The Neural Basis of Loss Aversion in Decision-Making Under Risk

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Abstract

It is a well-known fact that certain areas of the brain play a larger role in some tasks than others. What is not as well-known at the moment is which parts of the brain correspond to what roles, as well as how much they contribute to these roles. This study follows up on another investigation that found an area of the brain that plays a substantial role in decision-making, employing additional algorithms to corroborate and add to the findings reported. The goal of this project is to demonstrate the importance as well as the proper process of reproducible computational science.

1 Introduction

This study was inspired by "The Neural Basis of Loss Aversion in Decision Making Under Risk," a 2007 article by Sabrina M. Tom and her associates at the University of California, Los Angeles [1]. The original study it describes made several major findings that will be corroborated and further investigated using methods of computational research and machine learning.

One finding of interest to this study is that certain areas of the human brain responded with increasing activity given higher potential gains, but that no area responded similarly given higher potential losses. Furthermore, many of the same areas responded with decreasing activity given higher potential losses, but no area responded similarly given higher potential gain. This would suggest that the same areas of the brain are responsible for processing possible gains and losses, an idea that will be investigated in detail.

This report describes in detail attempts to reproduce many of the exact methods used in the original study, as well as a two novel methods that were not. The hope is that the fundamental differences between the new and the original methods allows for the potential of this follow-up study to shed light on discoveries that may not have otherwise been possible.

Lastly, this study will place heavy emphasis on the theme of reproducibility, which is defined to be how easily a line of analysis can be replicated in its entirety, either by the original analyst or an independent party. To achieve this, any code that is used to interpret the data, be the outcome conclusive or not, will be well-written, documented, and reviewed prior to publication.

2 Data

The original study recruited sixteen right-handed, English-speaking individuals between the ages of 19 and 28. There is confusion about the sexes of the individuals as the supplement to the published article reports seven males and nine females, while the data made publicly available reports eight males and eight females. It is known that all subjects were physically healthy and free of neurological and psychiatric history, and that their informed consent was acquired prior to their participation in the study.

These subjects participated in three runs of 85-86 trials of a single task. This task involved offering the subject a wager with an equal chance of winning or losing known amounts of money. Potential gains were in even denominations between \$10 and \$40, while potential losses were in integer denominations between \$5 and \$20. The participants were prompted to either strongly accept, weakly accept, weakly decline, or strongly decline the wager in each trial. At the same time that investigators collected these behavioral responses, data pertaining to neural activity was recorded via fMRI. This data set is available

for download from OpenFMRI.org under the name "Mixed-gambles task" (accession number ds005), and offers both the neural activity data as well as the behavioral data.

The raw neural activity data for each run is saved under the filename `bold.nii.gz`, each file containing 240 volumes obtained over the course of eight minutes. Volumes were taken two seconds apart and each further contains exactly 139264 voxels, being 64 points in length, 64 points in width, and 34 points in depth. As per usual with blood-oxygen-level dependent (BOLD) analysis, each voxel also corresponds to a signal at a given time. A larger signal indicates increased oxygenated blood flow to the corresponding area of the brain, which this paper will refer to as "activation."

Some analyses performed in this investigation instead use a second set of the BOLD data that has undergone preprocessing algorithms, including motion correction, high-pass filtering with respect to time, and registration to the Montreal Neurological Institute's standardized anatomical template. These files are also provided by OpenFMRI.org and there exists one by the alias of `filtered_func_data_mni.nii.gz` for each run of the raw data.

The behavior data for each run is stored separately under the alias `behavdata.txt`. Each file contains a table for the run, in which each trial of the task is stored as a row. Each row then contains seven elements, referred to in the file as `onset`, `gain`, `loss`, `PTval`, `respnum`, `respcat`, and `RT`. The first three elements respectively denote the time at which the trial was presented, the proposed monetary reward given in the event the subject wins the trial, and the proposed monetary loss suffered in the event the subject lost the trial. The fourth element is a standardized value indicating the relative expected gain from the wager. The fifth element represents the subject's response: `1` for strong acceptance, `2` for weak acceptance, `3` for weak rejection, `4` for strong rejection, and `0` for nonresponse. The sixth element contains the patient response converted to a binary variable: `0` for rejection, `1` for acceptance, and `-1` in the outstanding case of nonresponse. The final element is the time it took the subject to submit a response, measured in seconds and with precision to within a millisecond.

In both this study and the investigation that inspired it, an additional explanatory variable called the `distance from indifference` is also used. Each value of this variable is computed using the values of `gain` and `loss` referenced above. With respect to these studies, the gain/loss matrix is defined to be the two-dimensional array that contains combinations of parametric gain and parametric loss. The first column from the left contains all combinations with a potential to gain ten dollars. The second column then holds all combinations with a potential to gain twelve dollars. The third, fourteen dollars, and so on. Likewise, the first row from the top contains every combination with the possibility of losing five dollars, the second row six dollars, the third row eight dollars, and so on. The diagonal referred to here is the one running from the top-left of the matrix to the bottom-right, which includes all combinations in which the possible gain is exactly equal to twice the potential loss. The so-called "distance to indifference" therefore refers to the length of the orthogonal vector from the diagonal to the point on the matrix representing the specific combination of parametric gain and loss. In terms of `gain` and `loss`, this value can be computed explicitly using the formula

$$\text{distance to indifference} = \frac{\sqrt{2}}{4} \cdot \text{gain} - \frac{\sqrt{2}}{2} \cdot \text{loss}.$$

