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 als 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 experiment runs. 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 was 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 defined these responses as maximal response. In order to gain more insights from the non-overlapping parts of the responses, the study tested whether the patterns of non-maximal responses carry category-related information. Voxels that responded maximally were excluded from this calculation of correlations. The

results shown that the removal of maximally responsive voxels from correlation calculations barely diminishes the accuracy of identification. The study concluded 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).

The preprocessed data for this ds105 dataset can be found and download from https://nipy.bic.berkeley.edu/rcsds/. The processing applied to these fMRI scans includes: high-pass filtering in time (to remove low frequency drifts / noise, and registration to a standard anatomical template (the MNI template).

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 the 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 took 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.

event2neural function.

Figure 2: Task Time Course

Figure 1: Remove Outliers

Then, we generated task time course with the

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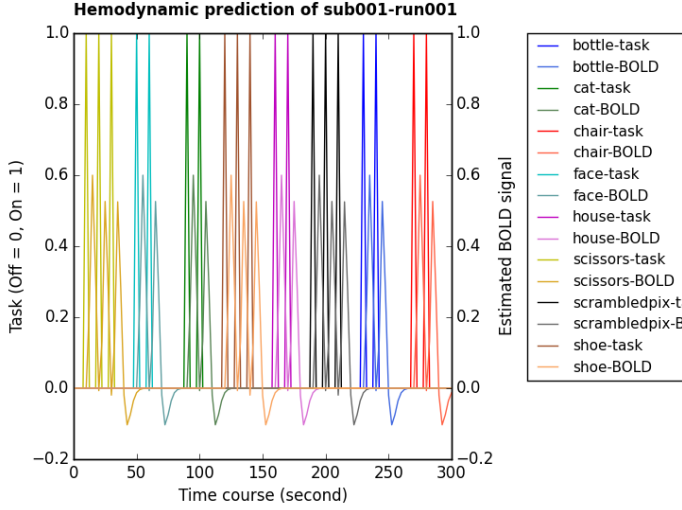

Figure 3: Stimulation Bold

Figure 4: Design Matrix

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 (as shown i Fig. 4). The final design matrix was arranged as followed: bottle, cat, chair, face, house, scissors, scrambledpix, shoe, drift1, drift2, and ones (for background)

As for the dataset, after removing the outliers and smoothing the data, we subset the brain region to perform analysis on brain areas. We then used the design matrix to run linear modeling on the brain subset to get beta values. These beta bata values helped us to identify specific brain area and pattern for a subject under specific visual stimulation like house:

As mentioned above, we want to run correlation analysis on the beta values. We first focus on the correlation analysis on a 2D brain slice. To do that, we selected the most responding 2D brain area to perform the analysis. In the initial analysis, we tried to compare between run1 and run2 of subject1. We expected to see high correlation within category and low correlation between category. For instance, the run1 house and run2 house should have high correlation, whereas the run1 house and run2 face should have a low correlation. The 2D brain slice for the corresponding conditions are shown here:
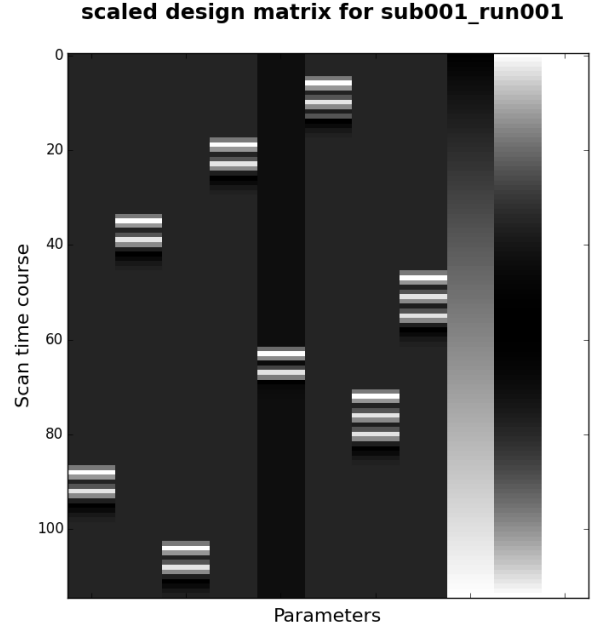
Unfortunately, after performing this initial study,
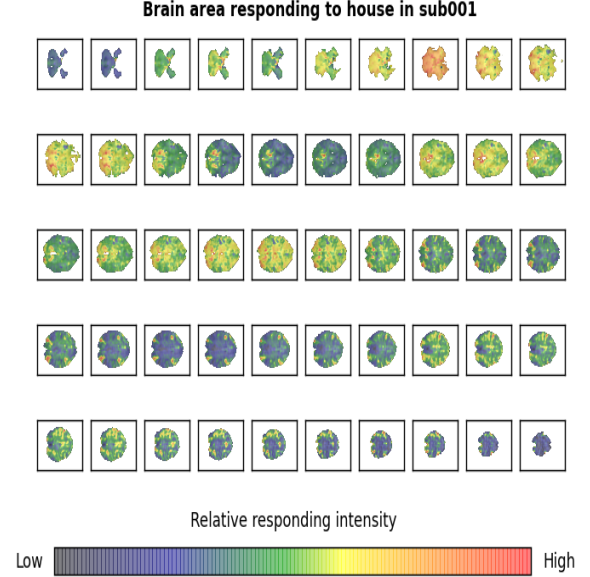

