Team Zeta Project Report

Linear Modeling and Time Series Analysis of Visual Pattern Recognition

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Abstract

Visual recognition is a complicated process in our brain. Studying how the brain performs during it helps us improve our understanding of brain functionality. Therefore, we want to use the dataset from Haxby et al's study, Distributed and Overlapping Representations of Faces and Objects in Ventral Temporal Cortex to answer the following questions. If one presents different types of visual stimuli to a subject, would each stimulus evoke the same category-specific pattern of response in the ventral object vision pathway? Furthermore, can one fit a time series model to replicate the behavior of the BOLD signal from the responses? Also, can one use time series to match the correlation values of categories found in the study?

To study these questions, we performed linear modeling and ARIMA based times series analysis with this dataset. We found there is a consistent pattern for a subject to recognize one specific object. Even when we excluded maximally responding areas from the analysis, there was still a consistent pattern for visual recognition. Interestingly, our analysis showed that different subjects have different visual recognition patterns. Although these patterns differed greatly across subjects, they were consistent within subjects, In other words, even though subject one has different patterns from subject two, they both had similar patterns among themselves when visually stimulated.

1 Introduction

In Haxby et al's study, *Distributed and Overlapping Representations of Faces and Objects in Ventral Temporal Cortex*[1], researchers collected data from six subjects, including five females and one male. Different categories of pictures were presented to subjects as visual stimuli. The categories are faces, cats, chairs, shoes, bottles, tools, houses, and a control category of phase-scrambled images. The study aimed to answer the following questions: if we present different categories of visual stimuli to a subject, will category-specific response be evoked in the ventral cortex?

Each subject was placed into a functional magnetic resonance imaging (fMRI) facility for 12 times. One complete experiment run lasted 300s. It began with 12s of rest, followed by 8 stimulus blocks of 24s duration, one for each category of visual stimuli. There were 12s intervals of rest between every two blocks, and the whole procedure ended with another 12s of rest. Each picture stimulus were presented for 0.5s followed by an inter-stimulus interval of 1.5ms. 12 stimuli were presented during each stimulus block, and a total of 96 stimuli in a complete experiment run.

In the study, the data collected for each subject were split into two runs: odd runs and even runs. Correlation was used as the indication of response similarity. Results from analyzing within-category and between-category correlations suggest that a lot of response patterns are overlapping. In the overlaps, there are parts of the cortex that respond more to a certain stimuli than others. The study defines these responses as maximal response. In order to gain more insights from the non-overlapping parts of the responses, the study tests whether the patterns of non-maximal responses carry category-related information. Voxels that responded maximally to were excluded from this calculation of correlations. The results show that the removal of maximally responsive voxels from correlation calculations barely diminishes the accuracy of identification. The study concludes that both the pattern of large and small responses and the location of large responses carry category-related information; and small responses are an integral part of the representation.

2 Data

The study's curated dataset can be found and downloaded on the OpenfMRI database with ds105's accession number. The ds105 sub-directory contains files detailing this study, including general information (README file), related research articles (references.txt), detail information and update for this released dataset (release_history.txt), the MR repetition time (scan_key.txt), the name (study_key.txt), and the major task for this study (object viewing) (task_key.txt). In addition, the models folder contains files with the key conditions (list of object categories) (condition_key.txt) and the comparison setting in this study (tast_contrasts.txt).

Subjects have individual directories storing their results. There are four sub-directories in each of the respective directories. The anatomy sub-directory contains high-resolution scans of the subject's head (highres001.nii.gz), mask for obtaining the "brain only" scans (highres001_brain_mask.nii.gz), and the "brain only" anatomy result (highres001_brain.nii.gz). The "behav" sub-directory is empty since subject's behavior is irrelevant to this study. The "model" sub-directory provides information such as the onset time (in seconds), and the duration and weighting for each conditions (object category) for the 12 task runs in this study. The "BOLD" sub-directory contains fMRI results for all 12 task runs for each subject respectively. In each task run directory, we can find the fMRI result (bold.nii.gz) and a QA sub-directory with that run's time series analysis report, fMRI results pre-processing and confound files, and visualization of the brain (nii files).

3 Methods

For each subject, there are eight condition files corresponding to each of the eight objects for each of the twelve runs. Each condition file consists of time points of when the object was presented during the run. We started our analysis with subject 1, where we first wrote helper functions to identify and remove outliers. Then we ran the event2neural function on subject 1's condition files, which returned an array of 121 zeros or ones. These values indicate time intervals at which the subject was looking at the object. We then used the numpy convolve function to convolve the BOLD signal onto the specified time intervals needed. After repeating this process for all objects, we created regressors and built our design matrix. Lastly, we fitted a linear model to the predicted BOLD signals from convolution, and gathered a mean RSS value. We then applied the contrast function to investigate whether each object shows a response pattern in the brain. Unfortunately, initial images produced did not show sufficient contrast, making it difficult to observe patterns. Thus, we used smoothing techniques to produce better images. For smoothing, we applied Gaussian filters over an array of voxel intensity values to generate images that are more appealing to the human eye and easier to identify different parts of the brain. The downside of this technique is that the new patterns identified can potentially be false since the data is transformed. We then repeated our data analysis with the rest of the subjects.

We used various statistical methods and tests in our analysis. First, we built a general linear model to provide estimates for the magnitude of the response for respective stimulus. Then we applied this model to obtain beta values for different objects. We then ran correlation analysis on the beta values, which is further explained below. Moreover, the BOLD signal data are time series, and we performed appropriate analysis such as an object correlation table for each subject and an autoregressive integrated moving average model to predict and fit the BOLD signal responses. Finally, in order to validate our models and data analysis, we looked at mean squared errors to judge how well our model performs.

