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

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Our paper is the *Neural Basis of Loss Aversion in Decision-Making Under Risk* [1]. The experiment investigates the phenomenon of loss aversion - where individuals' decisions are influenced by the amount of potential loss more than they are by the amount of potential gains.

Our analysis of the paper aims to verify this result and to replicate the connections found between neural loss aversion (shown in brain activation) and behavioral loss aversion (shown in the actual decisions to accept or reject gambles based on potential gain/loss). Our work has found that the neural loss aversion is significantly correlated with behavioral loss aversion in specific regions of the brain. Our work also shows that there are increasing neural activation to increasing potential gains and negative neural activation to increasing potential loss.

1 Introduction

The experiment conducted in the paper itself involved giving 16 subjects a total of 256 combinations of gain/loss in dollars with a 50 percent chance of winning. The subject's decision of whether to accept or reject each proposed gamble was recorded as well as the their brain activity in the fMRI machine as they made their decision. The neural activity is measured in BOLD signals.

We determine the beta coefficients for each voxel in the subject's brain based on a linear regression on the BOLD signal data. We use these coefficients as evidence for increasing activation in certain voxels in the brain when the subject is making a decision to accept or reject, and so in this way we have a proxy for which regions of the brain are involved with loss-aversion decision-making. We also determine the p-values to validate these results.

We also run a logistic regression to determine each subject's willingness to accept or reject based on the values of potential loss and gain. This is the measure of behavioral loss aversion, and in the end we correlate this with our neural loss aversion, making it clear that increasing gains correspond to increasing activity in certain parts of the brain.

2 Data

2.1 Overview

The study used 16 right-handed, healthy, English-speaking participants recruited through ads posted on UCLA. Out of 16 subjects, 9 were female and the mean age was 22 ± 2.9 years.[1]

2.2 Behavioral Data

The behavioral data consists of each subject undergoing 3 trial runs for the "gamble" task, in which each subject is presented with a combination of potential monetary gains and losses given a 50/50 chance of to win/loss. Each trial run consists of 86 different combinations of rewards/penalties spread out across

474 seconds. Intervals between each onset of task range from 4 to 8 seconds. Subjects were given the 4 choices in response to each gambling proposal:

1. Strong Accept
2. Weak Accept
3. Weak Reject
4. Strong Reject

The choices are recorded by denoting response numbers 1, 2, 3, and 4, respectively. Furthermore, the response time for each gambling decision was recorded in seconds.

2.3 BOLD Data

2.3.1 RAW Data

Raw Blood-oxygen-level dependent (BOLD) imaging data were collected from each subject as he/she performed the gamble tasks. 240 time scans were done on each run with a time between each scan of 2 seconds. So total scanning time is 480 seconds. Each scan consists of a snapshot consisting of a 64 by 64 by 34 image matrix.

2.3.2 Standardized Data

We also used the provided filtered, preprocessed BOLD data. Again, 240 time scans were done on each run with a time between each scan of 2 seconds. So total scanning time is 480 seconds. Each scan consists of a 91 x 109 x 91 snapshot image matrix. Besides the preprocessing, this data also has the advantage of each voxel being mapped to a standard MNI template. There are also 4 model conditions, with events corresponding to

1. Task
2. Parametric Gain
3. Parametric Loss
4. Distance from Indifference

We refer to this provided dataet as filtered or standardized to differentiate from the raw BOLD dataet of which we preprocess and also run analyses on.

2.4 Processing

Before we run our analyses and fit betas to our data, we first take a few steps to clean the raw BOLD dataets. We graph the dvars (RMS of the signal derivatives) and the framewise displacement, and we use that in conjunction with the mean signal of the BOLD data to determine outliers to remove. The BOLD data is smoothed spatially in order to make clearer the signal in relation to the noise present. We also take the mean signal of the BOLD data across the run and plot the histogram for each run and subject to help manually determine a good threshold for a mask we use to isolate more active voxels in the brain. This helps us find beta coefficients for more relevant voxels. We also model and remove the linear and quadratic drift that may be present in the runs. We use subject 2 run 2 to show an example of our outliers r esults. (Green dotted line in DVARS: thredhold for outliers, Greenline in mean signal: fitted smooth curve of the bold signal)

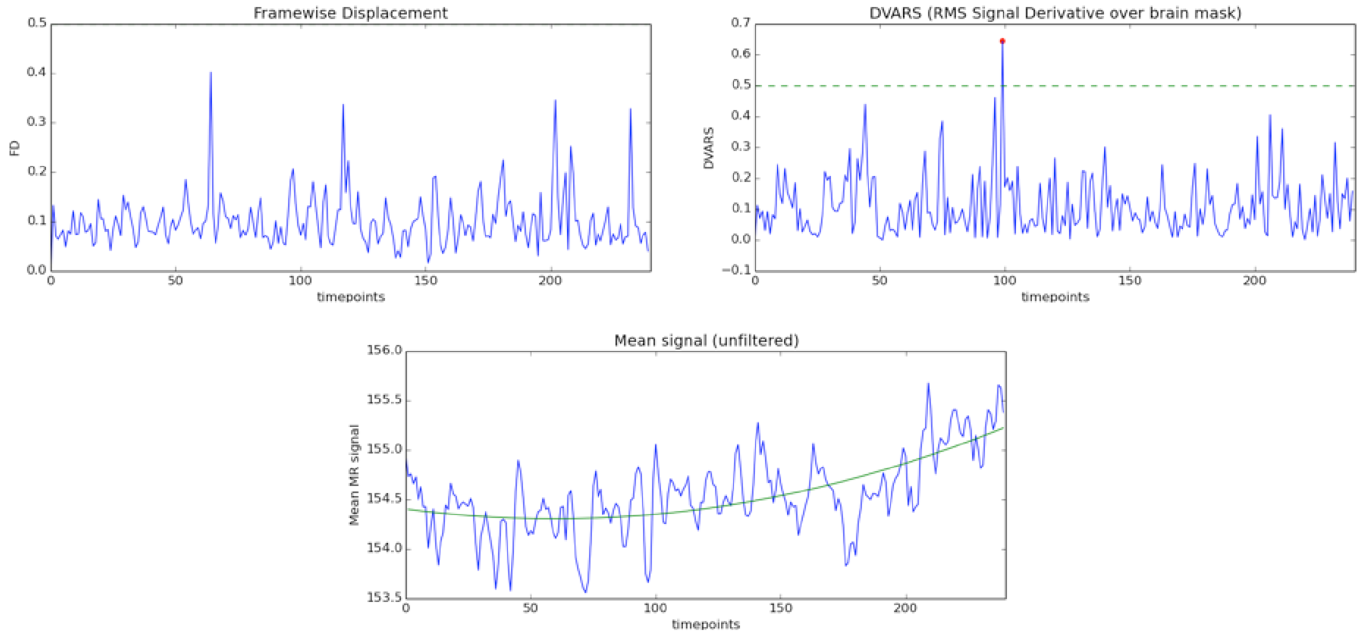


Figure 1: DVARS, Framewise Displacement and Data mean for subject 2 run 2

3 Models and methods

3.1 Models

In this section, we present the models we used to find the relationship between behavioral and neural loss aversions cross participants as well as how participants react to different loss and gain levels. For behavioral data, we fit the logistic regression models for each subject and use the coefficients of loss and gain to calculate the behavioral loss aversion levels. For neural d ata, we fit both linear multiple regression models and mixed-effects models in order to collapse three runs for each subject into one model. We analyze the fMRI data using both models and compare the results we obtained. Neural loss aversion levels are calculated using the coefficients of loss and gain, and are done for both the raw and filtered dataets. However we do not run a mixed effects model on the filtered dataet due to size constraints.