Figure 5: Betas for Sub001 Run001

we didnt get what we expected. However, some comparison across different runs shown our expected results. These observations indicated that there might be a variation in the results across runs. Therefore, to reduce the impact of variation across runs, we compiled the even run results and odd run re-
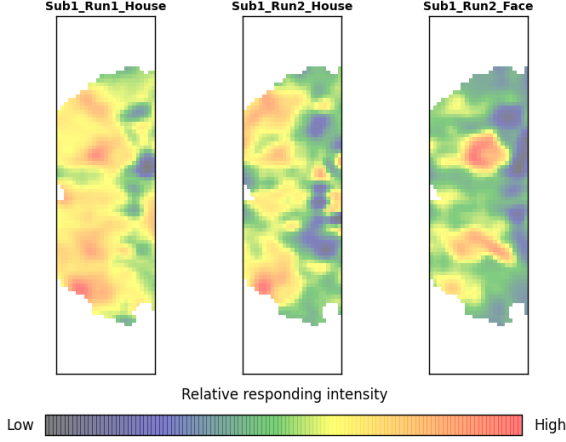
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Figure 6: Sub001 2D Compiled

sults separately and used them to perform correlation analysis. The mean results for even run and odd run shown similar patter:
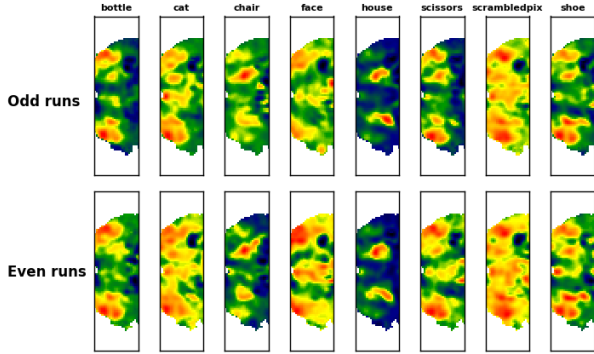

Figure 7: Sub001 Odd and Even run results

The within category correlation increased and is relatively higher than between category correlation (as shown in appendix). Excluding maximally responding areas shown the similar pattern indicating the both the pattern of large and small responses and the location of responses carry category-related information.

Since the brain is a 3D structure, the visual recognition is processed in the entire brain. Therefore, we next focus on the 3D brain slice to perform correlation analysis. The correlation table between even and odd runs are listed below and shown as bar plots in appendix:

As shown in the tables above, none of the

Correlation between 3D odd runs and even runs for sub001

		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

(Even runs labels the rows)

Figure 8: 3D Correlation Table for Subject 1

3D Correlation of non_maximal responded brain of sub001

		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

(Even runs labels the rows)

Figure 9: 3D Correlation Excluding Maximally Responding Voxels for Subject 1

correlation values are perfectly 1. The diagonal values are correlations between each object with their respective odd or even runs (within-category correlations). All 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. Removing the maximally response area gave us the similar analytic results. This is consistent with our findings on 2D correlation analysis.