For correlation analysis, we divided all the runs into two groups (odd and even) , and we aggregated all the results from each object within the group. Then, we computed the correlations between the average beta values of each object of each group and all objects in the opposite group. Take all the even runs where the subject was shown an image of a face as an example. We take the compiled array of beta values, and found the correlation between this array and that generated from all the odd runs where the subject was shown the images of a face, bottle, cat, chair, house, scissors, scrambledpix, and shoe respectively. This gives us 8 correlation values. By repeating the same procedures with all the other objects, we created a 8x8 correlation matrix.

4 Results

Since we started our analysis with subject 1, run001, we will first display those results. We performed initial analysis to attempt to identify specific brain region for recognizing specific object, such as face or house.

Here are the outliers we identified and removed.

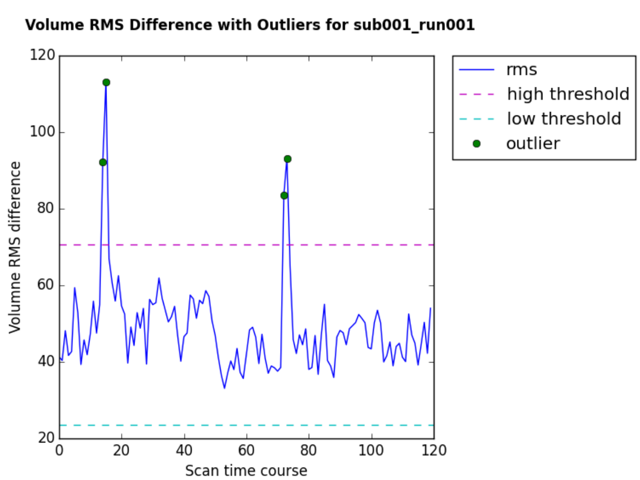

Figure 1: Remove Outliers

Then, we generated task time course with the event2neural function.

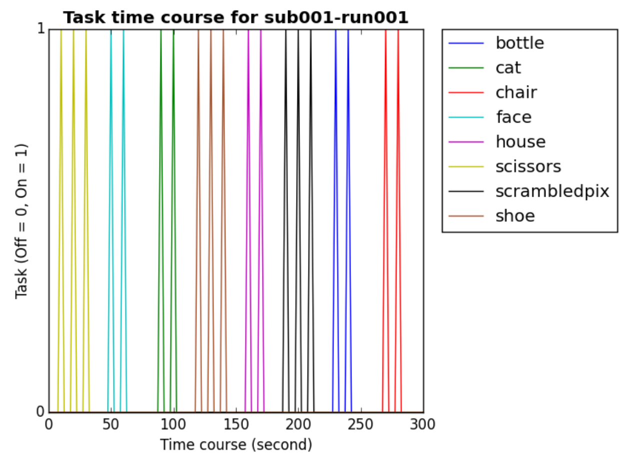

Figure 2: Task Time Course

Afterwards, we performed convolution to generate predicted BOLD signals for this dataset.

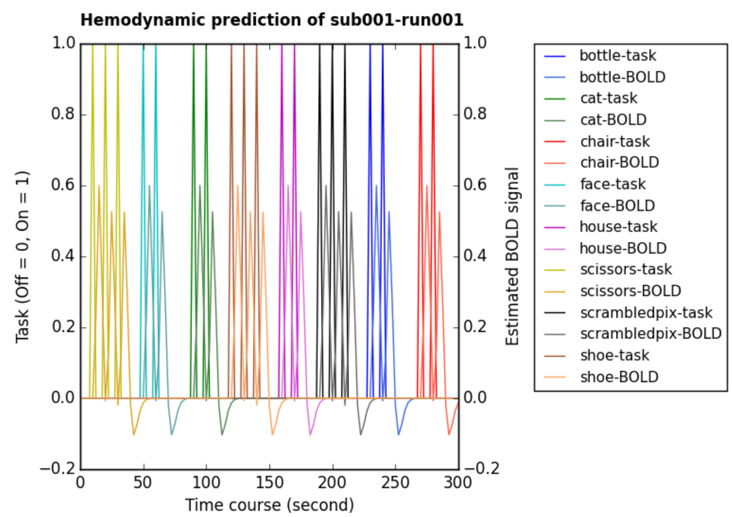

Figure 3: Stimulation Bold

These convolved results for each objects were used as parameters in our design matrix for linear regression. To avoid the drifting problem, we also included two drift parameters in the design matrix. The final design matrix was arranged as followed: bottle, cat, chair, face, house, scissors, scrambledpix, shoe, drift1, drift2, average(all ones).

As mentioned above, we ran correlation analysis on the beta values. None of the correlation values are perfectly 1. The diagonal values are correlations between each object with their respective odd or even runs (within-category correlations). All

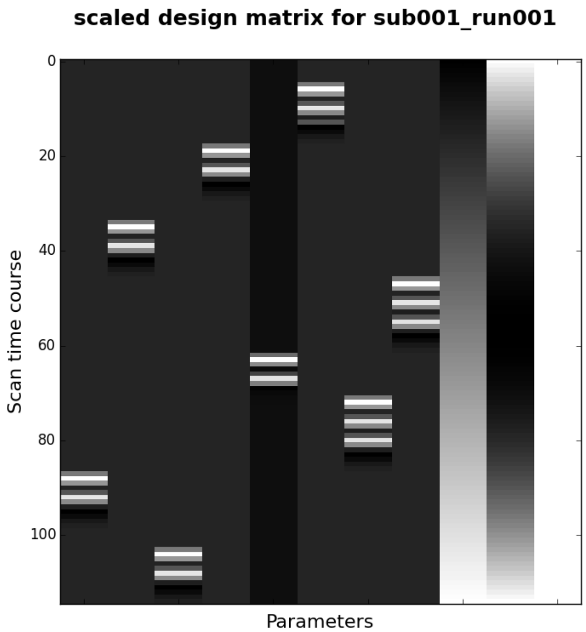

Figure 4: Design Matrix

within-category correlation values are larger than 0.6. For bottle, cat, face, house, scrambledpix, and shoe, the respective within-category correlations are higher than all of that object?s between-category correlations with other objects. For chair and scissors, the within-category correlations are not higher than all of their between-category correlations.