3.1.1 Behavioral analysis using Logistic regression

We fit a Logistic regression model on the behavioral data to examine how the response of individuals relates to the size of potential gain and loss of a gamble. Originally there are four acceptability judgments categories, here we collapse the categories into binary response (accept/reject). Following is the model:

$$\log\frac{p(X)}{1-p(X)} = \beta_0 + \beta_{loss} * X_{loss} + \beta_{gain} * X_{gain} \tag{1}$$

where X_{loss} and X_{gain} are the potential loss and gain value separately, Y_{resp} is a categorical independent variable representing the subjects' decision on whether to accept or reject the gambles:

$$Y_{resp} = \begin{cases} 1 & \text{If the subject accepted the gamble.} \\ 0 & \text{If the subject rejected the gamble.} \end{cases}$$

Then we calculate the behavioral loss aversion (λ) for each subject as follows, note that for simplicity, we collapse 3 runs into one model for each participant.

$$\lambda = -\beta_{loss}/\beta_{gain} \tag{2}$$

We use λ as the metric for the degree of behavioral loss aversion for each participant.

3.1.2 Linear Regression on fMRI data

Raw Data Regression

For each voxel i, we fit a multiple linear model:

$$Y_i = \beta_{i,0} + \beta_{i,gain} * X_{gain} + \beta_{i,loss} * X_{loss} + \beta_{i,ldrift} * X_{ldrift} + \beta_{i,qdrift} * X_{qdrift} + \epsilon_i \tag{3}$$

where Y_i is the BOLD data of voxel i, X_{ldrift} and X_{qdrift} are linear and quadratic drift terms.

Pre-processed Data Regression

For each voxel i, we fit a multiple linear model:

$$Y_i = \beta_{i,0} + \beta_{i,gain} * X_{gain} + \beta_{i,loss} * X_{loss} + \epsilon_i \tag{4}$$

where Y_i is the BOLD data of voxel i. For the pre-processed data, we no longer need to include the drift terms. The drifts are taken care of in the pre-process steps.

For each voxel, we calculate the neural loss aversion η_i:

$$\eta_i = (-\beta_{loss}) - \beta_{gain} \tag{5}$$

Using the voxelwise neural loss aversion, we do a region-specific analysis on BOLD data for each participant. That is, we calculate and plot heat maps of the t valuesfor β_{loss} and β_{gain} for each participant to find out the regions with significant activation and regions, which show a significant positive or negative correlation with increasing loss or gain levels.

3.1.3 Mixed-effects model on fMRI data

The fact that we have 3 runs of data for each participants leads us to consider using mixed effects model to analysis the data set. The mixed effect model adds a random effects term, which is associated with individual experimental units drawn at random from a population. In this case, it measures the difference between the average brain activation in run i and the average brain activation in all three runs. For each voxel i, we fit the following mixed-effects models, note that here we only include the intercept term for random effects (the following model is for the raw data, for the filtered data, we subtract the drift terms).

$$Y_{i,k} = \beta_{i,0} + \beta_{i,1} * X_{ldrift} + \beta_{i,2} * X_{qdrift} + \beta_{i,loss} * X_{loss} + \beta_{i,gain} * X_{gain} + \gamma_{i,k} + \epsilon_{i,k}, \quad k = 1,2,3 \tag{6}$$

Then we calculate the neural loss aversion level and plot heat maps in the same way as the about section for multiple linear regressions and compare the results of two models.

3.1.4 Whole brain analysis of correlation between neural activity and behavioral response across participants

We then apply the above model on the standard brain to analysis the neural activity and behavioral response across participants. For each participant, we pick up several regions with highest activation level, calculate the mean neural loss aversion $\bar{\eta}$ within these specific region. Thus we could examine the relationship between neural activity and behavioral using the following regression model:

$$\lambda = \alpha_0 + \alpha_1 * \eta + \epsilon \tag{7}$$

where the sample size is the number of participants(16).

3.2 Methods

3.2.1 Cross-validation

To estimate how accurately a predictive model will, we do a k-fold cross-validation for each linearmodel. We choose to use 10 fold cross-validation for both behavioral and neural model, which means the original sample is randomly partitioned into 10 equal sized subsamples.

In the behavioral analysis using Logistic regression, since the response variables are binary, we calculate the misclassification error rate to summarize the fit. In the neural linear regression model using BOLD data, we use the mean squared error to summarize the errors.

3.2.2 ROC curve

ROC curve and AUC are mostly used for model selection of a binary classifier. In the behavioral analysis, we use logistic regression as the binary classifier for the response of reject and accept. To check the performance of the logistic classifier as its discrimination varied, we plot the ROC (receiver operating characteristic) curve and calculate the corresponding AUC (areas under the curve). In the model analysis, we prefer models with bigger AUC values.

3.2.3 Inferences on regression models

After fitting regression models on our BOLD and behavioral data, we assess and validate our models. We calculate the following statistics:

- *t-statistics and p-value* Calculate the t-statistics and p-value for our beta coefficients to check whether our beta parameters are statistically significant.
- *R-Squared value and the adjusted R-squared value* Calculate R-Squared value and the adjusted R-squared value to see how close the data are to the fitted regression line, that is the proportion of variability of the response data explained by the model.

3.2.4 Normality assumption on linear models

Since the performance of the test statistic of linear models are largely depend on the normality assumption on the independent variables, the check of normality assumption is indispensable. We choose the following methods for normality assumption:

- QQ plot The quantile-quantile plot (QQ plot) is the most commonly used visualization method to check the validity of a distribution assumption. The basic idea is to compute the empirical quantile the and compare it with the theoretically expected value of a normal distribution. If the data follow a normal distribution, then the points on the Q-Q plot would fall on a straight line.
- Residuals vs. fits plot A residuals vs. fits plot is another most frequently created plot. Under the normality assumption, the residuals should be independent and scatted around.