Next, to further study whether the observation is consistent across subjects, we performed the same analysis in all subjects of this dataset. Interestingly, the brain pattern for visual recognition is different across subjects. This might increase the variation for cross subjects analysis. The mean correlation table was then created to statistically study the correlation pattern across subjects with and without maximally response areas:

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3D Total correlation between odd runs and even runs

		bottle	cat	chair	face	house	scissors	scrambledpix	shoe
					Odd runs				
Even runs	bottle	0.7313	0.6519	0.6548	0.6046	0.3133	0.7504	0.6674	0.7123
	cat	0.639	0.7445	0.6062	0.6615	0.3954	0.7613	0.4426	0.6453
	chair	0.5509	0.521	0.6607	0.406	0.4247	0.5887	0.4731	0.6035
	face	0.6098	0.7103	0.3969	0.8229	0.3235	0.7085	0.3924	0.5916
	house	0.2753	0.1862	0.3157	0.1812	0.8506	0.2715	0.1584	0.373
	scissors	0.715	0.6745	0.7447	0.5807	0.3722	0.7797	0.614	0.7425
	scrambledpix	0.4841	0.4337	0.4878	0.4367	0.1759	0.4715	0.6883	0.4047
	shoe	0.6748	0.7224	0.6047	0.5907	0.4981	0.7753	0.4423	0.7875

Figure 10: Mean 3D Correlation Table Across Subjects

3D Non-Max Total correlation between odd runs and even runs

		bottle	cat	chair	face	house	scissors	scrambledpix	shoe
					Odd runs				
Even runs	bottle	0.5755	0.5027	0.5371	0.4662	0.2964	0.5801	0.5779	0.5267
	cat	0.4099	0.5572	0.4279	0.4715	0.3548	0.583	0.4149	0.4762
	chair	0.3381	0.3616	0.4534	0.2752	0.3014	0.3826	0.3654	0.4327
	face	0.413	0.5743	0.2974	0.6659	0.3287	0.5425	0.3913	0.4484
	house	0.226	0.2245	0.238	0.1886	0.5867	0.2264	0.1832	0.2525
	scissors	0.5215	0.5088	0.5961	0.4247	0.3655	0.5918	0.54	0.5858
	scrambledpix	0.424	0.3918	0.3989	0.4099	0.2127	0.4375	0.6074	0.3476
	shoe	0.4534	0.61	0.4374	0.4423	0.3914	0.5947	0.3963	0.6228

Figure 11: Mean 3D Correlation Table Excluding Maximally Responding Voxels Across Subjects

Since there is high variation across subjects, all the correlation numbers increased. However, the within category correlation was still relatively higher than between category correlation. The correlation without maximally responded areas shown similar pattern. This again confirmed our and Haxby et als finding that both the pattern of large and small responses and the location of responses carry category-related information.

In time series 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 lin-

ear 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.
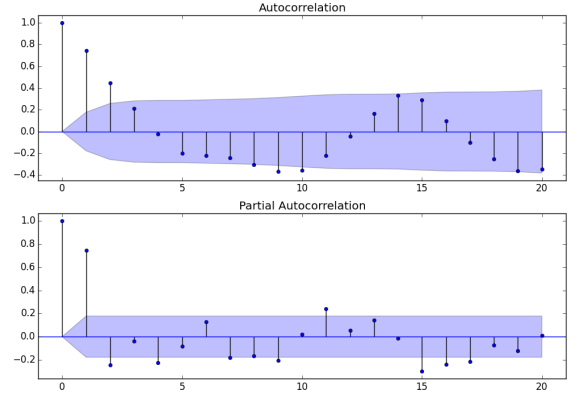

Figure 12: Autocorrelation and Partial Autocorrelation for Subject 1 Run 1

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 ensure 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.
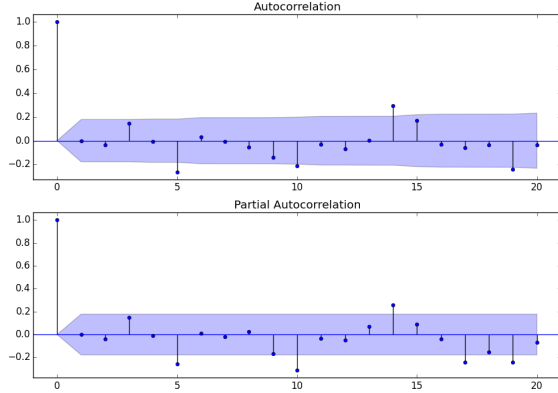

Figure 13: Autocorrelation and Partial Autocorrelation for Subject 1 Run 1 Residuals