Correlation between 3D odd runs and even runs for sub001

Even runs \ Odd runs	bottle	cat	chair	face	house	scissors	scrambledpix	shoe
bottle	0.8463	0.7851	0.686	0.6109	0.4754	0.8412	0.6555	0.7881
cat	0.5695	0.8051	0.5667	0.4423	0.5197	0.7111	0.6391	0.7563
chair	0.4946	0.4263	0.6074	0.0801	0.7431	0.478	0.5011	0.6893
face	0.5304	0.7219	0.1517	0.8216	0.015	0.6558	0.4736	0.4314
house	0.2378	0.3052	0.5539	-0.1112	0.944	0.2509	0.3033	0.5638
scissors	0.7995	0.7231	0.7685	0.3876	0.6552	0.7447	0.6113	0.8356
scrambledpix	0.5859	0.7326	0.4432	0.411	0.4052	0.6958	0.8567	0.7611
shoe	0.7401	0.7604	0.6607	0.5456	0.5088	0.8777	0.7317	0.8587

Figure 5: 3D Correlation Table for Subject 1

In the correlation analysis, some questions we wanted to answer were would the time series correlation tables be similar to ones produced from the linear regression process if we looked at the raw nii data, how would the correlations differ between the same and different objects, and was the experiment designed in such a way so that correlations are the approximately the same with different runs and subjects. The first step in the time series analysis was retrieving a particular subset of the brain from the raw data. This was done by getting the entire 4-D data, applying a mask on the 4-D data to remove any noises, and using the same subsetted brain as the linear regression process. Then, we averaged the subsetted brain into an array that represents the BOLD signal responses from the beginning to the end of each run. The array has a length of 121, which is the same as the length of each run. Next, based on the condition files of each subject and run, we segmented the array and created a time series array for each of the eight objects. The condition files specified when an object was shown and for how long; thus, giving us a particular range to subset precisely. Finally, we grouped the object time series arrays into either even or odd runs. This allows us to compare averaged even and odd object runs to one another and generate Pearson Correlation coefficients. At the end of this analysis, six correlation tables were generated.

3D Correlation of non_maximal responded brain of sub001

Even runs \ Odd runs	bottle	cat	chair	face	house	scissors	scrambledpix	shoe
bottle	0.5476	0.5021	0.4307	0.4034	0.3646	0.5907	0.4688	0.4701
cat	0.1807	0.5181	0.3663	0.118	0.4106	0.3787	0.3641	0.4258
chair	0.3518	0.2872	0.3744	0.1469	0.4606	0.3136	0.3957	0.4614
face	0.3759	0.5821	0.2007	0.7741	0.1813	0.5525	0.5564	0.2893
house	0.0935	0.3017	0.3444	0.0703	0.7768	0.2449	0.3099	0.325
scissors	0.4488	0.4123	0.4882	0.0696	0.4708	0.3983	0.3314	0.5193
scrambledpix	0.3459	0.5914	0.2617	0.333	0.2021	0.4936	0.7176	0.5272
shoe	0.3773	0.5189	0.3647	0.3885	0.2974	0.6973	0.5557	0.6603

Figure 6: 3D Correlation Excluding Maximally Responding Voxels for Subject 1

On the time-side analysis, we were able to fit autoregressive integrated moving average (ARIMA) models to the BOLD signal responses. This allowed us to see how good of a fit a time series model is compared to the raw data and predict BOLD signal responses without having to know an object a subject is looking at. To see if we could initally fit a time-side model, we looked at subject one run one's data. An autocorrelation and partial autocorrelation plot of the run's raw BOLD signals was generated.

There is a significant lag cut-off after lag two in the partial autocorrelation plot, which means the autoregressive order should be at least two. The cut-off in the autocorrelation plot was at lag four, indiciating the moving average order should be four. To en-

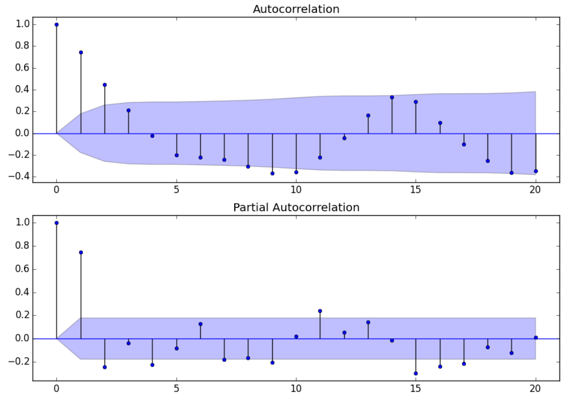

Figure 7: Autocorrelation and Partial Autocorrelation for Subject 1 Run 1

sure these are the right orders for the ARIMA model, an auto.Arima() function was used to automate the parameter search process. In subject one run one, the best ARIMA model was ARIMA(2, 0, 0). Upon fitting the model, the residual's autocorrelation and partial autocorrelation plot were looked at to ensure a goodness of fit.

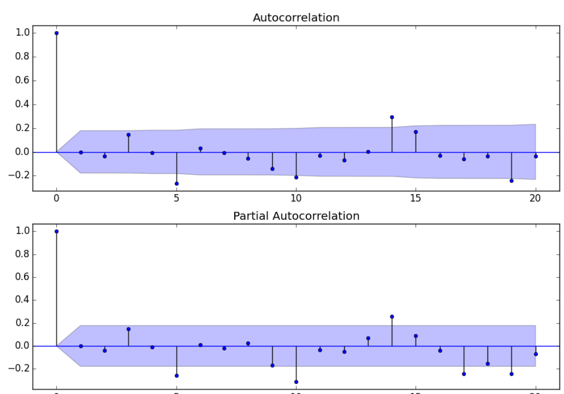

Figure 8: Autocorrelation and Partial Autocorrelation for Subject 1 Run 1 Residuals

In both plots, the significant lag cuts off after lag one; thus, showing that the residuals have no serial correlation. In addition, the Ljung-Box test was used to validate this assumption. It has a null hypothesis that the residuals are independently distributed and uncorrelated, with an altnerative hypothesis that they are correlated. The p-value came out to be 0.6071, so we accept the null. One trend that came up was that there were no periods of volatility in the residuals plot; thus, we could not look into an ARIMA-GARCH hybrid model.