Lastly, the data for each run also includes a set of four plaintext files: `cond001.txt`, `cond002.txt`, `cond003.txt`, and `cond004.txt`. These essentially contain information concerning different conditions whose manipulation is believed to have a significant effect on the subject's behavioral response. Each of the four files contains data that is organized into three columns. The first column consists of the trials' onset times in seconds after the start of the run. The second column contains the amount of time that was alloted to the subject to provide a response. In the case of `cond002.txt`, `cond003.txt`, and `cond004.txt`, the third column contains values between -1 and 1 that correspond to each particular trial's value of a parameter relative to the set of all possible values for that parameter (which will be referred to as "amplitude" for the purposes of this paper). These parameters are parametric gain, parametric loss, and the distance from indifference, respectively. In the special case of `cond001.txt`, the parameter is the subject's assigned task, and because this study required only a single task to be repeated over and over, the value of this parameter was 1 for all trials.

3 Methods

3.1 Diagnosis

The diagnostic analysis essentially has two parts: the first concerns finding outliers in standard deviation over all voxels for each volume, while the second concerns outliers in root-mean-square difference over all voxels between consecutive volumes.

The interquartile range (IQR) of a set of numerical data is defined to be the difference between the 75th percentile and the 25th percentile of the data. In the first part, the standard deviation over voxels for each volume is computed and outliers are defined to be volumes whose standard deviation is greater than or equal to 1.5 times the IQR *above* than the 75th percentile or greater than or equal to 1.5 times the IQR *below* the 25th percentile. The standard deviation values and the indices of their outliers are saved to a separate file for analysis and future reference.

The root-mean-square (RMS) difference here is defined to be the square root of the mean (across voxels) of the squared difference between the ith volume and the $(i+1)$th volume. In the second part, the RMS difference was computed for each volume and outliers are once again defined to be volumes whose RMS difference is greater than or equal to 1.5 times the IQR *above* the 75th percentile or greater than or equal to 1.5 times the IQR *below* the 25th percentile. The RMS values and the indices of both the ith volume and the $(i+1)$th volume, in the case of an outlier, are saved for analysis future reference.

3.2 Smoothing

Prior to further statistical analysis, it is a good idea to perform a few preprocessing steps to minimize the influence of errors in data acquisition and discrepancies that arise due to physiological artifacts. The use of a Gaussian filter to "smooth" data has the effect of lowering higher frequencies, while at the same time enhancing lower ones. The earlier diagnosis analysis showed that outliers were nonfrequent and not out-of-hand so one way to remedy the few problems left in the filtered data set is to undertake this step of Gaussian smoothing. The result is data whose intrinsic spatial correlation is more pronounced.

The Gaussian kernel used here has a full-width-at-half-maximum measurement of 5 millimeters, which corresponds to a standard deviation of approximately 2.355 millimeters. It is now necessary to convert this value into units of voxels. Each voxel of the data corresponds to a $2 \times 2 \times 2$ cubic region in space, so the following conversion gives the necessary standard deviations σ for smoothing by our specifications:

$$\sigma_{smoothing} = \frac{5 \text{ mm FWHM}}{\sqrt{8 \ln 2} \text{ FWHM}} \cdot [\ 0.5 \ \ 0.5 \ \ 0.5\ ] \ \frac{\text{voxels}}{\text{mm}} \approx [\ 1.062 \ \ 1.062 \ \ 1.062\ ] \text{ voxels.}$$

3.3 Convolution

The study is built upon an event-related experimental design, in which the onsets are unevenly-spaced. Convolved hemodynamic response function (HRF) predictions for parametric gain, parametric loss, and the distance from indifference were computed using the data obtained from the condition files `cond002.txt`, `cond003.txt`, and `cond004.txt`, respectively.

The analysis assumes the canonical hemodynamic response function, which has the distribution of the difference between two gamma probability density functions: the peak (that with shape parameter 6 and scale parameter 1) minus 0.35 times the undershoot (that with shape parameter 12 and scale parameter 1). That is,

$$\text{canonical HRF} \sim \Gamma(6,1) - 0.35 \cdot \Gamma(12,1).$$

For each of the three conditions per run of each subject, the neural time course is first initiated as a one-dimensional vector of zeros with length 480, with each element representing exactly one second of the run. The time of onset and duration for each trial is then extracted, and the "amplitude" for each trial is inserted into elements in which that particular trial took place. The end result is a vector of length 480 that contains zeros at indices that correspond to time between trials and the appropriate "amplitudes" for indices that correspond to time during trials.

3.4 Generalized Linear Regression

The generalized linear model in this study makes a few advancements that draws from earlier statistical analyses. Firstly, the diagnosis analysis finds that outliers in the BOLD data are nonfrequent and not particularly out-of-hand so the process used here skips the step of dropping outlier volumes and/or trials. A subsequent decision made here is to substitute the raw data in favor of the smoothed filtered data produced in the earlier smoothing analysis, as the spatial correlation within the data is more pronounced in the latter.