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.
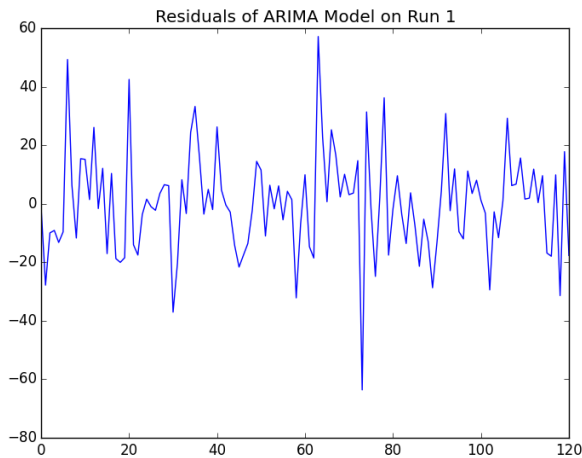
Figure 14: Residuals of ARIMA Model
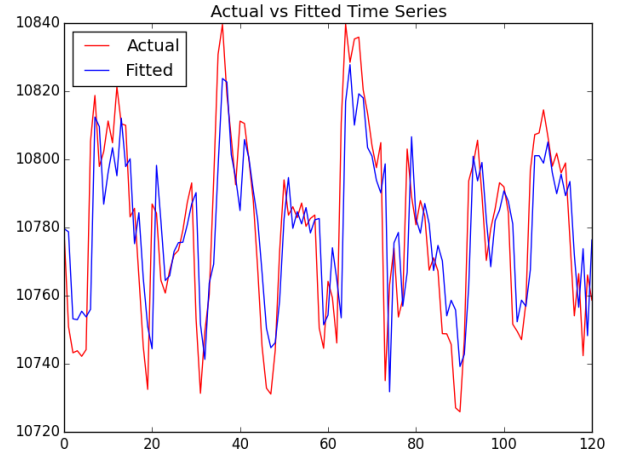
Figure 15: Actual vs Fitted Values of Subject 1 Run 1

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

	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

(Odd runs across columns; Even runs down rows)

Figure 16: 3D Correlation Time Series Table for Subject 1

Correlation of TSA brain images of sub003

	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

(Odd runs across columns; Even runs down rows)

Figure 17: 3D Correlation Time Series Table for Subject 3

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 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.
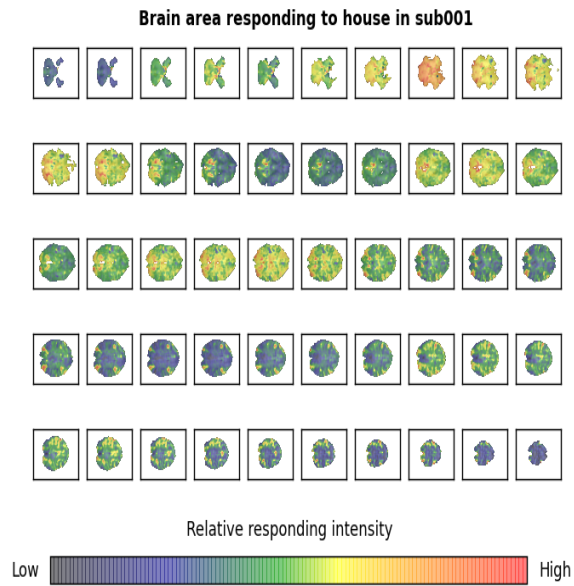
6 Appendix

