted; testing tens of thousands of permutations raises the risk of misleading statistical significance. A correlation with p value of 0.01 will, *by definition*, erroneously appear roughly ten times if we test a thousand features. To minimize this risk, we limit the number of color combinations we will test.

The feature set defined by each image's average colors will be very useful, but it is a bit blunt. As the neurons studied are associated with *recognition*, we will also look for more abstract features. We convert each image into grey-scale and then look for how much of the screen is actually comprised of "image" and how much is blank, by checking for the "presence" of individual pixels (evident by having a non-background color). We also compare each pixel to its neighbors to determine an average "difference"/"sameness" for the entire image. We also include counting the number of times three pixels are "present" in a row or column to determine a metric of verticality/horizontal-ness for the image as a whole. Each metric is devised as a simple loop which adds values for each pixel in the image. This sum is then divided by the area of the entire image to determine an average.

We went further, making very blunt use of cutting-edge computer vision techniques provided by the `skimage` package from scikit. Assuming we used this library correctly, we included the number of "corners" present in an image (using the Harris algorithm), and the number of "blobs" (via the Difference of Gaussian approach). We use these features as tech demos more than anything else, though skimming the research behind them has been quite fascinating.

In summary, in addition to combinations of colors, we have the following base features:

Feature	Description
red	Average hue of red
green	Average hue of green
blue	Average hue of blue
alpha	Average intensity of alpha
present	Average non-background pixels
horiz	Average "horizontal" rating
vert	Average "vertical" rating
diff	Average difference between adjacent pixels
blob	Number of blobs (Difference of Gaussian)
corners	Number of corners (Harris)

3 Deducing Correlations

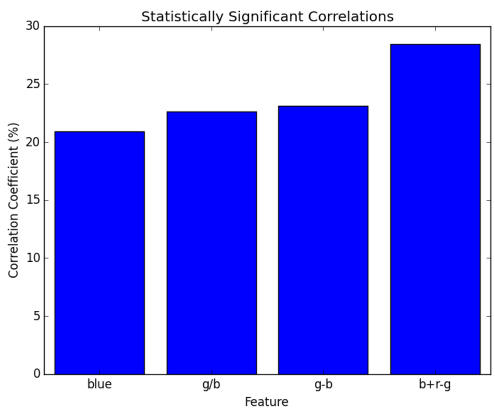
Once we have a set of features, we can test each feature against the spike rates encountered. We will look for *correlations* between each feature and spike rate by calculating a correlation coefficient, using the `scipy.stats.spearman` function. Correlations which are statistically significant (as determined by having a p value less than 0.05 over the number of features tested) are kept, while the majority are cut. The remaining features are then sorted to see which have the largest effect on the spike rate.

To calculate correlation coefficient, we will need to quantify how individual images include such features. For some features, we need only boolean '0' and '1' values, as we only care about the feature's presence. For others, we will need a scale, preferably normalized to the zero-to-one range. We will use the Spearman correlation algorithm, which does not require the data be linear and is more forgiving about normalization than many other algorithms (e.g. Pearson's algorithm).

Here, we should take a brief moment to describe a problem that plagued this work for quite some time. With just enough knowledge to be dangerous, our initial effort attempted to use machine learning techniques to determine which features were most relevant. This lead us down winding roads hinting at regression models, linearity, feature decomposition, and a wealth of other minutia which repeatedly gave us no usable results. These systems can no doubt be used to solve our problem, but we lacked the knowledge to use them effectively. Always start with a simple strategy rather than wasting time on more delicate, advanced techniques.

4 Results

For the data set in question, we found some surprising results. The majority of our features have no statistically significant correlation with spike rate. The somewhat abstract features, such as blob detection, internal similarity, and verticality, are no where to be seen. The features which *are* present correlate relatively well, with between 20 and 30% correlation coefficients.



While the color blue clearly correlates with heightened neural activity, the combinations give a slightly more detailed perspective. When the ratio between green and blue is high (creating either a green or yellow hue), neurons appear to fire less often. When the blue and red are present but green is absent (creating purple), the neurons are most excited.

Figure 1: Least to Most Stimulating Colors (In This Study)

5 Verifying the Method

How do we know that these features are the strongest influencers of neural activity? Clearly we cannot compare these features to those which we did not consider, but can we know whether our method "worked" *within* the features we chose?

Our first instinct would be to run the same test using one of the other data sets. The third dataset is too small, but we can try our method on the first. Unfortunately, the results are drastically different, with only the ratio between red and green statistically significant. So what went wrong? On the forgiving hand, the two data sets come from two different sensors in two different subjects; they simply are not comparable. On the more probable hand, the authors must recognize that our knowledge of statistical methods is limited; we no doubt made several mistakes.

At the very least, we can throw some "sanity" tests at our algorithm; these are junk features which have an expected outcome. Our feature decomposition will include these features and should give an expected correlation for each. "Constant" features, which always return zero or always return one, should have very low correlation. A feature composed of random values may have some correlation, but should not be statistically significant. Correlating the spike count with itself should provide a perfect correlation coefficient. Luckily, when we test our method with these features, we see that it passes each with expected values.

6 Next Steps

The method described hinges on the types of features we can devise from each image. To find stronger correlations, we need to develop more sophisticated features. In particular, we know that the portion of the brain measured is related to image *recognition*, so knowledge of the subject's familiarity with each image would be immensely valuable. Labeling images with other suspected patterns, such as the presence of "eyes" in the image or the perspective with which the image was taken could also correlate to neural activity.

As with any statistical analysis, the more data with which we have access, the more accurate our results will be. To develop the most robust model, we would want to track the neural pulses through millions of images. While the described experiment could be extended by a small factor, displaying single images on the screen cannot scale. A more alluring alternative would be to place a camera on the subject's head to capture their line of sight. If a long-term neural sensor could be installed, we could look for features and spikes within small time spans. This would be messy, but would scale in ways the single-image approach could not.

7 Thank You

This exploration took place as part of Monica Linden and David Sheinberg (both of Rice University)'s Coursera course, "Exploring Neural Data". It makes direct use of Sheinberg's data and snippets of code provided by both. The course is excellent; I recommend it to anyone with some programming skill who is interested in the brain.

All source code for this project is available on GitHub:
`https://github.com/cmc333333/neuraldata-final`