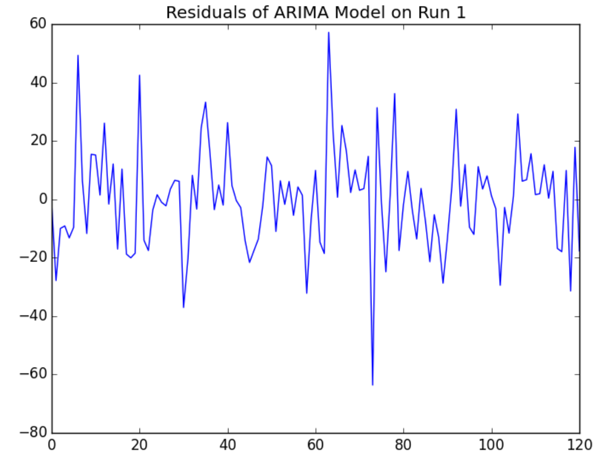

Figure 9: Residuals of ARIMA Model

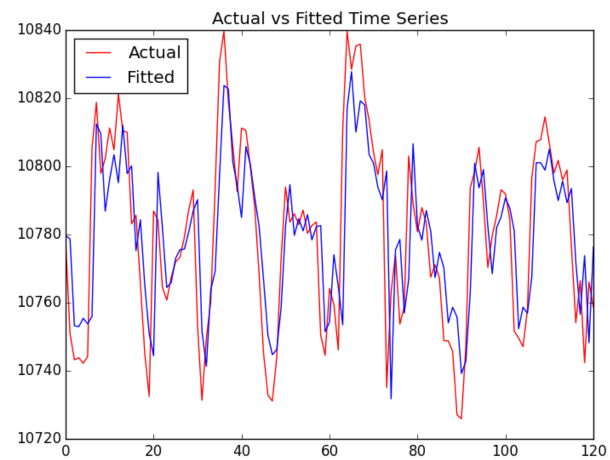

Figure 10: Actual vs Fitted Values of Subject 1 Run 1

5 Discussion

Most of the within-category correlations we found are fairly similar than the paper?s. Some of the values from our analysis are higher than the paper?s, which could be due to the fact that we only analyzed correlations between runs for one subject, while the original research paper studied all subjects. It would make sense that correlations are higher when only analyzing brain activity from one brain.

Correlations between different objects (between-category correlations) seem fairly random, which also seem to be in line with the original paper?s finding. We observe that our between-category correlation values also tend to be higher than those from the paper.

To test the reproducibility of the study, we also redid our correlation analysis after excluding the maximally-responsive voxels. With the exception of some within-category correlations, most correlation values across all categories dropped after we removed the maximally-responsive voxels. This might be an indication that most of the highly correlated areas tend to have higher responses.

Looking at the correlation tables, the first thing that we noticed was that the time series correlation tables were much more different from the linear regression correlation tables. Even though the same subset of the brain was used, the time series tables exclusively had negative correlations, higher correlations with dissimilar objects against same objects, and even negative correlations with the same objects.

Correlation of TSA brain images of sub001

Odd runs

Even runs

	bottle	cat	chair	face	house	scissor	scram	shoe
bottle	0.3454	0.6363	0.7885	0.7682	0.7026	0.3043	0.4386	0.6945
cat	0.6529	0.1697	0.1478	0.4152	0.2525	0.7512	0.3418	0.2102
chair	0.6472	0.5139	0.5447	0.5289	0.6622	0.7868	0.7787	0.6565
face	0.1619	0.2414	0.1569	-0.0772	0.2303	0.1656	0.4892	0.2837
house	0.5647	0.8326	0.8894	0.8262	0.9389	0.6679	0.8645	0.9442
scissor	0.7463	0.7027	0.9064	0.9268	0.863	0.7191	0.7423	0.8578
scram	0.8554	0.4071	0.6878	0.8397	0.572	0.806	0.6717	0.6138
shoe	0.6264	0.761	0.6908	0.6235	0.7937	0.7137	0.9336	0.826

Figure 11: 3D Correlation Time Series Table for Subject 1

These differences could have come from how the two processes were executed. For example, the linear regression process involved convolving the data and transforming the data with beta values, whereas the time series analysis only looked at the raw data. Thus, this is the most likely reason as to why the tables differed. The second thing the time series correlation tables had was that across the six subjects, no two subjects had similar correlation results. This confirms one of our hypothesis that

Correlation of TSA brain images of sub003

Odd runs

Even runs

	bottle	cat	chair	face	house	scissor	scram	shoe
bottle	-0.08	0.0479	0.4139	-0.3066	-0.053	0.4759	0.5464	0.2207
cat	-0.1846	0.4838	-0.7414	0.7432	-0.1214	0.1884	0.1459	-0.292
chair	-0.4274	-0.2332	-0.1252	-0.13	0.5582	0.4485	-0.0063	-0.0402
face	-0.4132	0.2926	-0.3895	0.3096	-0.362	0.6446	0.8016	-0.629
house	-0.1321	-0.5763	0.289	-0.4433	0.0576	0.2247	0.2629	-0.0878
scissor	0.012	-0.601	0.2141	-0.1925	0.0618	-0.1896	-0.3603	0.0625
scram	0.0265	0.2714	0.2084	-0.1771	-0.1535	0.0875	-0.257	0.7007
shoe	-0.5113	0.018	-0.2648	0.1214	-0.3278	0.5827	0.7447	-0.4559

Figure 12: 3D Correlation Time Series Table for Subject 3

the brain is a complex structure that will never give consistent results even with a well designed experiment. What this means is that the BOLD signal responses are not exactly 100% comparable and it should be expected to have contrasting correlation coefficients. One last point to bring up is that the BOLD signals were not consistent across a subject's runs. In one run, a cat BOLD signal would come out at an intensity of 10,800 and then in another, it would come out to 10,500. One question we wanted to answer was given the objects, can we predict the BOLD signal responses? Given that an object's BOLD signal was never the same, this showed us that we couldn't answer that particular question. Thus, we were unable to conclude anything regarding predicting a BOLD signal given the objects.