Brain area responding to house in sub001

Relative responding intensity

Low — High

Figure 18: Betas for Sub001 Run001

Sub1_Run1_House   Sub1_Run2_House   Sub1_Run2_Face

Relative responding intensity

Low — High
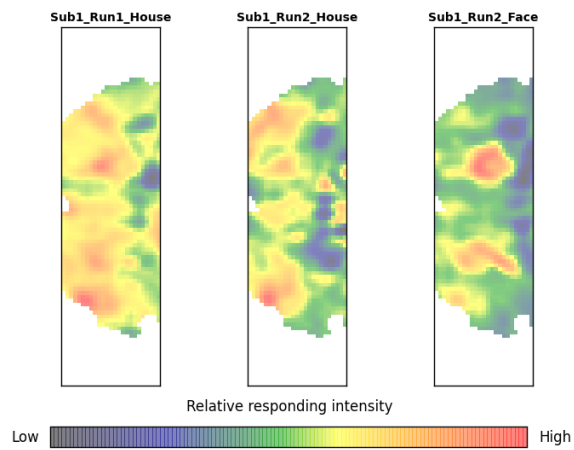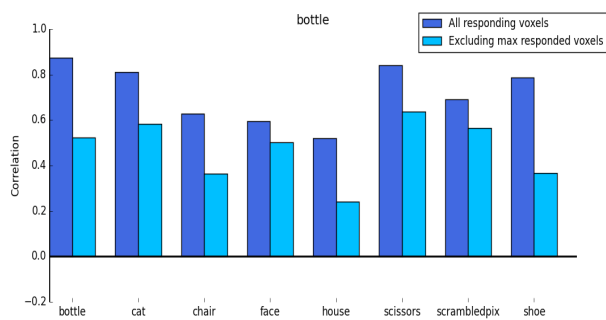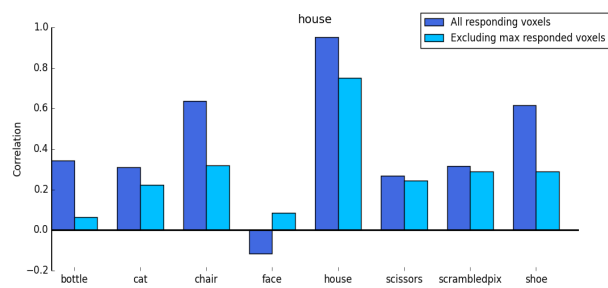
Figure 19: Sub001 2D Compiled
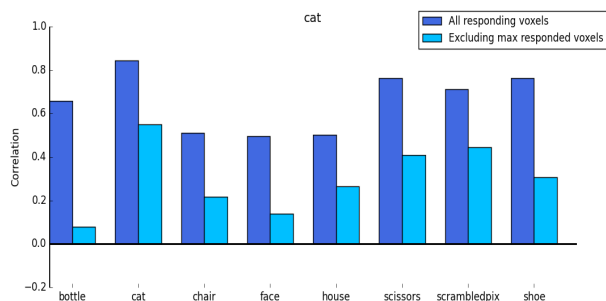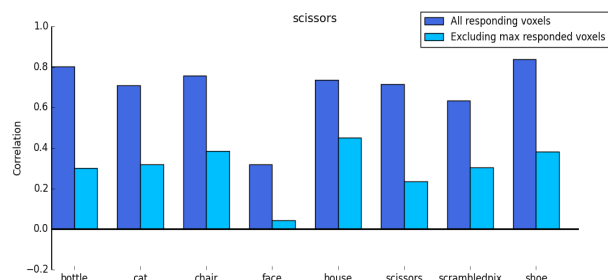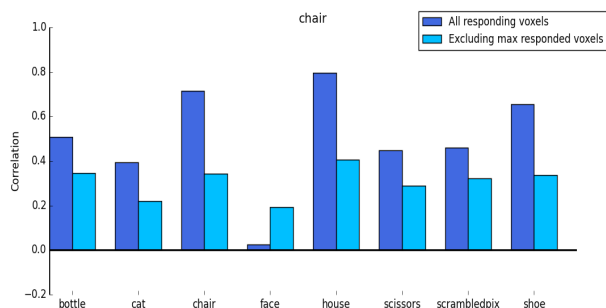