3.2.5 ANOVA test

In our dataet, each participant repeated the test for three times, in other words there are data of 3 runs for each subject. Before collapsing the three runs into one model, we need to check the assumption whether they are i ndiscriminate. To do this, we perform an ANOVA test on each subject to check the difference of means across runs. The significance of an AVOVA test may show that there are difference across runs, thus we may seek other methods to eliminate the influence due to the variance across runs.

3.2.6 Multiple Test correction

In statistical inference for fMRI data, usually we have more than tens of thousands of hypothesis tests, thus massive multiple correction problems. Using thresholds without correction could be problematic. Common multiple correction methods (such as Bonferroni) require adjusting the p-values. However, imposing high statistical thresholds that may mask voxels that do have real effects. To avoid this loss, we use uncorrected threshold and choose the threshold on a case-by-case basis.

3.2.7 Cluster analysis

We use K-means clustering to detect the homogeneity of regions. We concatenate the betas obtained from linear models and the coordinate of voxels as the clustering vector (dimension = 16 + 3 = 19). Then do cluster analysis for beta gains and beta loss separately to detect regions activated by increasing beta losses and beta gains.

4 Results

4.1 Behavioral analysis

We performed statistical analysis using both Python and R (The original paper use R package to fit the Logistic models). We use the library *scikit-learn* in Python and the *glm* function in *stats* in R to fit the models. Models from two library yields the same results. We shows the plot of the behavioral loss aversion λ for every subject (median=1.94, mean=2.18, min=0.99, max=0.75). This result is consistent with that of the paper, which indicate that participants are indifferent to gambles whose gain are approximately twice as the loss.

Following are the model diagnosis:

- *Accuracy on the training dataet* We uses the fitted models on the original dataets and compared the estimated class and the true class using the Logistic classifier. The accuracy (proportion of correct classifies) of Logistic models (for 16 participants, 16 models in total) on the training set yielded a median of 89.78% (min=80.97%, max=99.21%).

- *Cross-validation* We did the model evaluation using 10-fold cross-validation for every subject, they are still performing accuracies of a median of 89.86% (min=79.92%, max=98.45%).

- *ROC Curve and AUC* We plot the ROC (receiver operating characteristic) curve to see how the logistic classifier perform as the its discrimination threshold is varied for every subject. We also calculated the corresponding AUC (areas under the curve) for every curve, the area is large for the models (min=0.886, max=0.996), which shows the model

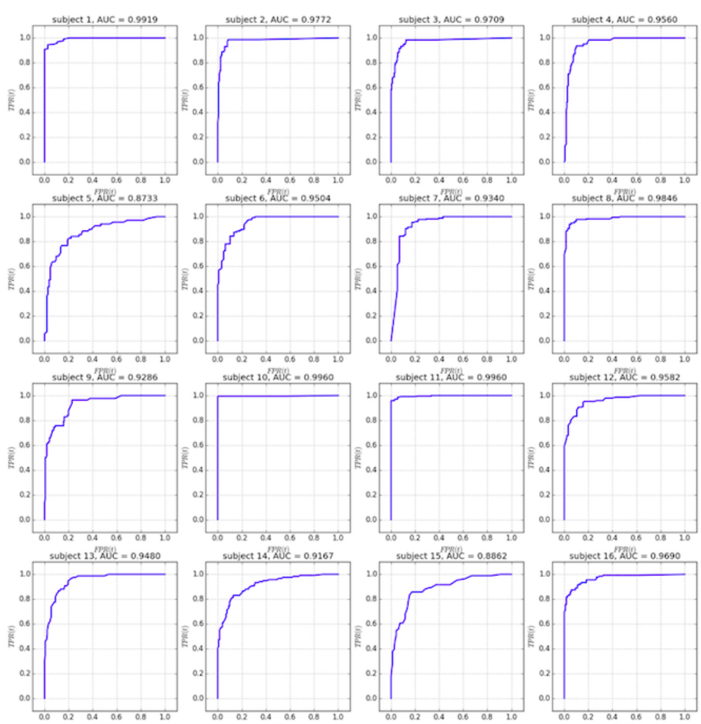


Figure 2: ROC Curve for all subjects

performs well under various discrimination threshold.

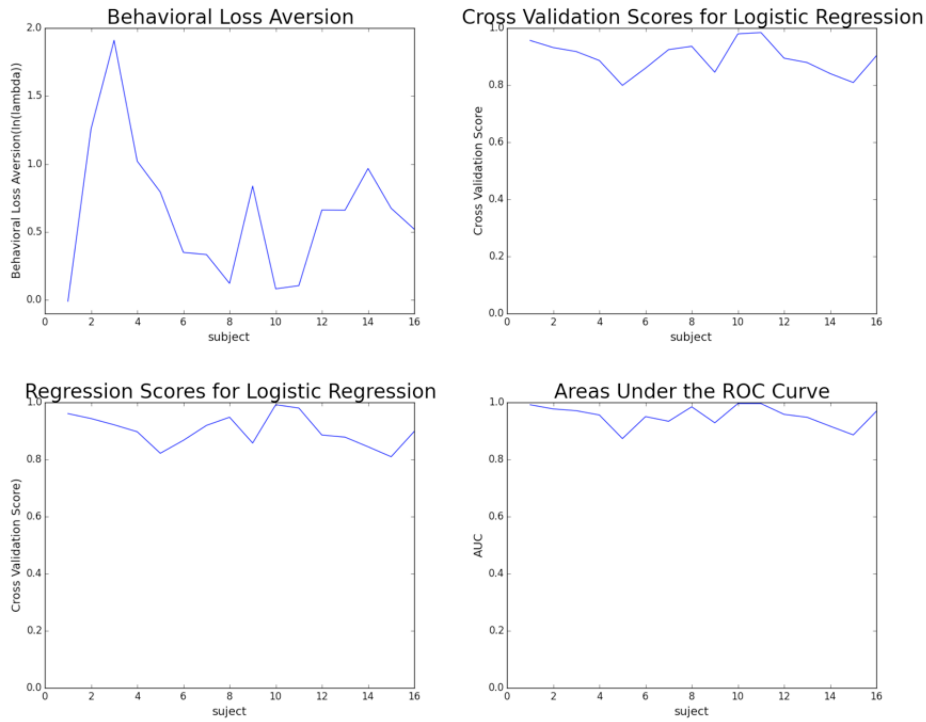


Figure 3: Results summary of the Logistic regression

4.2 Linear Regression on BOLD data

The topic we are interested in exploring is whether loss aversion reflects the engagement of distinct emotional processes when potential gains and losses are considered. In the process, we want to explore the correlation between neural and behavioral loss aversion in whole brain analysis. We also want to try to identify the regions of brain that is more activated by this loss aversion activity.

