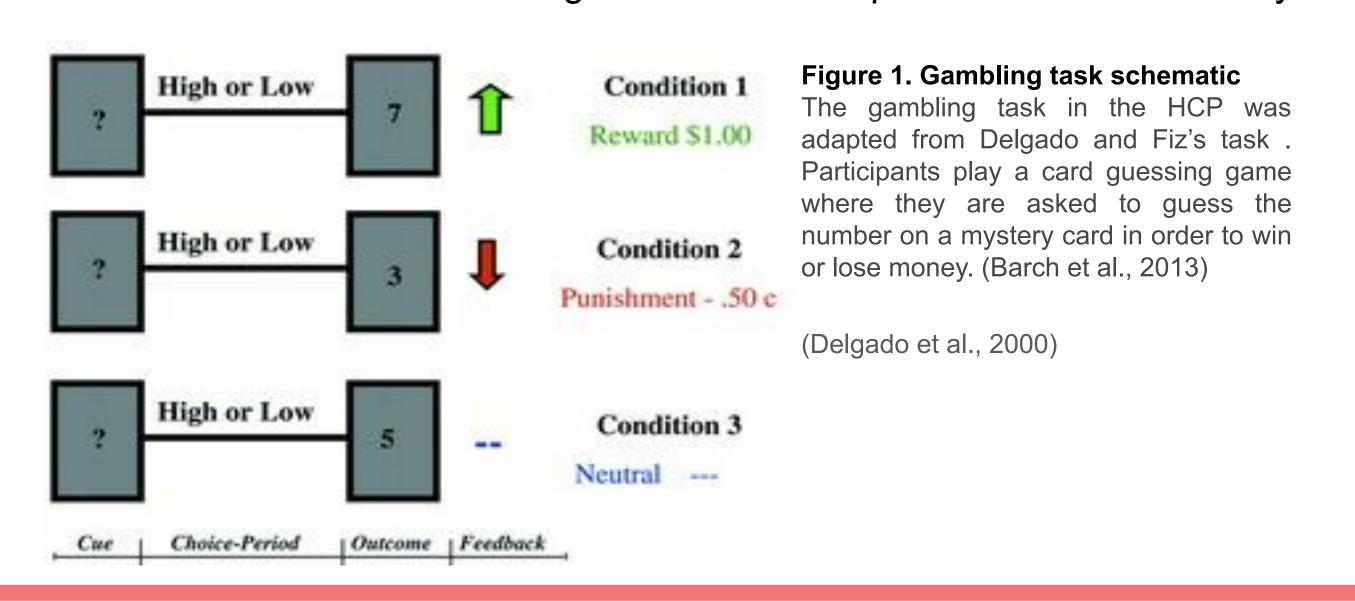


Decoding Reward Processing and Sensitivity Using Task-Based And Resting State fMRI

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Background

- Reward processing elicits blood-oxygen level dependent (BOLD)
 responses in regions of the brain such as the ventral striatum (Grill et al.,
 2021).
- Orbitofrontal cortex, anterior cingulate cortex, and the inferior frontal gyrus have been mentioned alongside reward processing (Rolls et al., 2000, Rogers et al., 2004, Fuentes-Claramonte et al., 2016).
- Individual differences in this process have been associated with gambling disorder (Meng et al., 2014), and identifying biomarkers of these differences could be of clinical use.
- Our study addresses the most important neocortical brain areas for processing wins and losses in the gambling fMRI task conducted by the Human Connectome Project (Barch et al., 2013), and assesses whether individual differences in resting-state fMRI data predict reward sensitivity.



Objectives

- 1. We hypothesize that neocortical regions such as the orbitofrontal cortex, anterior cingulate cortex, and the inferior frontal gyrus will be the most important features in our model because these particular regions were identified as important for reward processing in previous literature.
- 2. We hypothesize that individual differences in resting-state brain activity could predict individual differences in reward sensitivity, as other resting-state fMRI has shown to predict different aspects of task-based activation on a subject-level (Cohen et al., 2019).