Figure 20: Sub001 2D Correlation: Bottle
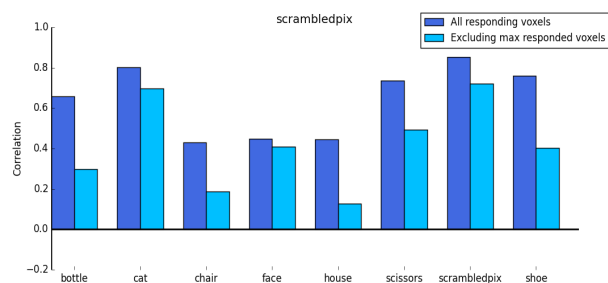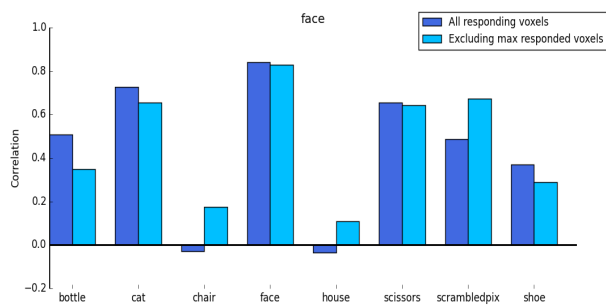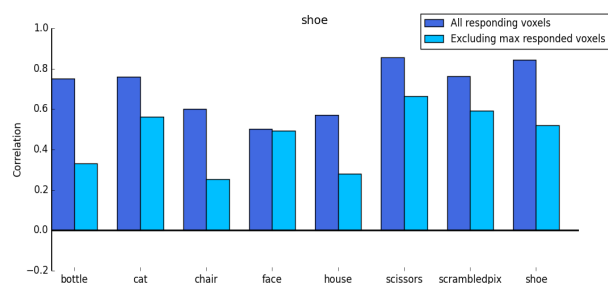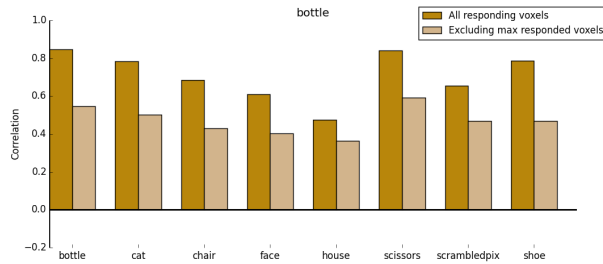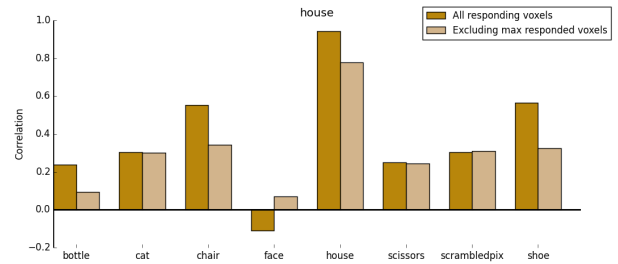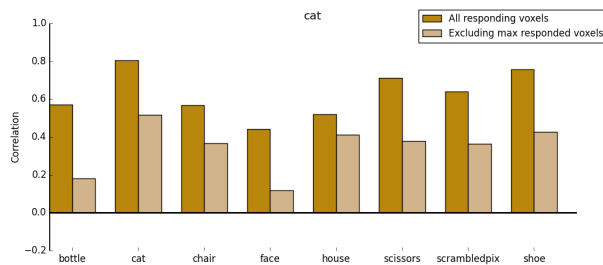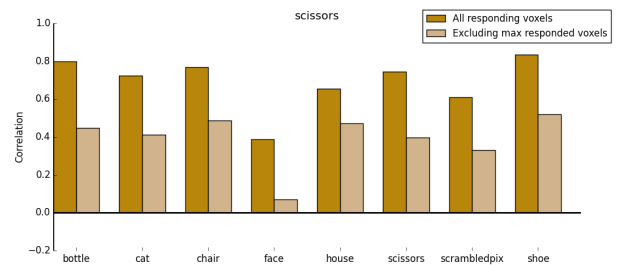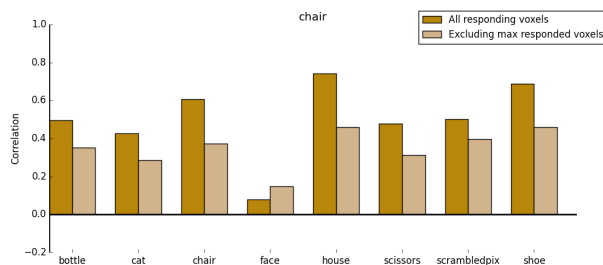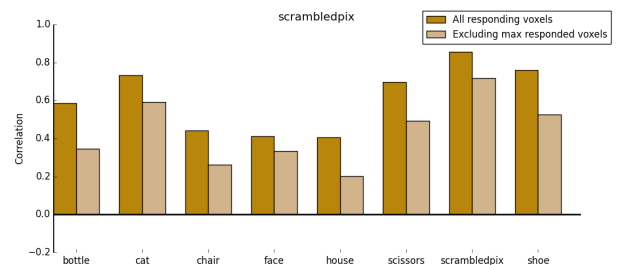