This generalized linear model approach requires producing a new design matrix containing as many rows as volumes in the BOLD data and exactly six columns. The first column from the left contains all ones. The second, third, and fourth columns contain the convolved neural time courses for parametric gain, parametric loss, and the distance from indifference, respectively, that were computed in the convolution analysis. The fifth column contains 240 equally-spaced and sequential values between -1 and 1, inclusive, that represents a *linear drift* component, included to partially or fully cancel systematic linear offset of the data over time. The last column contains a *quadratic drift* component, computed as the absolute deviation among squared values of linear drift, included for reasoning similar to that for the *linear drift* component. Explicitly, the *linear drift* component is defined to be

$$\text{linear drift component} \equiv \mathbf{L} = \begin{bmatrix} -1 & -\frac{237}{239} & \dots & \frac{237}{239} & 1 \end{bmatrix},$$

and the *quadratic drift* component to be

$$\text{quadratic drift component} = \mathbf{L}^2 - \bar{\mathbf{L}^2}.$$

Next, a threshold must be determined to identify which voxels in the data are located inside the brain. The procedure used here sets the threshold at 80th percentile with respect to voxel means. This means that the mean signal strength of each voxel is computed over the dimension of time. Those voxels whose mean signal strength falls in the top twenty percent of voxels' mean signal strengths are determined to represent a location inside the brain. In order to save time and memory, computations are done only for voxels located inside the brain.

After the fitting of a generalized linear model, each voxel that is determined to be inside the brain has three values associated with it for each of the six regressors (including the intercept): the regression coefficient, and the t-statistic and corresponding p-value that indicate the regression coefficient's statistical significance.

Lastly, the neural loss aversion is computed for each voxel located in the brain as the additive inverse of the regression coefficient for parametric loss divided by the regression coefficient for the parametric gain, or

$$\hat{\lambda}_{neural} = \hat{\beta}_{loss} - \hat{\beta}_{gain}.$$

This study was particularly interested in the voxel associated with the B ventral striatum, which had MNI coordinates of $(3.6, 6.3, 3.9)$ in millimeters. This particular value of neural loss aversion was saved and set aside for later.

3.5 Logistic Regression

This analysis uses the behavioral data, particularly the regressors parametric gain, parametric loss, and the distance from indistance. Two logistic regression models are fit for each run: one that uses the distance from indifference, and one that does not. The reasoning behind this decision is that the distance from indifference is partially dependent on both the parametric gain and the parametric loss, so including it may underestimate the effect of its precursors.

For the purposes of logistic regression, the values of these variables are placed into a design matrix. The design matrix for each run contains as many rows as there are trials associated with that run, and one more column than the number of regressors used. In both the case that the distance from indifference is included and the case that the distance from indifference is excluded, the first column contains all ones, the second contains the values of potential gain, and the third the values of the potential loss. In the case that the distance from indifference is used, the values of said distance are contained in the fourth column. Responses are taken from the sixth column of the behavioral data matrix (which contains the subject's binary responses: simple acceptance or declination of the wager).

Once each logistic model was fit, the values of the behavioral loss aversion (denoted `Lambda` or $\hat{\lambda}$) is computed as the additive inverse of the regression coefficient for parametric loss divided by the regression coefficient for the parametric gain. That is,

$$\hat{\lambda}_{behavioral} = -\frac{\hat{\beta}_{loss}}{\hat{\beta}_{gain}}.$$

These values are placed aside for subsequent conjunction analysis.

Lastly, each logistic regression model fitted has its accuracy accessed via computation of its misclassification rate and its statistical significance accessed via a Wald test.

3.6 Conjunction Analysis

In the conjunction analysis, two figures depicting behavioral loss aversion (both with and without the distance from indifference as a regressor) are produced. Each figure shows three scatterplots (one for each run) complete with ordinary least squares regression models. Each plot has on its horizontal axis neural loss aversion and on its vertical axis the natural logarithm of behavioral loss aversion. Outliers identified by robust regression are also indicated by red dots on their respective plots, whereas "inliers" (non-outliers) are indicated by green dots.

In each case, an ordinary least squares regression model is first fit to the paired data points. The resultant model is then subjected to RANSAC, an iterative algorithm which takes a subset of inliers and produces a robust estimation of the model's parameters.

4 Results

4.1 Behavioral Results

In the second half we would focus on behavioral loss aversion analysis. We assessed behavioral sensitivity to gains and losses by fitting a logistic regression to each participant's acceptability judgements collected during scanning, using the amount of gain, loss and the amount of the absolute diference between gain-loss combination as independent variables. On top of this, we perform another logistic regression withought the third varialbe which is the difference between gain-loss pair. The purpose of doing the second regression is to set up a comparison and see the to what extent does having a weaker preference contribute to accept or reject the offer. Based on this analysis, we computed a measure of behavioral loss aversion λ as the ratio of the (absolute) loss response to the gain response, which is yielded a median $\lambda = 1.882939$ (range: 0.9505497 to 4.8956078) if the euclidean distance of gain/loss combination from the diagonal of the gamble matrix is not included, and a median of 1.861554 (range: 0.652284 to 5.345733) otherwise. Both measurements are slightly different form the statistics stated in the paer that lambda is a median of 1.93, ranging from 0.99 to 6.75. In general, this finding is consistent with the observations that participants were, on average, indifferent to gambles in which the potential gain was twice the amount of the potential loss. The estimated coefficients in front of gain, loss and with/without euclidean distance vastly vary across participants.

We first investigate individual behavioral reponse in decision making.The data set contains three runs for each subject, meanwhile, each run from each subject corresponds to one particular gain/loss combination. We take subject001 and run001 for example, the results are displayed below. We observe that with the additional parameter of euclidean distance, the p values are all considered to be significant under the 0.05 significance level. The interpretation of β is that is represents the increase in log-odds of the event that the subject takes the offer for a unit increase in one of the three conditions when all other explanatory variables are held constant. In other words, the e to the power of β denotes the factor by which the odds of sucess (success means response accepts the gain/loss combination) change for a unit increase in one of three explanatory variables (all other explanatory variables remaining unchanged). Undoubtedly, we obtain positive estimated coefficients for gain and negative estimated coefficients for loss with the latter slightly smaller.