Since we want to explore the correlation between neural and behavioral loss aversion, the second step is to find out the neural loss aversion. In order to find the neural loss aversion, we perform a linear regression on the BOLD data against the parametric gain values and the parametric loss values, as explained in our model section. (While implementing the linear regression for the raw data, we also added linear and quadratic drift in our model. These drift terms are modeling for gradual drifts across the time series.)

We are especially interested in the beta coefficients of our parametric gain and parametric loss regressors, which are the first two columns in our design matrix. To find out the regions with significant positive or negative correlation with increasing gain or loss levels, we calculate the t statistics for each voxel. Plotting heat maps of the t statistics will show us regions with significant parametric increase in fMRI signal to increasing potential gains and regions with significant parametric decrease to increasing potential losses.

By looking at the heatmaps, we can get a general idea of how potential gains and potential losses affect brain activation. We can also identify the areas that have large coefficients; these are the areas that the brain activation is highly connected to the potential gains and losses. We choose the preprocessed data for subject 2 to plot heat maps since the preprocessed data is mapped onto the standard brain. We plot slices 31 to 60 from the third dimension of the brain (top to bottom). The red color is associated with positive t values and blue color is associated with negative t values. We can see that for the significant t values for the gain coefficients are mostly positive while the the significant t values for the loss coefficients are mostly negative.

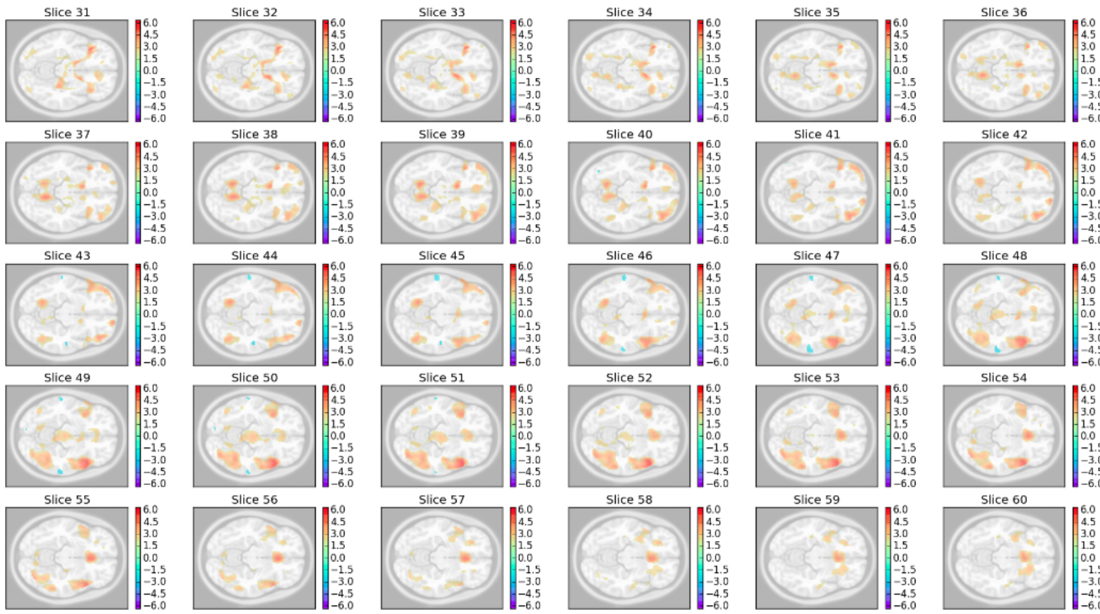


Figure 4: t values of the gain coefficients for subject 2

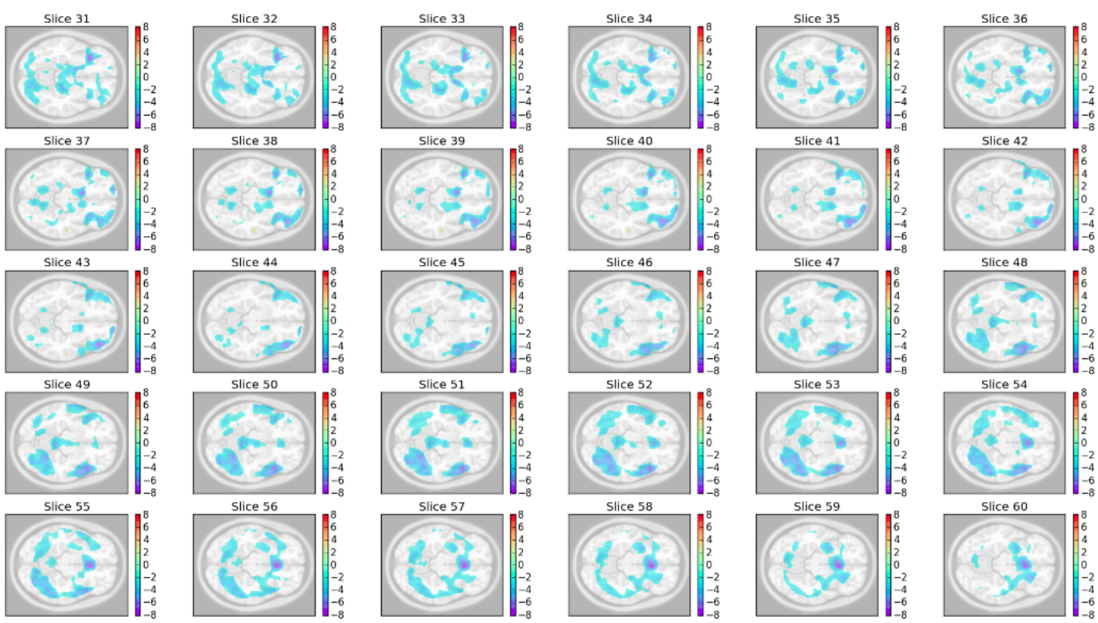


Figure 5: t values of the loss coefficients for subject 2

We can see that significant areas for the gain coefficients and those of the loss coefficients are mostly the same. This suggests that opposite of what most people believes that increasing potential losses should affect the areas of the brain that mediate negative emotions in decision-making, potential losses were represented by decreasing activity in the same areas that are sensitive to potential gains.

From the gain and loss coefficients, we can also compute the neural loss aversion. This serves the next step of looking at the correlation between neural and behavioral loss aversion. The neural gain and loss coefficients were broadly distributed and spanned zero, so it is not possible to compute the ratio of loss to gain coefficients, nor does it make much sense. Therefore, we compute the neural loss aversion at every voxel by subtracting the slope of the gain response from the (negative) slope of the loss response. With the neural loss aversion values calculated, we can explore how loss aversion affects brain activation when potential gains and losses are considered.