Figure 21: Sub001 2D Correlation: Cat

Figure 22: Sub001 2D Correlation: Chair

Figure 23: Sub001 2D Correlation: Face

Figure 24: Sub001 2D Correlation: House

Figure 25: Sub001 2D Correlation: Scissor

Figure 26: Sub001 2D Correlation: Scram

Figure 27: Sub001 2D Correlation: Shoe

Figure 28: Sub001 3D Correlation: Bottle

Figure 29: Sub001 3D Correlation: Cat

Figure 30: Sub001 3D Correlation: Chair

Figure 31: Sub001 3D Correlation: Face

Figure 32: Sub001 3D Correlation: House

Figure 33: Sub001 3D Correlation: Scissor

Figure 34: Sub001 3D Correlation: Scram
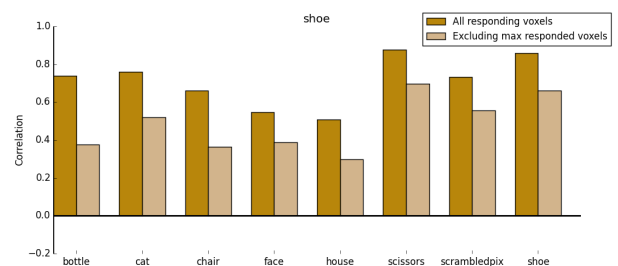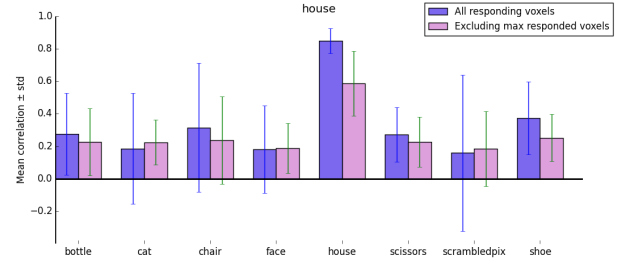

Figure 35: Sub001 3D Correlation: Shoe
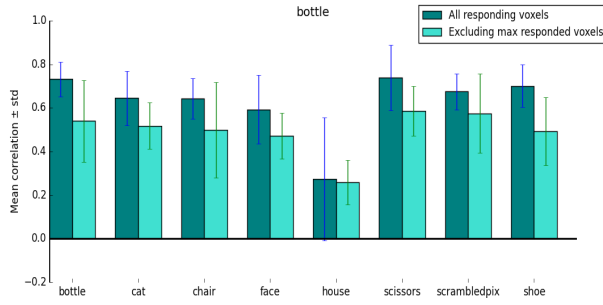
Figure 36: Cross Subject 2D Correlation: Bottle

Figure 37: Cross Subject 2D Correlation: Cat

Figure 38: Cross Subject 2D Correlation: Chair

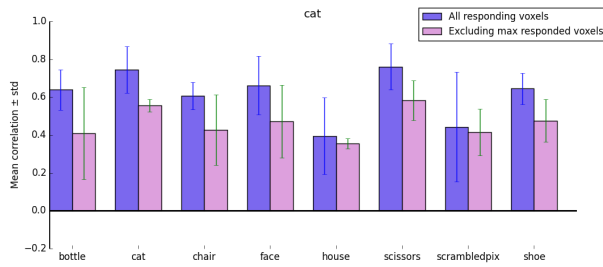Figure 39: Cross Subject 2D Correlation: Face
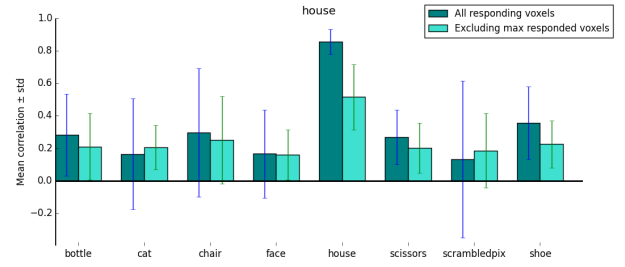
Figure 40: Cross Subject 2D Correlation: House
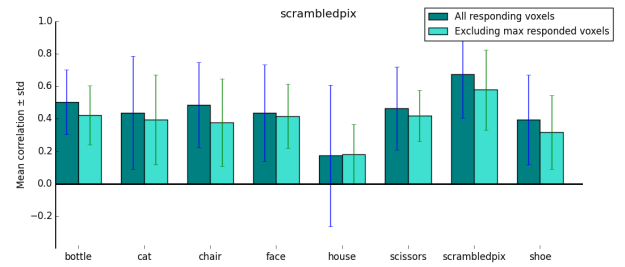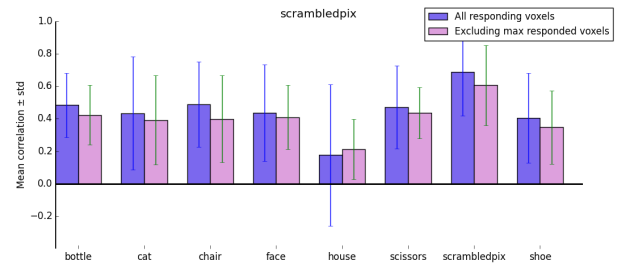