4.2 Smoothing Results

In order to apply a multi-dimensional Gaussian filter to 'smooth' the bold image, we use `gaussian_filter` function from scipy module. We make this decision because convolution does not truncate the kernel.

```
With euclidean distance from Indifference
Coefficients: [-0.32449366  0.69583192 -0.60834336 -0.63748965]
Loss aversion (lambda): 0.874267681187
Misclassification rate: 0.0117647058824
P value: [  3.10653241e-01   1.53587365e-10   4.83496377e-03   4.54815155e-02]

Without euclidean distance from Indifference
Coefficients: [-0.3146438   0.85185941 -0.97664702]
Loss aversion (lambda): 1.14648851017
Misclassification rate: 0.0117647058824
P value: [ 0.29504648  0.          0.        ]
```

Figure 1: Behavioral Logistic Regression Result for Subject001 Run001

Using zero padding, the points towards the edge get pulled down towards zero because they are part-made of the results of taking the product of zero sith the kernel values. This way, we prefer some other method of dealing with the data off the edge of the image. [Figure 2]

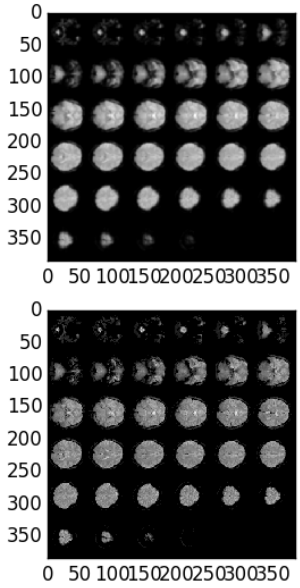

Figure 2: Compare two bold images before and after smoothing

4.3 Diagnosis Results

Diagnosis identifies outliers in the time course according to three measures: volume standard deviation values, RMS difference values, and extended difference values. The script returns plots for the volume standard deviation values3, the RMS vector4, and the extended RMS vector5. Outliers are labeled as red dots in the figures.

4.4 Convolution Results

The convolution process returns three haemodynamic response predictions corresponding to neural conditions for parametric gain, parametric loss, and distance from indifference respectively, where are shown in the figures below 6. These haemodynamic responses are crucial to fMRI analysis because fMRI measures haemodynamic responses of the brain to locate neural activities regions.Using the three haemodynamic responses as linear regressors, we obtain three coefficient estimates corresponding to each haemodynamic response for each voxel. The larger the absolute value of a coefficient is, the stronger relationship a haemodynamic response and a voxel have. The figures below show the coefficient estimates for each condition, and each figure contains all slices across the third dimension. The parameter maps

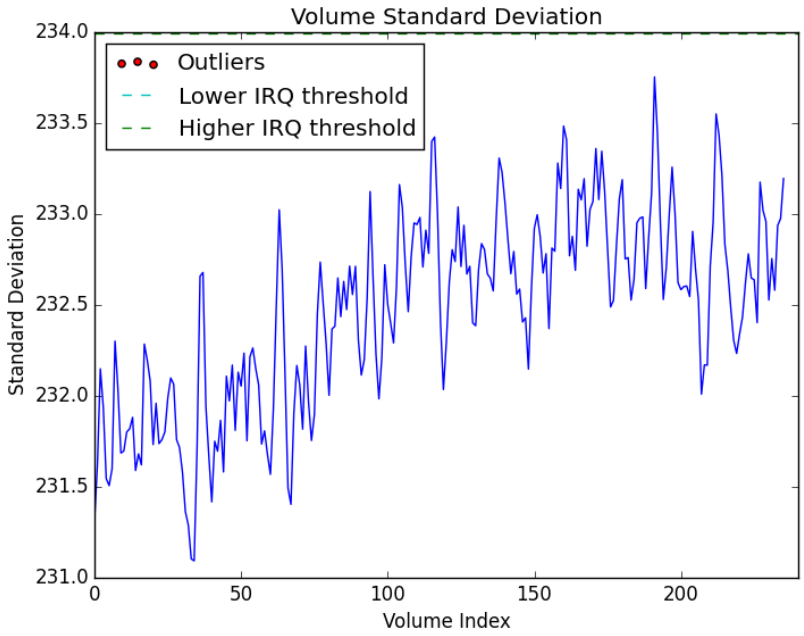

Figure 3: volume standard deviation for Subject 1 in Run 1

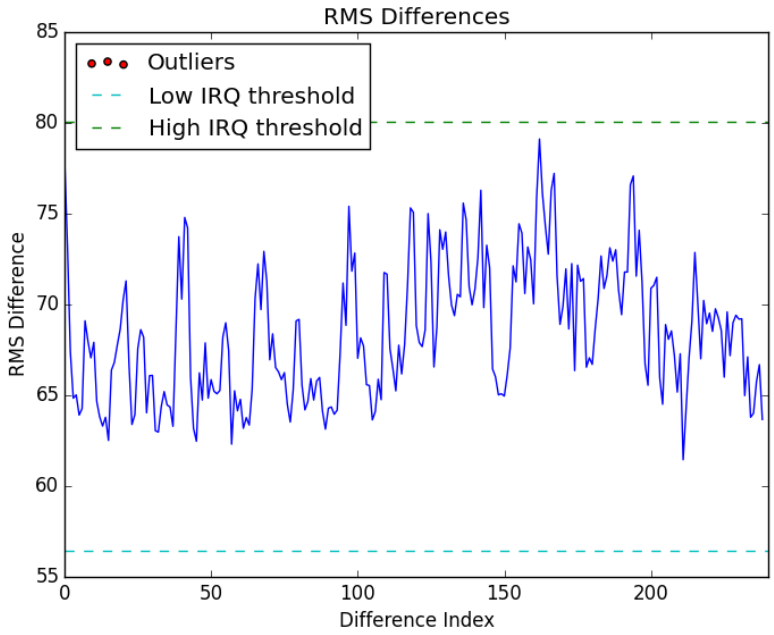

Figure 4: RMS difference values for Subject 1 in Run 1

show the activation regions in brain corresponding to each task, even though we still need to apply t-test to check the significance level later.