4.2.1 Model Diagnosis for linear regression

From the results of the QQ plot, we can see that in this randomly picture. The residuals are approximately normal distribution and showed constant variance. The green line is the QQ plot of the normal distribution. The blue line is the QQ plot of residuals. They look quite similar. The second plot is the scatter plot of the residuals. We can see that the residuals are approximately equally distributed by 0. This means that the residuals are not correlated to the fitted values. To conclude, the residuals are approximately normal distributed.

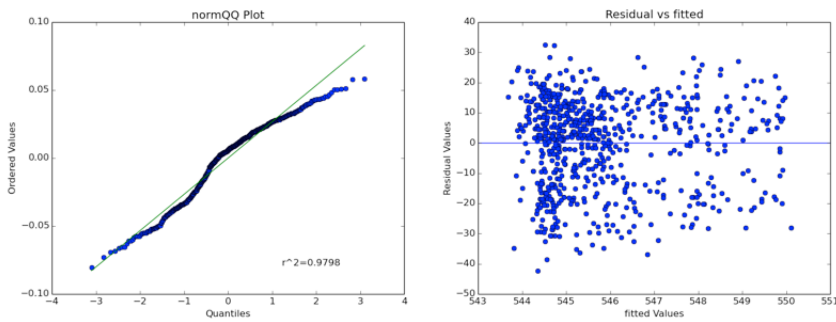


Figure 6: QQ plot and fitted-residual plot for a randomly chosen voxel

4.2.2 Cluster Analysis for betas from linear regression

We applied k-means clustering and minibatch k-means clustering on the betas obtained from the neural linear regression models. We choose 20 as our number of clusters. Following are the slices of our clustering results. We will use the clustering maps to detect underlying significant regions in the later part in the whole brain analysis.

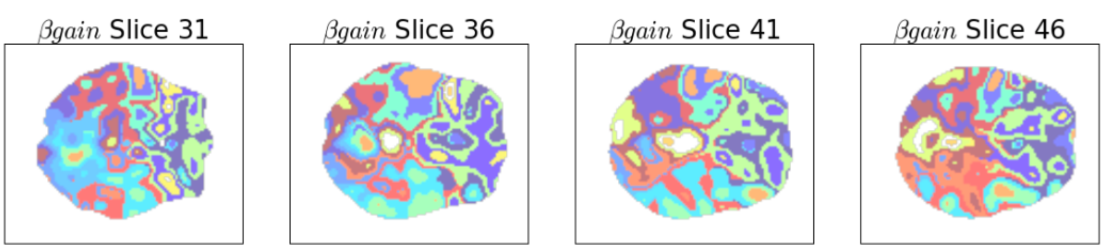


Figure 7: Clusters for beta gains in linear regression across subjects (#clusters = 20)

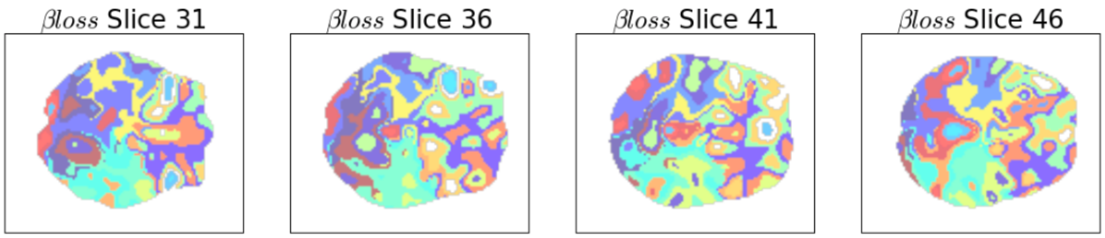


Figure 8: Clusters for beta losses in linear regression across subjects (#clusters = 20)

4.3 Mixed-effects model on fMRI data

First, we did the ANOVA test for each subject each voxels, grouping by runs. The high proportion of significant ANOVA F-test (after Bonferroni correction under 0.05 significant level) shows that mixed effects model may perform well when collapsing three runs into one model.

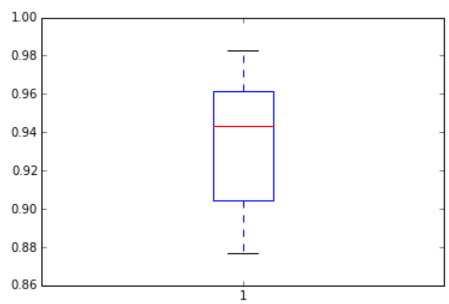


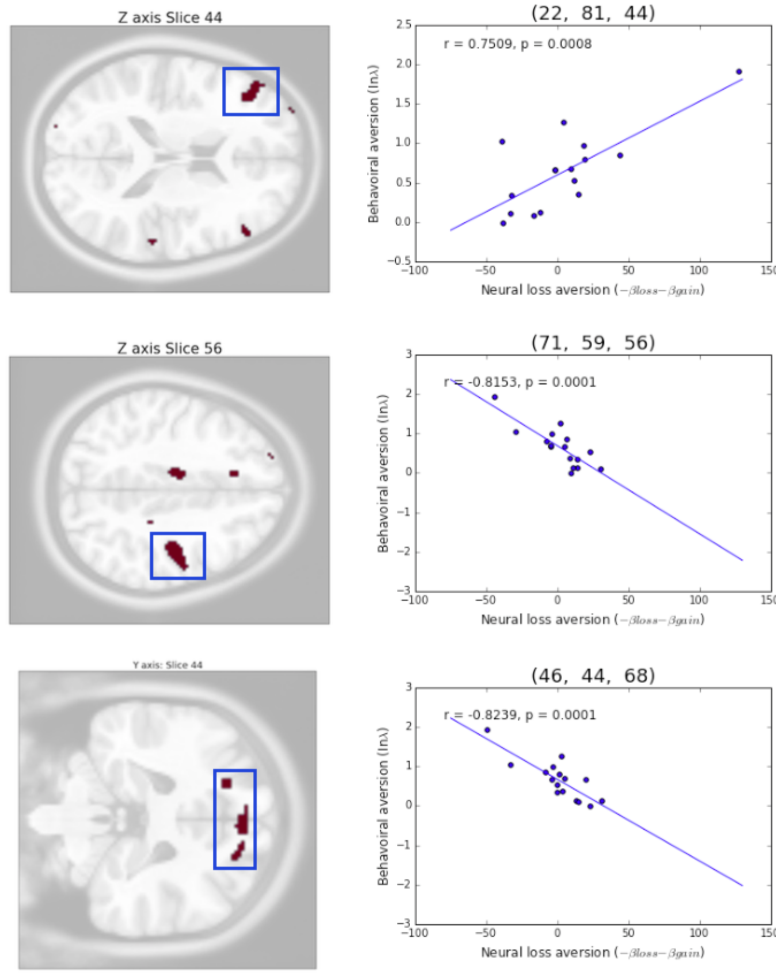
Figure 9: Box plot of the significant ANOVA test

The mixed-effects model for each subject yielded a a median of 9.4% (min=6.4%, max=21.5%) and 8.3% (min=4.6%, max=15.4%) of proportion of significant coefficient for gain and loss separately.