Figure 41: Cross Subject 2D Correlation: Scram
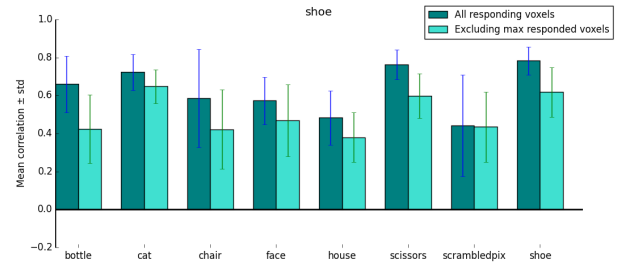
Figure 42: Cross Subject 2D Correlation: Shoe
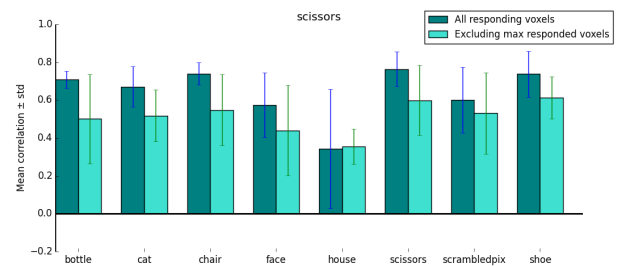
Figure 43: Cross Subject 2D Correlation: Scissors
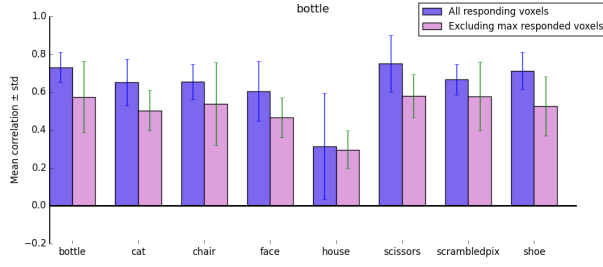
Figure 44: Cross Subject 3D Correlation: Bottle

Figure 45: Cross Subject 3D Correlation: Cat

Figure 46: Cross Subject 3D Correlation: Cat

Figure 47: Cross Subject 3D Correlation: face

Figure 48: Cross Subject 3D Correlation: House

Figure 49: Cross Subject 3D Correlation: Scram
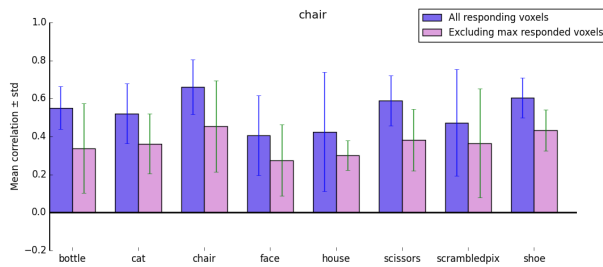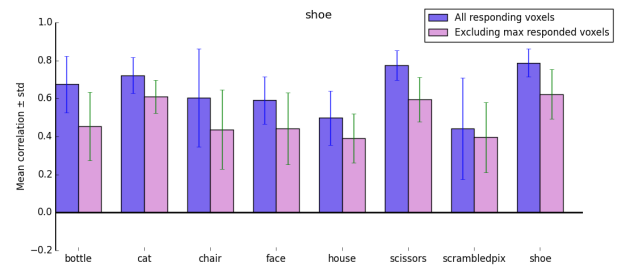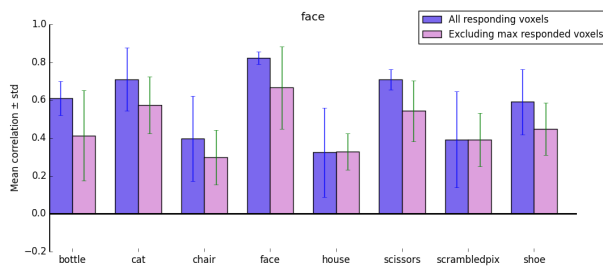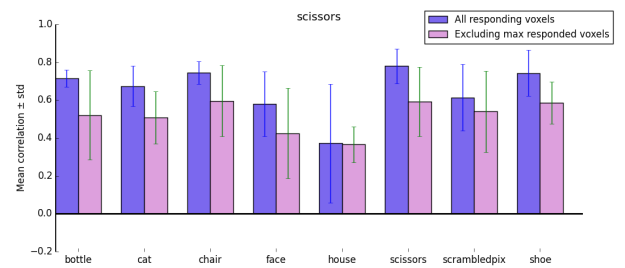

Figure 50: Cross Subject 3D Correlation: shoe

Figure 51: Cross Subject 3D Correlation: Scissors