4.5 General Linear Regression Results

In the parameter map for gain7, red-orange regions reflect positive activation, while blue-green regions reflect negative activation. Yellow regions reflect no activation. Most of the voxels in the brain are at

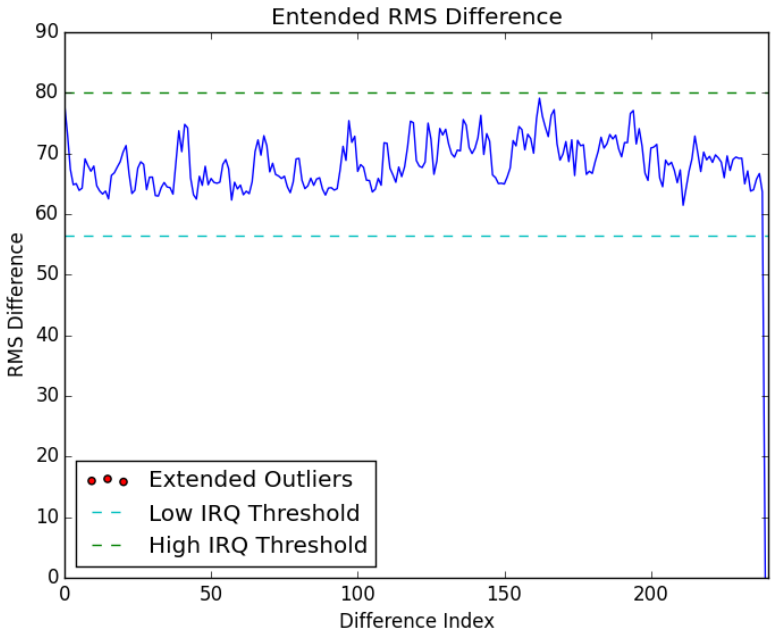

Figure 5: Extended RMS difference values for Subject 1 in Run 1

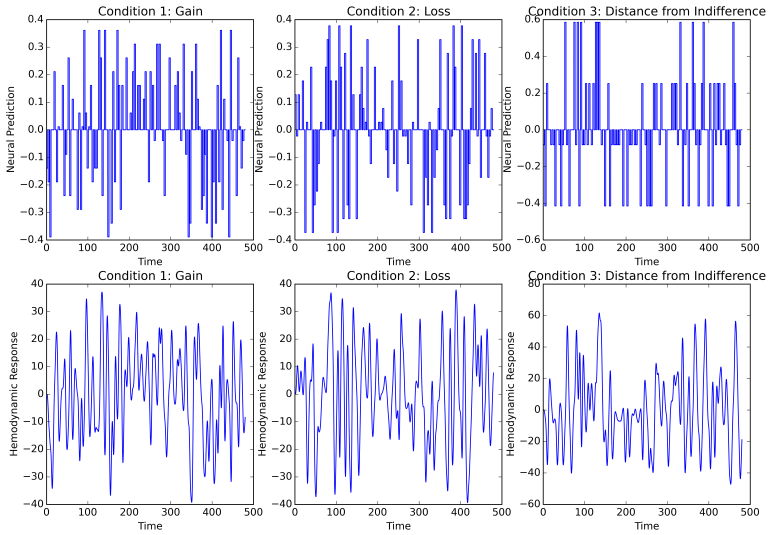

Figure 6: Neural and Haemodynamic Response Predictions for Three Conditions for Subject 1 in Run 1

yellow-orange scale.

In the parameter map for loss8, the color scale for this map is different from the one for the gain, here dark green and blue regions reflect negative activation, while red-yellow-green regions reflect positive activation.

In the parameter map for distance from indifference, the main color on the map is yellow-orange, which corresponds to no activation. However, there are still some green regions inside the red circle on the figure below. The green regions are near to ventral striatum which is closely associated to decision-making and risk. Then it is reasonable that other regions of brain are not activated9.

The parameter maps are not very clear to show the activation regions since there exists some insignificant coefficients. Therefore, it is necessary to perform t-test to find the significance level for each

coefficient estimates. The results of the t-test are shown in the figures below. All figures are generated by the Python package `nilearn`. The maps use the brain template, which is the smoothed mean brain image for each subject10. By performing t-test on linear regression, each coefficient estimate gets a corresponding t value and p value. T-statistic shows how significant the coefficients are. If the p-value is less than 0.05, then we can reject the null hypothesis which is that the coefficient can be zero. The t-score maps below shows that t-statistic for each condition: parametric gain11, parametric loss12, distance from indifference13. The cut coordinate is (0,0,0). For better view, we plot the absolute t values on the glass brain below . The red regions reflect high t-values. We can observe the general activated regions in the brain corresponding to the task. However, in order to determine the actual location, we need other tests and techniques.