The run time issue (takes 26 hours for raw data on a 1.3GHz Intel Core i5 Macintosh Machine) makes it rather hard to fit the standard brain data (the size is 7 times of the raw data) to a mixed-effects model on our computer. We performed the mixed-effects model on the raw data only. Due to the limited space, we did not presented the heat map in the paper. Figures are under the figure folder.

4.4 Whole brain analysis of correlation between neural activity and behavioral response across participants

The figure on the right shows the correspondence between neural and behavioral loss aversion. Left panel presents statistical maps of the correlation between neural and behavioral loss aversion in whole brain analysis (Significant level = 0.001). We pick 2 slices by Z axis, one slice by Y axis and analyzed 3 regions. Right panel presents scatterplots of behavioral versus neural loss aversion in corresponding clusters. Regression lines and p-values were computed using multiple linear regression. While in the original paper there is no clusters which shows negative significant correlation between the neural loss aversion and behavioral loss aversion, our results shows that there are both significant positive correlation and significant negative correlation. We use the following three clusters to illustrate these.



- *Region 1: Voxel coordinates [22, 81, 44]* The corresponding millimeters coordinates is [46, 36, 16], which is very closed to L inferior/middle frontal (-48.5, 24.7, 17.0). In this cluster, the number of voxels significant is 95, the range of x, y and z is (19, 25), (79, 86), (41, 50) separately.

- *Region 2: Voxel coordinates: [71, 59, 56]* In this cluster, the number of voxels significant is 151, the mean p-value is 0.000240. For the region, the range of x, y and z is (63, 71), (54, 60), (52, 57) separately. This cluster showed significant negative correlation between behavioral loss aversion and neural loss aversion.

- *Region 3: Voxel coordinates: [46, 44, 68]* In this cluster, the number of voxels significant is 136, the mean p-value is 0.000522. For the region, the range of x, y and z is (33, 57), (40, 45), (61, 69) separately. This cluster also showed significant negative correlation between behavioral loss aversion and neural loss aversion.

Figure S1 Regions with significant correlation between the parametric r esponse to potential loss and behavioral loss aversion ($\ln(\lambda)$) across participants (Significant level = 0.001). Most of the regions show significant negative correlation, only one region showed significant positive correlation. This is slightly different from the original paper, in which no regions showed significant positive correlation, which is consistent with the original paper [1].

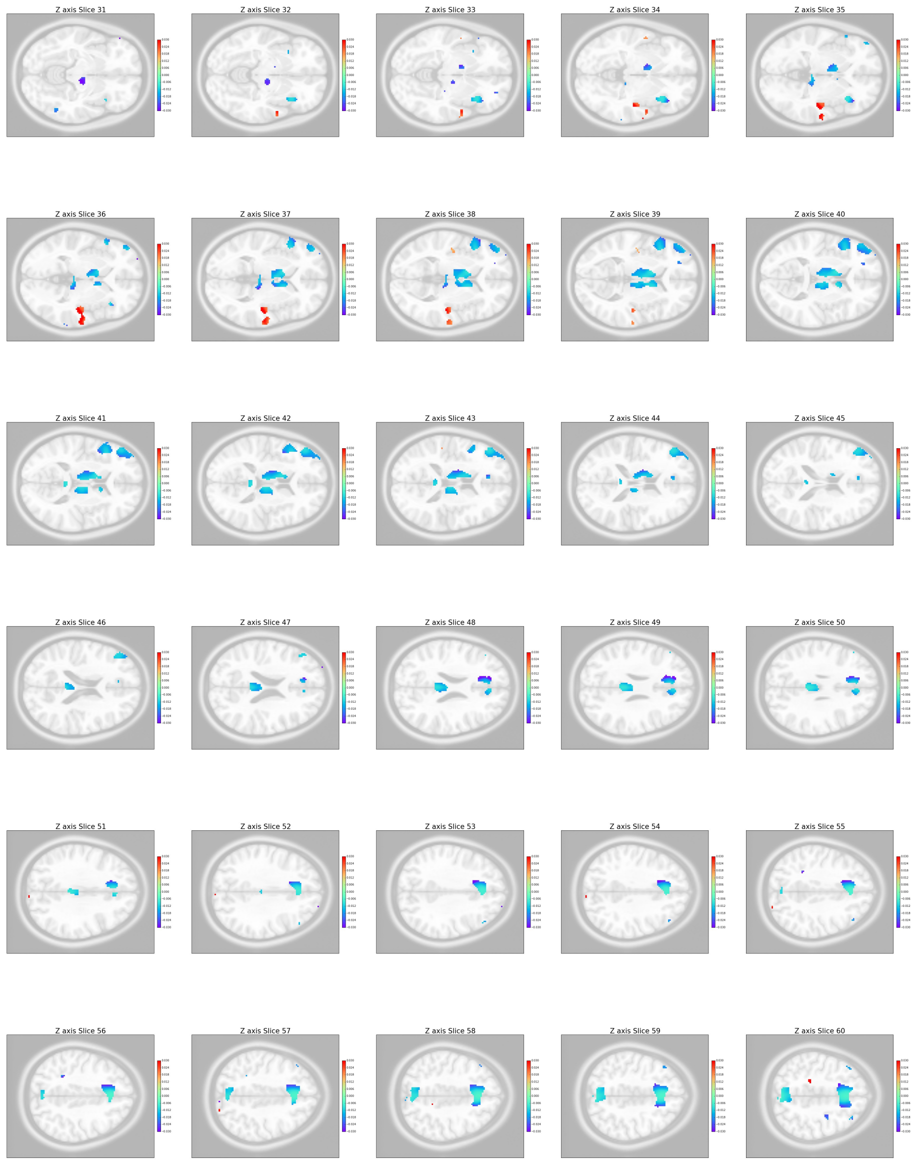


Figure 10: Our results: heat map of regions with significant correlation

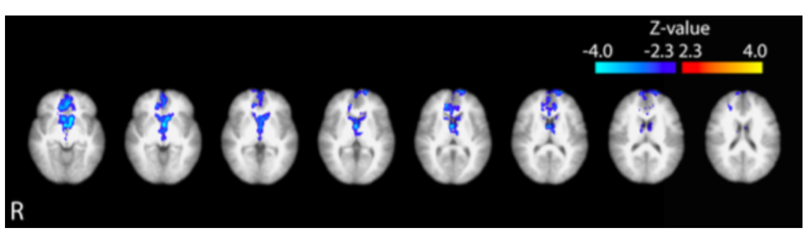


Figure 11: Original paper: Heat map of regions with significant correlation

Figure S2 Regions with significant correlation between the parametric response to potential gains and behavioral loss aversion ($\ln(\lambda)$) across participants (Significant level = 0.001). No regions showed significant negative correlation.