In terms of time series analysis, now that there is a good model for one particular run, we can go about answering the original questions we had with time-side analysis. When we plotted the actual to the fitted values, we see that the ARIMA model was able to capture the actual values very well. This allows us to get into forecasting and predicting future responses. However, one limiation with the python StatsModel package is that there are no forecasting methods available. Thus, no further progress could be done unless R was available as a tool.

There are a lot of problems that came up during our analysis. To begin with, since most of us have limited neuroscience knowledge, it was very difficult just to understand the study and the data itself. The research paper of the study uses specific and technical terms that make it hard to comprehend. More time was spent at the earlier stages rereading the original paper and exploring the data folders than expected, which slowed down our progress for analysis. Moreover, the values from correlation analysis did not come out as clean as we hoped, which also set our progress back. We did not end up have time to apply machine learning techniques for predictions as we originally splanned to.

References

[1] J. V. Haxby et al., *Distributed and overlapping representations of faces and objects in ventral temporal cortex*, Science, 293 (2001), pp. 2425–2430.

6 Appendix

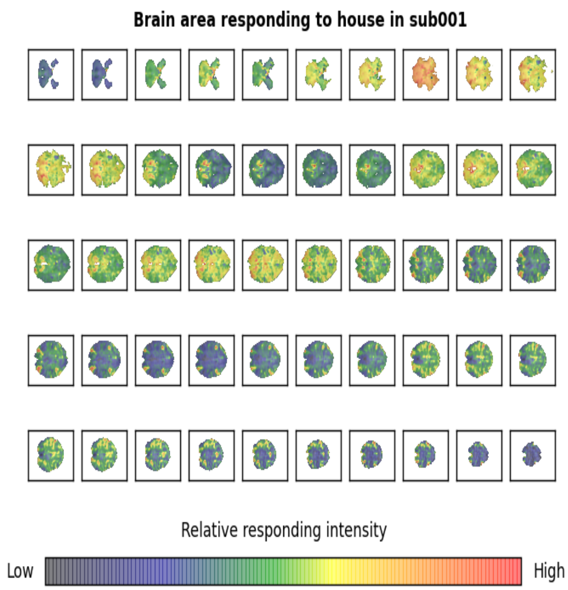

Figure 13: Betas for Sub001 Run001

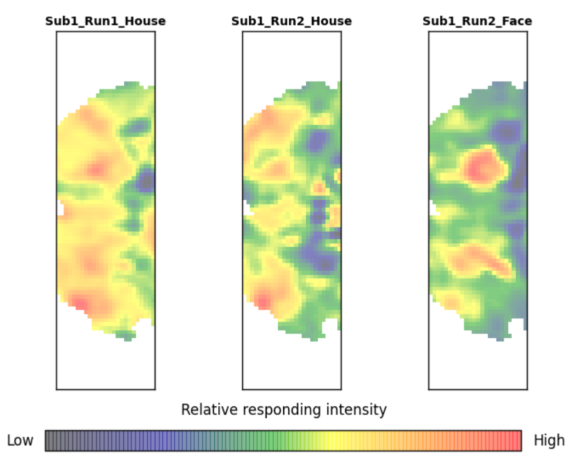

Figure 14: Sub001 2D Compiled

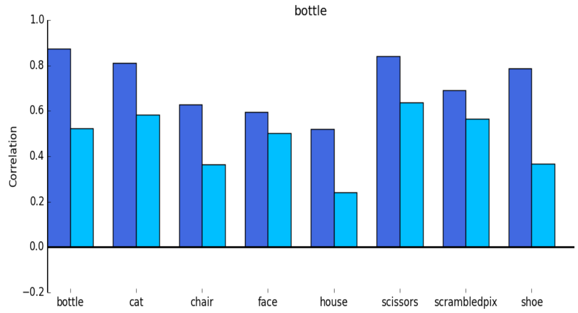

Figure 15: Sub001 2D Correlation: Bottle

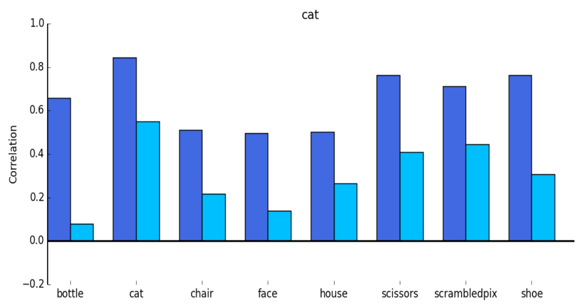

Figure 16: Sub001 2D Correlation: Cat

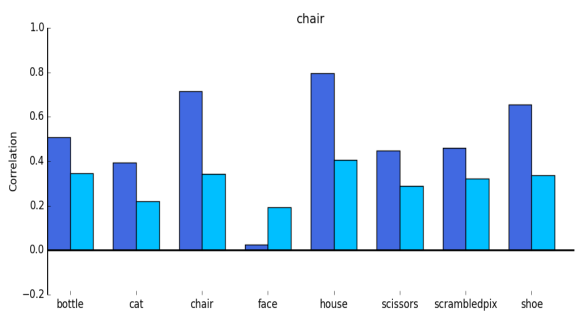

Figure 17: Sub001 2D Correlation: Chair

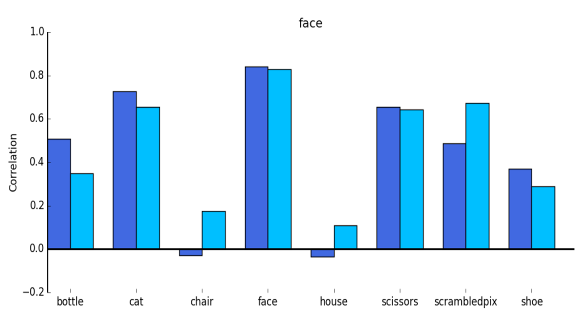

Figure 18: Sub001 2D Correlation: Face

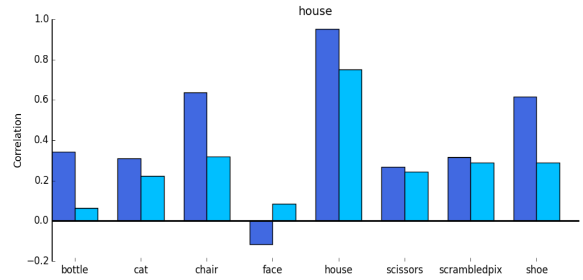

Figure 19: Sub001 2D Correlation: House

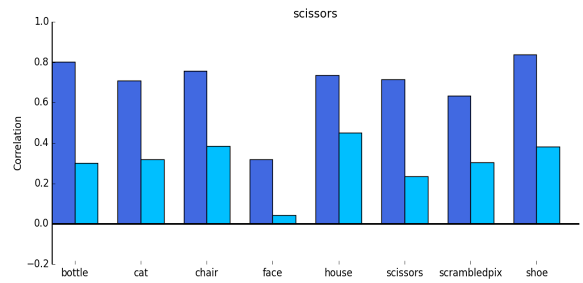

Figure 20: Sub001 2D Correlation: Scissor

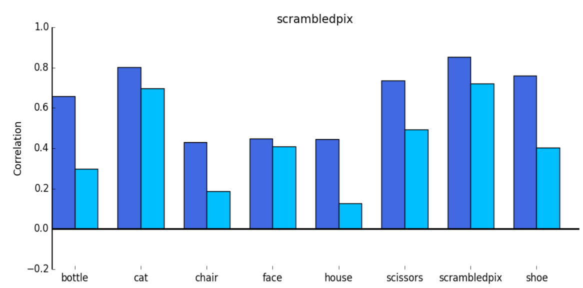

Figure 21: Sub001 2D Correlation: Scram