Methods

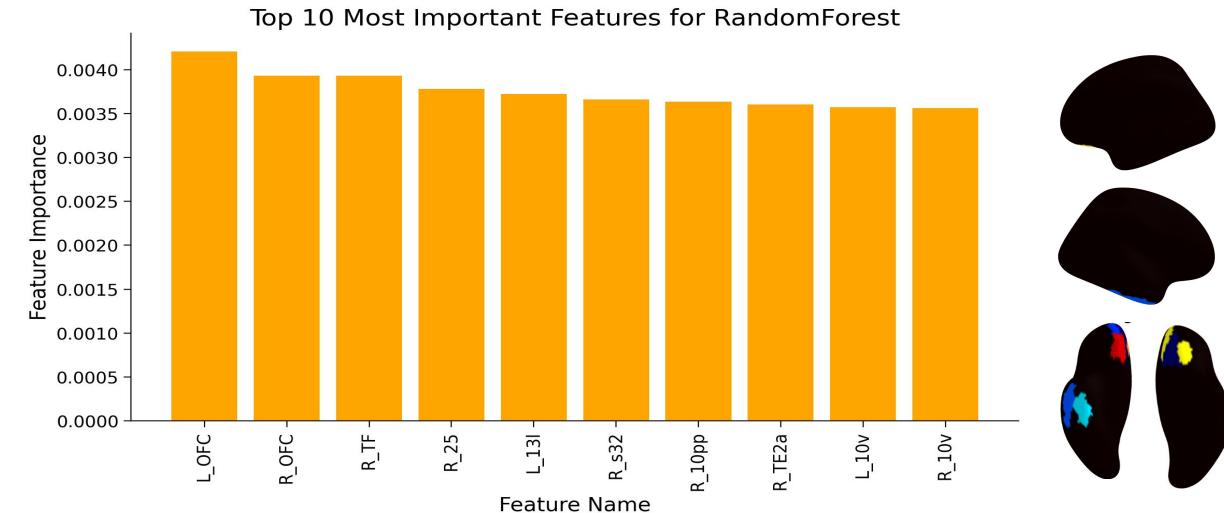
<u>Part 1</u>

- We fitted machine learning models (SVM, XGBoost and Random Forest) for a subject-level analysis of 338 subjects task-fMRI data to predict trial type (win or loss trials)
- From these models we identified the most important features (Glasser ROIs) for predicting trial type from task-fMRI data.
- Comparing the results, we decided to move on to Part 2 with the SVM model, as it had high mean accuracy as well as variability across subjects

Part 2

- We fitted multiple machine learning models to predict SVM model accuracy from Part 1 and win vs. loss contrasts in BOLD response from the top 10 most important regions from Part 1 from average BOLD response from rs-fMRI and functional connectivity from rs-fMRI
- We correlated SVM model accuracy from Part 1 to both:
- 1. Resting-state fMRI, average BOLD response
- 2. Resting-state fMRI, functional connectivity

Top 10 Most Important Features for XGBoost 0.005 0.001 0.001 RV6 R25 R47s L131 RMST RTE1a LOFC ROFC RO



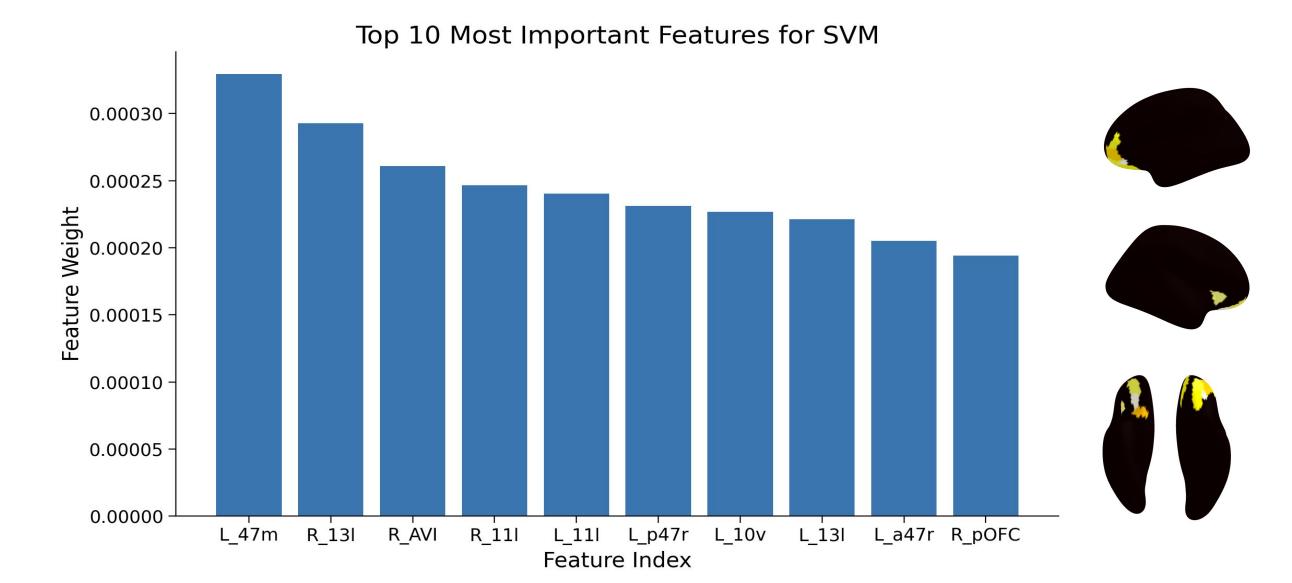


Figure 2 - Top 10 Brain Regions of Importance for SVM, Random Forest and XGBoost. XGBoost includes the visual cortex, perisylvian language area, anterior cingulate cortex and ventromedial prefrontal cortex. Random Forest includes inferior temporal sulcus/gyrus, perisylvian language area and anterior cingulate cortex. SVM includes the anterior ventral insular area. All models included regions in the orbitofrontal and polar cortex.