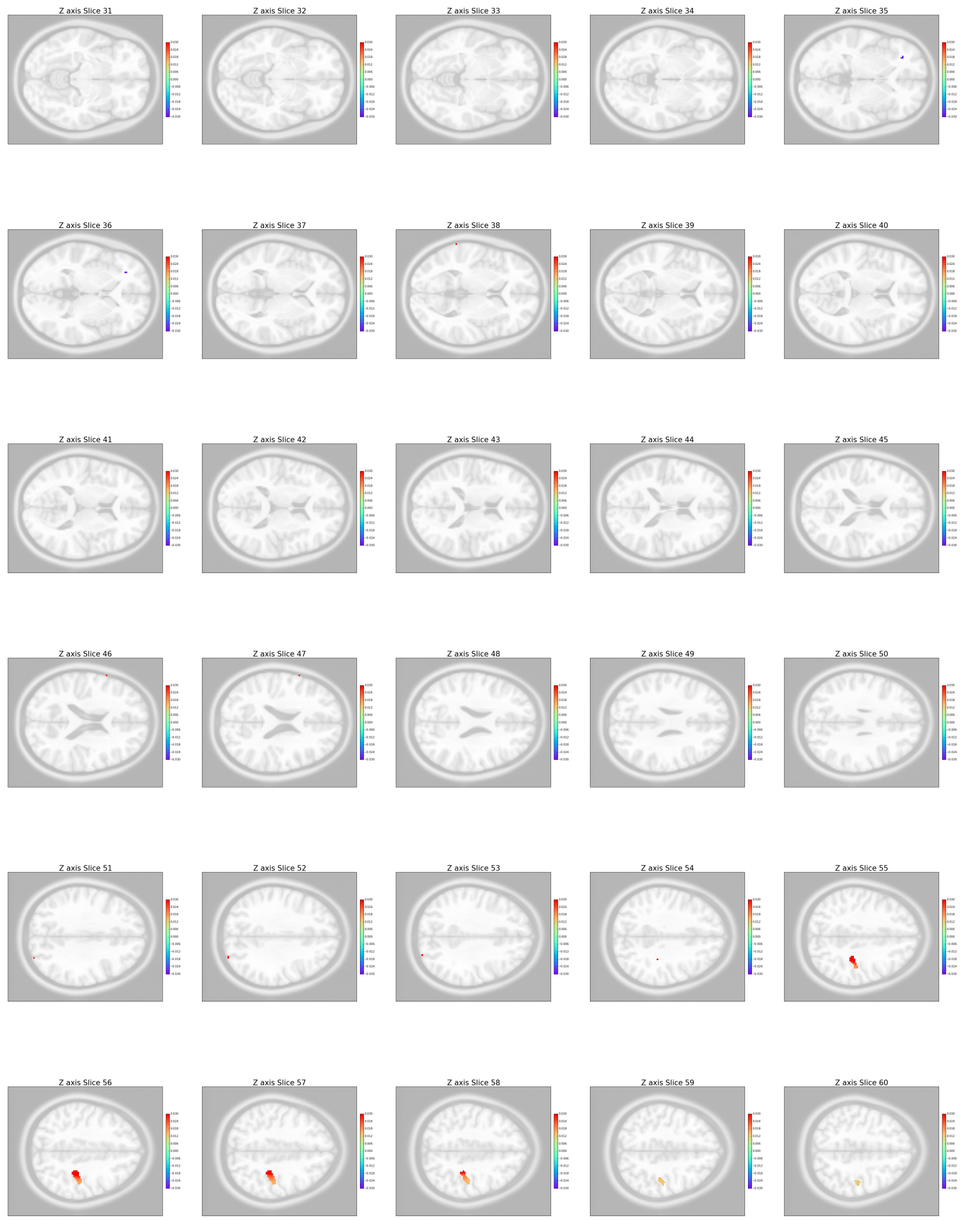


Figure 12: Our results: heatmap of regions with significant correlation

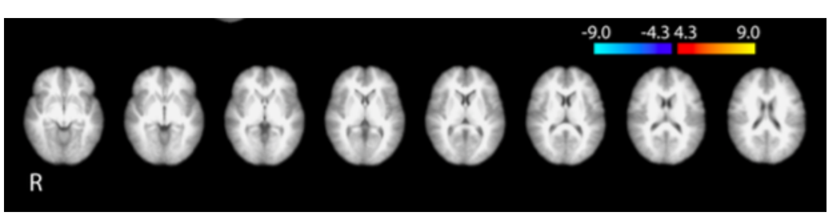


Figure 13: Original paper: Heatmap of regions with significant correlation

Figure S3 Regions showing significant correlation between behavioral loss aversion $\ln(\lambda)$ and neural loss aversion (difference between the absolute slopes of neural loss and gain responses) (Significant level = 0.001). There are both significant positive correlation and significant negative correlation. This result is different from the paper, in which no regions showed significant negative correlation.