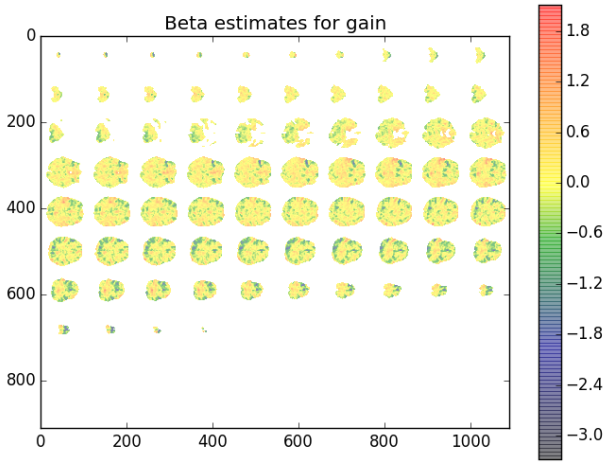

Figure 7: Parameter Map Corresponding to Parametric Gain

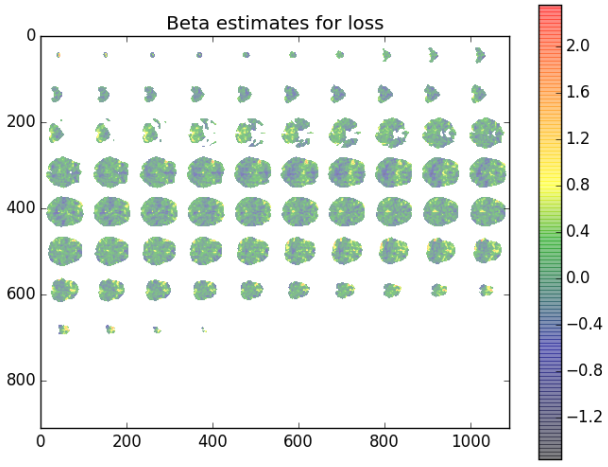

Figure 8: Parameter Map Corresponding to Parametric Loss

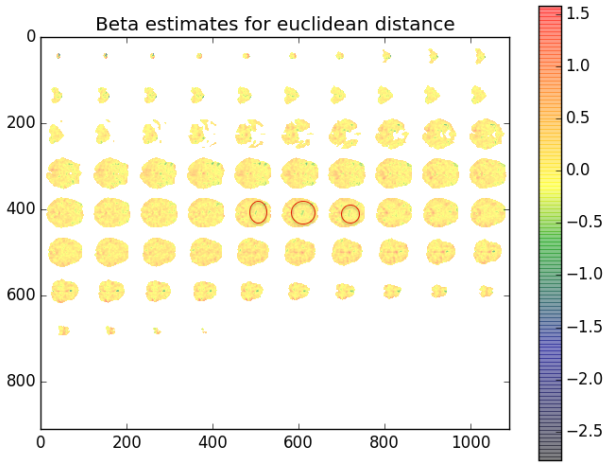

Figure 9: Parameter Map Corresponding to Distance from Indifference

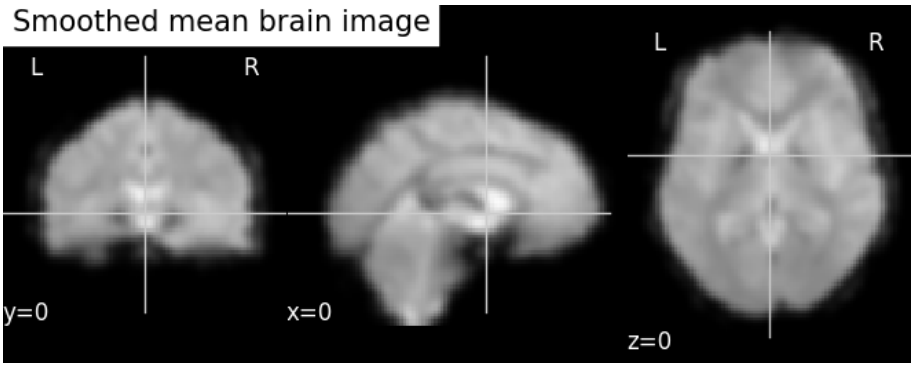

Figure 10: Background Image for t-statistic and p-value map

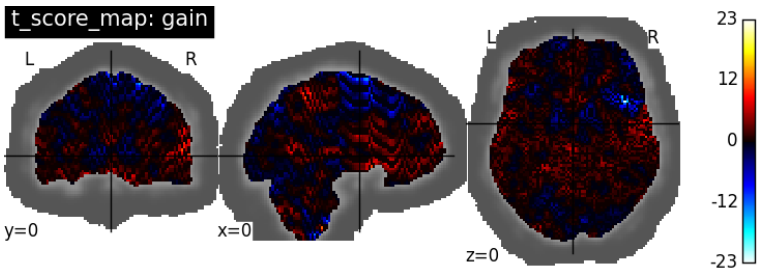

Figure 11: t-score map (gain)

4.6 Logistic Regression Results

Logistic regression is performed as a supplementary analysis for analyzing neural loss aversion and will be used in conjunction analysis. In the analysis, all trials were modeled using a single condition (i.e. overall tak-related activation), and three additional orthogonal parametric regressors were inlcluded representing:(a) the size of the potential gain, (b) the size of the potential loss, and (c) the Euclidean distance of the gain/loss conbination from the diagonal of the gamble matrix (i.e., the distance from indiference assuming lambda=2 and a linear value function). It is noted in the paper this latter variable was included because of behavioral evidence suggesting greater diffculty making a decision for trials in which participants had the weakest preference. The main purpose of the logistic regression is to test how