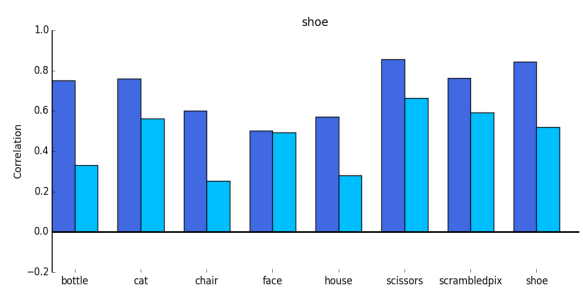

Figure 22: Sub001 2D Correlation: Shoe

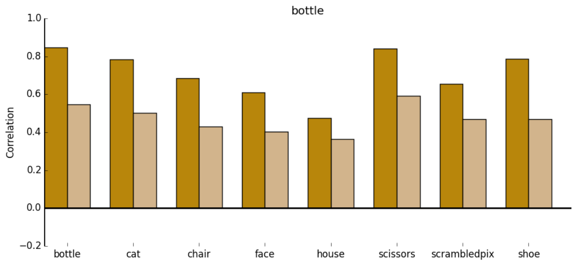

Figure 23: Sub001 3D Correlation: Bottle

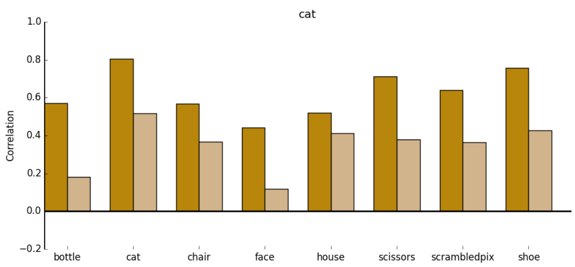

Figure 24: Sub001 3D Correlation: Cat

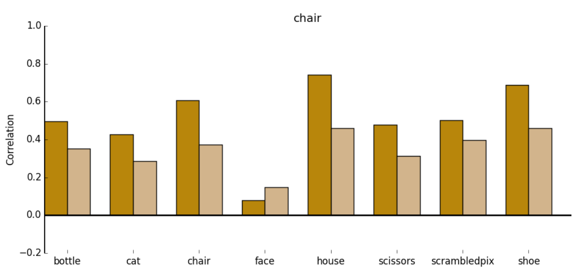

Figure 25: Sub001 3D Correlation: Chair

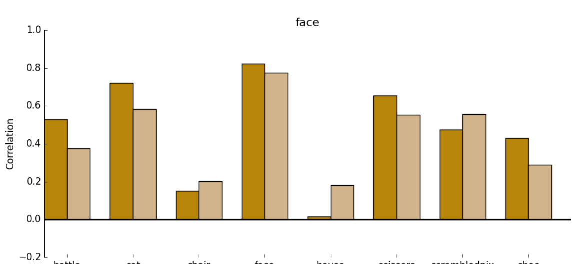

Figure 26: Sub001 3D Correlation: Face

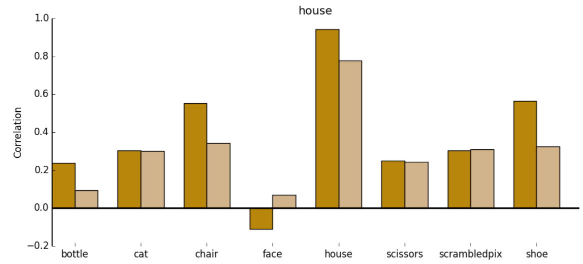

Figure 27: Sub001 3D Correlation: House

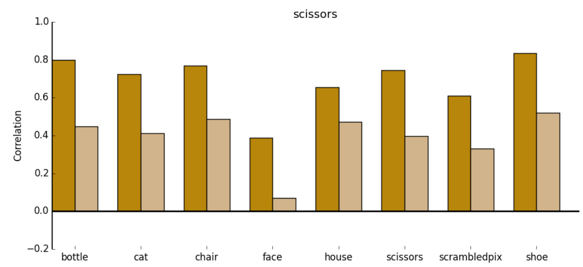

Figure 28: Sub001 3D Correlation: Scissor

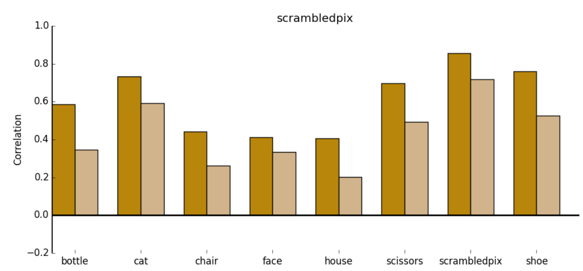

Figure 29: Sub001 3D Correlation: Scram

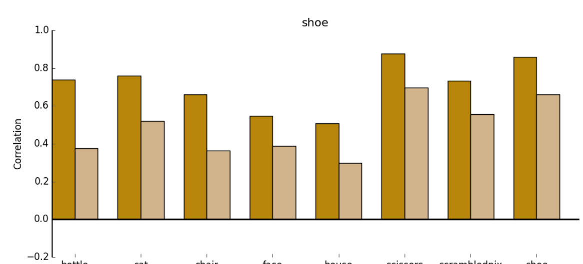

Figure 30: Sub001 3D Correlation: Shoe

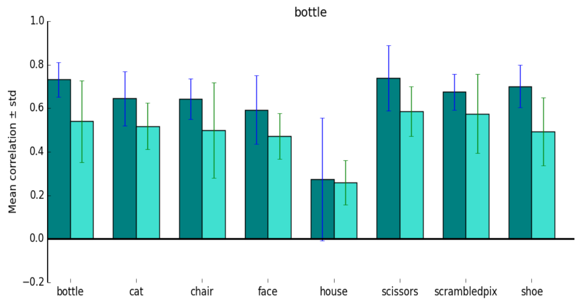

Figure 31: Cross Subject 2D Correlation: Bottle

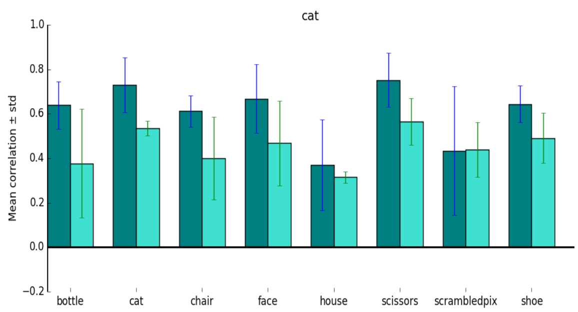

Figure 32: Cross Subject 2D Correlation: Cat

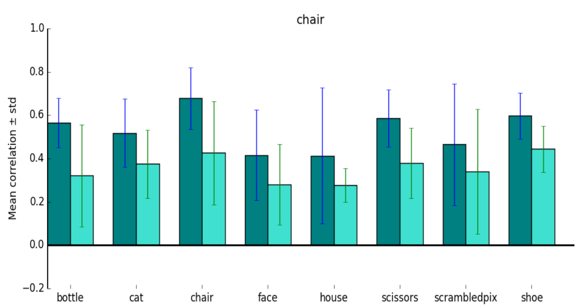

Figure 33: Cross Subject 2D Correlation: Chair

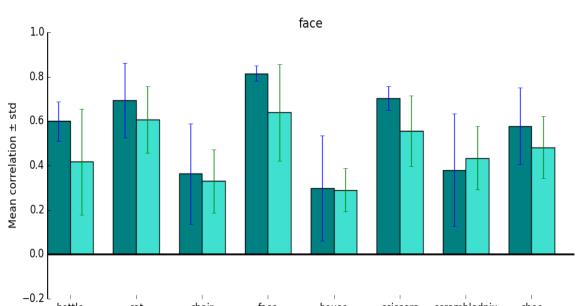

Figure 34: Cross Subject 2D Correlation: Face