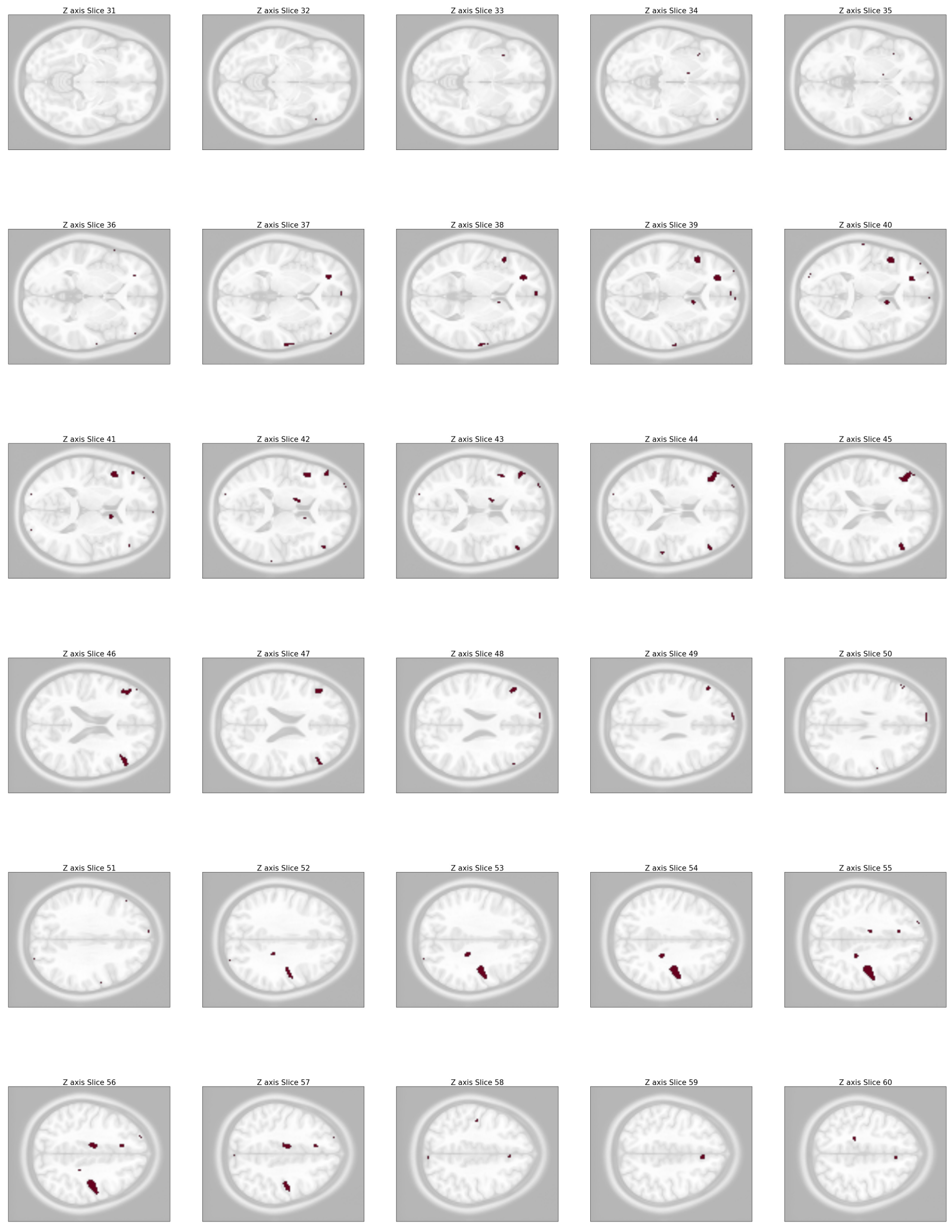


Figure 14: Our results: heatmap of regions with significant correlation

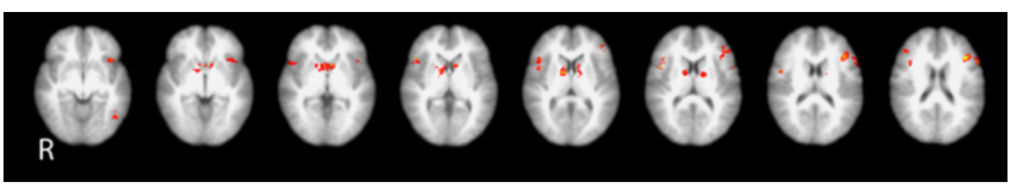


Figure 15: Original paper: Heatmap of regions with significant correlation

5 Discussion

5.1 Issues with analyses and potential solutions

5.1.1 Selecting specific regions to further explore correlation between neural and behavioral activity

Since we have no knowledge on the sections of brain that might experience large difference in activation, it is hard for us to identify the specific regions in terms of anatomy to explore the correspondence between neural and behavioral loss aversion.

There are two potential ways to deal with this issue. The first one is a top-down approach to isolate potential regions of analysis. This method requires us to read more paper and related articles to better our anatomical understanding of the specific brain regions that are more likely to react in our given scenario – loss aversion faced with potential gain and loss combinations.

Another way is a bottom-up approach. In this method, we can fit a regression for every part of the brain and look for the areas with higher correspondence (higher slope). Then, we select and graph a few areas with the most significant positive or negative correlation between the parametric response to potential losses and behavioral loss aversion (ln()) across participants by knowing the standard template of neural response. This second method is what we have attempted to complete in our paper, conducting whole brain analysis using standardized filtered data (provided by Matthew Brett) and producing significant results to compare with those of Tom et al. Please see *Methods* and *Results* for further discussion of analysis procedures and results.

5.1.2 Run Time Issues

One of the main issues is the run time of our analysis. More specifically, the scripts for running the mixed effects model is very time-exhaustive. On our laptop, that script alone took over a day (Boying can confirm). Perhaps this is due to the lower processing speeds on our laptops compared with the standard desktop/research computing hardware used in standard fMRI research settings. Additionally, by using the ds005 dataet with the standard mni template, the regression scripts takes more than 4 hours as well. This is due to the significantly larger size of the filtered data (almost 15 GB). Nonetheless, we managed to complete our analysis and generated the figures shown in this paper in a reproducible pipeline. We also note that hardware improvements is not the only way to address run time issues. In terms of software, code optimization may be another way to decrease the run time. Specifically, we can explore a better balance between performance and clarity with more experience in scientific computing and practice with code optimization.

5.2 Further Research

Looking at our data of subjects, it may be of interest to consider a demographic grouping by gender because our dataet contains the demographics of our 16 subjects, with the extra information of gender and age. A question to potentially address: Is there a significant difference to loss aversion across genders?

Additionally, it is interesting to see that the behavioral data contains a column for the response time of each gambling task. To further explore how decision are made in gambling task, we can use the response time as one of the logistic regressors. Through step-wise or criterion based model selection methods (eg. AIC and backward elimination), we can attempt to find the best regressors that influence loss aversion to most.

5.3 Discussion of Challenges

One of the major challenges is trying to make this project as reproducible as possible while following guidelines on documentation, testing functions, and attempting to produce the results of the paper using our limited understanding of fMRI data. Travis CI bugs with various versions of python, coverage failures, and errors with directory/path locations often hinder the process of smooth work-flows. Collaboration between five group members is no doubt difficult as we found it hard to come up with an attainable final goal that is still rewarding.

Technically, most of us are new to python programming and research using git workflows, thus we have only a preliminary understanding of the various python resources available for our use. Additionally, lack of statistical understanding of some aspects of the paper has urged us to do independent research. Yet the disconnect between theory and implementation has been a major obstacle because as we try to put our knowledge into practice, we realize that many pre-packaged software used in the original paper are unavailable to us. In addressing this, we have made our best attempt at creating a fMRI analysis pipeline.

Some problems can be solved or alleviated by defining checkpoints and makingthe effort to re-read the paper and ask questions. Further, as we familiarize ourselves more and more with various python modules and toolkits, results can be easier to attain and interpret. Nonetheless, we believe we have made significant gain in our understanding of not only fMRI research, but more importantly, the process of creating collaborative and reproducible research and navigating the rough learning road of scientific programming.

References

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