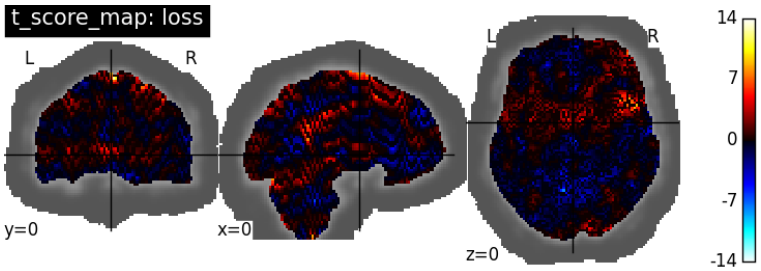

Figure 12: t-statistic map (loss)

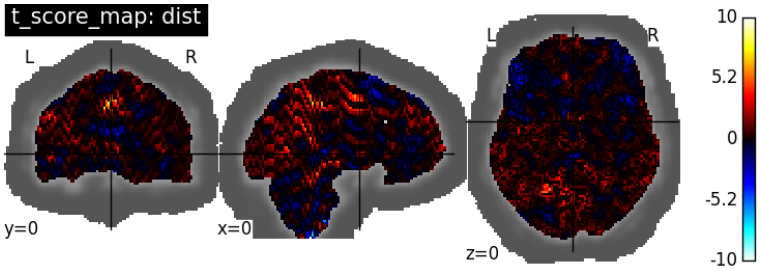

Figure 13: t-statistic map (dist)

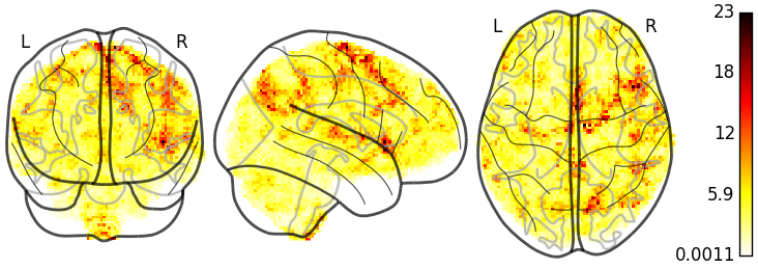

Figure 14: t value corresponding to gain on glass brain

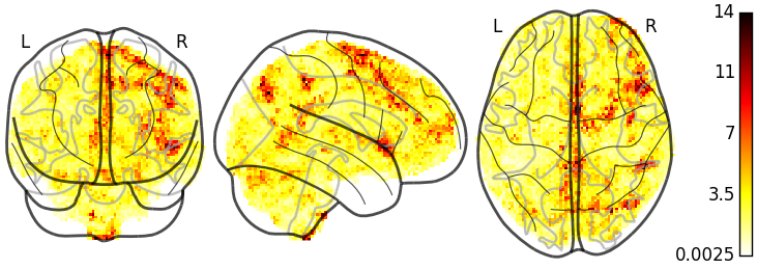

Figure 15: t value corresponding to loss on glass brain

significant is the estimated coefficient in front of this latter variable. Since the paper does not provide further discussion on the results of this logistic regression, we decide to directly look at the output from the logistic regression.

In design of the logistic regression, we select the feature gain, loss, response (0 or 1) behavioral data and calculate the euclidean distance from each gain/loss combination to the diagonal of the gamble matrix to perform the logistic regression. We construct logistic model according to the definition of logistic regression. We calculate the log likelihood and find the coefficients that result in the maximum log likelihood. In order to make the model more accurate, we add apenalty term to our model. Therefore, we have to estimate the tunning parameter for this penalty term using cross validation.

After running a for loop for all 16 subjects that each has three runs, we obtain a crude ovservation

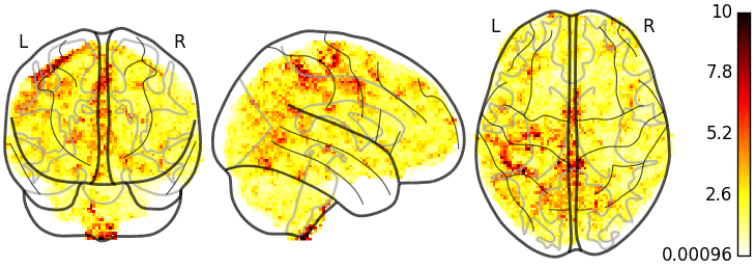

Figure 16: t value corresponding to distance on glass brain

that the estimated coefficient in front of the difference from indifference term vary braodly. We manually look at the results for each run and conclude the following observations: First, the p values for all 48 result text files showing the gain/loss term are always presented in the proposed models with significant estimated coefficients. Second, the intercept terms are not always insignificant for different subjects. For all the gain/loss combination in run001, we find out that Subject 1, 2, 8, 13, 15 appear to be a loss-aversion person (the coefficient of difference from indifference is negative, meaning strong preference of rejecting the offer). Subject 6, 12, 14, 16 appear to be the more risk-like. Noticeably, the p value we are looking at are p values based on each person of each run, thus lacking of a Bonderroni correction for doing multiple hypothesis testing.

4.7 Conjunction Analysis Results

After obtaining neural and behavioral loss aversion, by conjunction analysis, two figures below are generated to show the relationships between neural and behavioral loss aversion. One is for the condition when distance from indifference is included**??**, while the other exclude the distance from indifference**??**. Each plot contains three subplots for each run. Since two types of regression methods, original least square and robust regression,are performed, we obtain two regression line. The black line is for OLS, while the blue line is for robust regression. In the plots, the outliers are labeled as red dots.