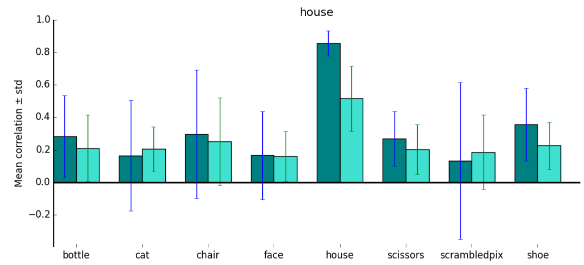

Figure 35: Cross Subject 2D Correlation: House

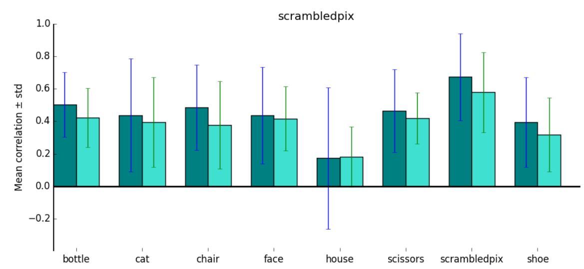

Figure 36: Cross Subject 2D Correlation: Scram

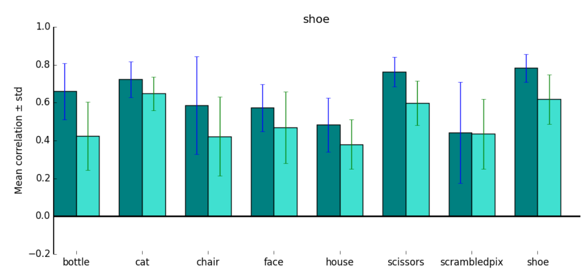

Figure 37: Cross Subject 2D Correlation: Shoe

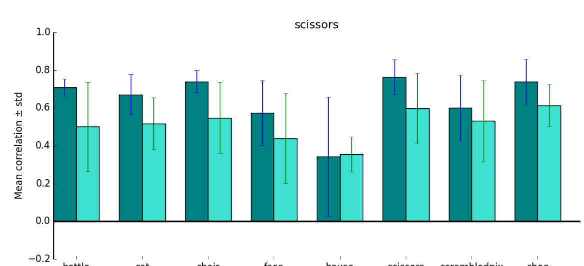

Figure 38: Cross Subject 2D Correlation: Scissors

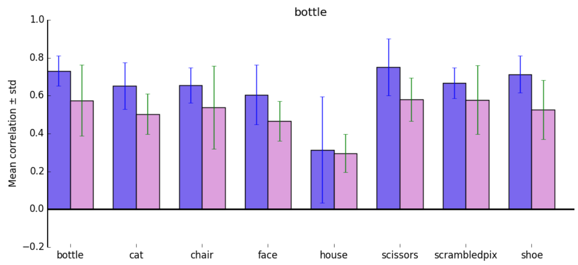

Figure 39: Cross Subject 3D Correlation: Bottle

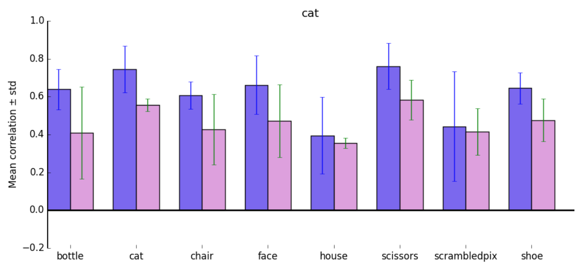

Figure 40: Cross Subject 3D Correlation: Cat

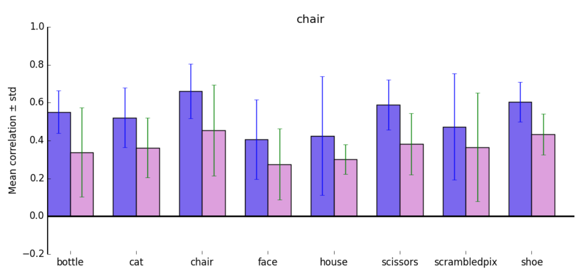

Figure 41: Cross Subject 3D Correlation: Cat

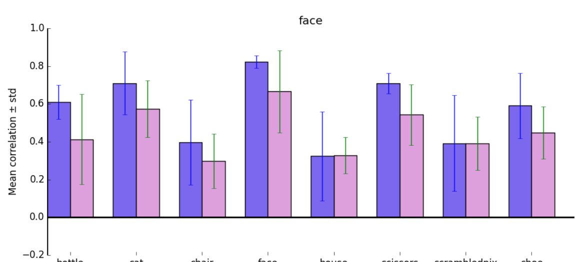

Figure 42: Cross Subject 3D Correlation: face

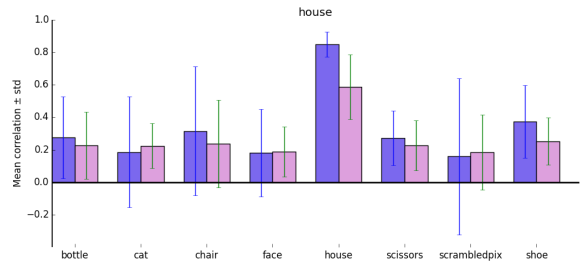

Figure 43: Cross Subject 3D Correlation: House

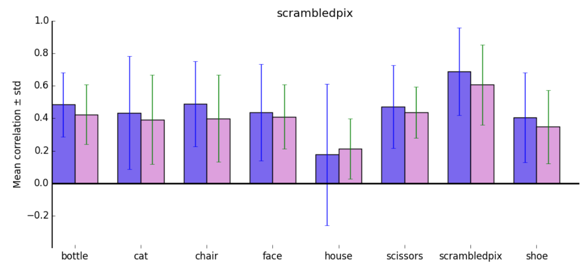

Figure 44: Cross Subject 3D Correlation: Scram

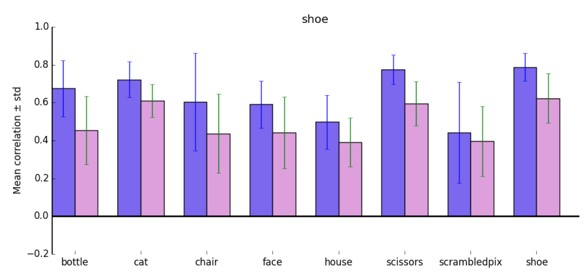

Figure 45: Cross Subject 3D Correlation: shoe

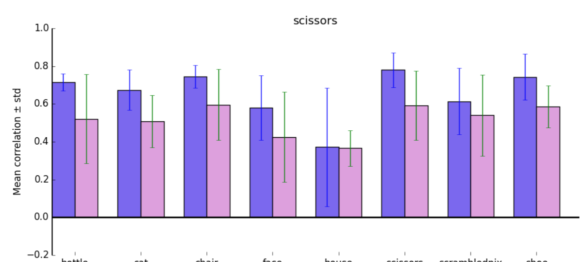

Figure 46: Cross Subject 3D Correlation: Scissors