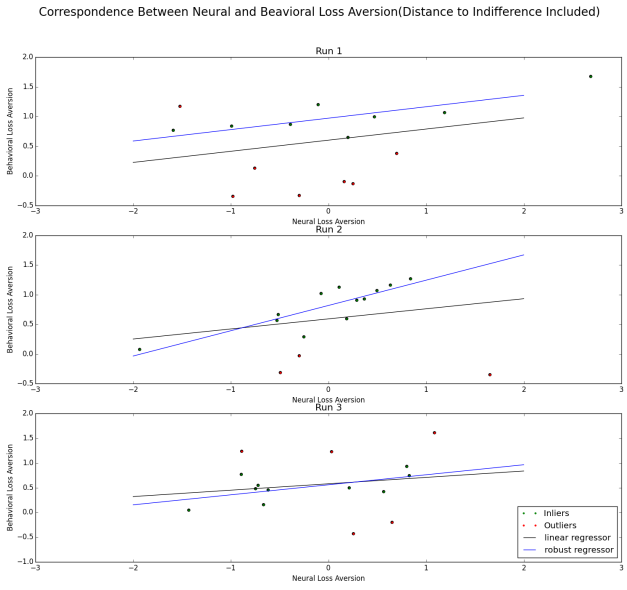

Figure 17: Correspondence between neural and behavioral loss aversion (Include distance from indifference)

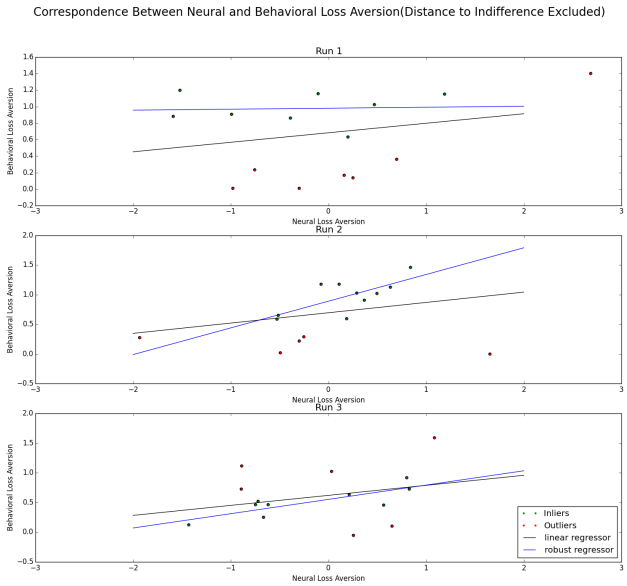

Figure 18: Correspondence between neural and behavioral loss aversion (Exclude distance from indifference)

5 Discussion

5.1 Discussion of Results

The general purpose for the general linear regression is to identify the activated regions. From the figures of t values for each condition for one subject, the red regions are very likely to be the location of activation. We cannot name the regions since we do not have professional neuroscience background. However, since the topic of this project is about loss aversion and decision-making, we know that the core region corresponding to the decision-making and risk is ventral striatum. We particularly observed these regions. The ventral striatum is located near the center of the brain. From the plots of t-values on glass brains, we can see that the color of the center is indeed red compared with yellow regions of other parts. The activated regions for both gain and loss task is very similar. It may reflect that the regions corresponding to these two tasks are very similar. However, connecting with the parameter maps for gain and loss, the regions are positively activated while facing gain task and the regions are negatively activated when facing loss task. From the color of the parameter maps, the brain seems more sensitive to the loss because the beta estimates at the activated regions are about -0.8 and the regions look dark blues. In the parameter map for gain, the beta estimates at the activated regions are about 0.6. This finding somehow confirms with the conclusion of the project paper that people are more sensitive to loss than gain.

In addition, by conjunct analysis, we analyze the relationship between behavioral loss aversion and neural loss aversion, which is core part in this research project. By observing the plots for correspondence of these two type of loss aversion, we can realize that the linear relationship between two is not very clear. We can see a general linear trend but not a perfect linear relationship. The robust regression identifies many outliers, which also suggests that they do not have a perfect linear relationship. However, one possible reason is that there are too few observations. So, if we would like to explore further the relationship between these two, we must need to have enough observations.

5.2 Discussion of Future work

Our main difficulty regarding logistic regression is on how to aggregate 48 text files together and draw conclusions on the corresponding 16 subjects of three runs respectively. Since we are only extracting beta estimates for each subject and each run, it makes sense to further calculate the predicted probablities of accepting the gain/loss combination in the end. However, without the priori information in the behavdata.txt on whether the subject take/reject the offer, the precision of the logistic regression cannot

be established.

Another major issue we have overlooked is the problem of doing multiple testing, we are doing statistical inferences simultaneously for all 16 subjects. Without correction, this might lead to incorrectly rejecting the null hypothesis. We did not include Bonferroni correction in the scripts when doing hypothesis testing.

The way we design the logistic regression might be different from what the paper suggested doing due to lack of information. Another possible interesting paramter to consider it RT, which possibly stands for 'Response Time'. The paper draws conclusion that participants are slower to decide whether or not to accept these gambles. We can include this as another explanatory variable in the logistic regression and observe the changes in the estimated parmaters and possiblly, perform model selction.

References

[1] S. M. Tom et al., *The neural basis of loss aversion in decision-making under risk*, Science, 315 (2007), pp. 515–518.