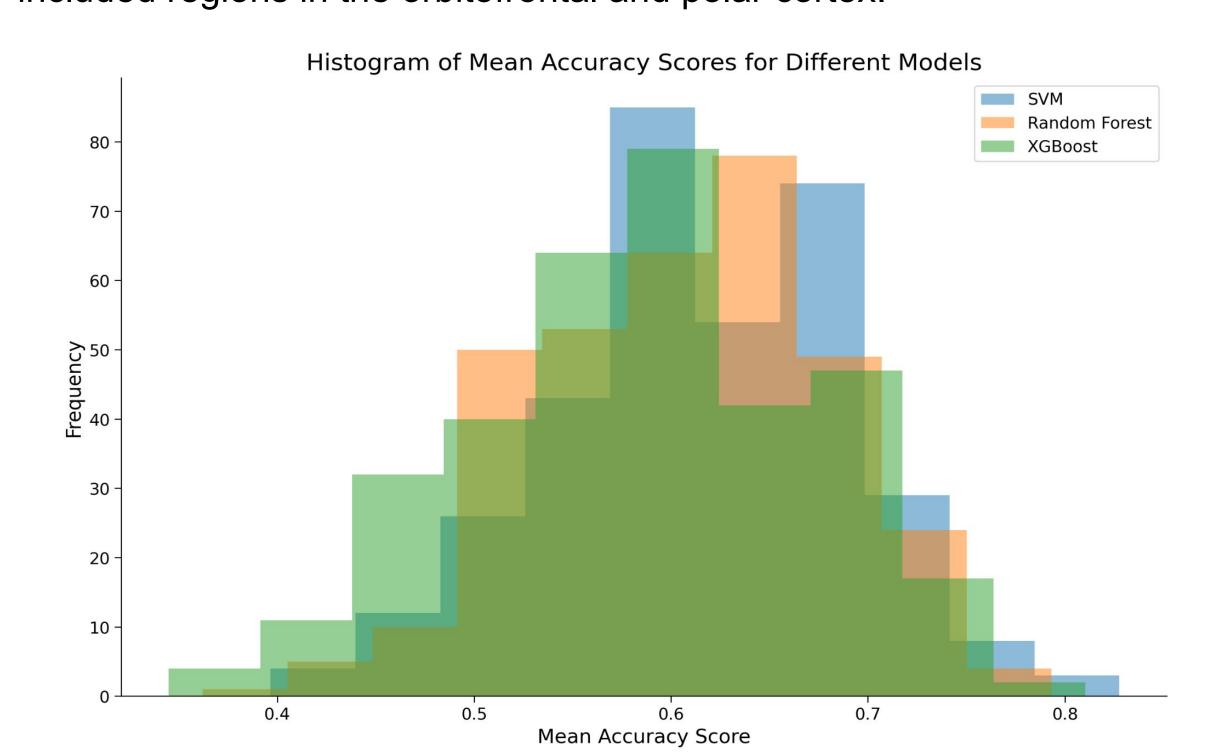


Figure 3 - Mean Accuracy Scores for SVM, Random Forest and XGBoost The histogram showcases the mean model accuracy scores for support vector machines, random forest and XGBoost model classifiers. From this data, we continued our analysis using SVM since it had the highest model accuracy.

Results - Part 2

- Decoding SVM model accuracy from part 1 resulted in coefficient of determination smaller than 0.05 while using as features both average BOLD response from rs-fMRI and functional connectivity from resting state fMRI.
- Decoding win vs. loss contrasts in BOLD response from ten regions identified as most important features for the SVM model from part 1 also resulted in insignificant coefficient of determination values. (Table 1)

ROI	R^2
L_47m	-0.0246
R_13l	-0.0092
R_AVI	-0.0322
R_11l	-0.0265
L_11l	-0.0228
L_p47r	-0.0089
L_10v	-0.0141
L_13l	-0.0075
L_a47r	-0.0191
R_p0FC	-0.0213

Table 1 - Lasso
Linear Model
Outcome (R^2) for
Predicting Win vs.
Loss BOLD
Contrasts in Top
Ten Regions of
Feature Importance
for Part 1's SVM
Model

 Functional connectivity measurements from resting state fMRI data were correlated to SVM model accuracy scores from part 1, and correlation coefficients as high as .3 were found. (Table 2)

> Top 10 positively correlated FC features: L_a10p X L_43: 0.16757778424983188 R_PHT X R_PHT: 0.16779945445609418 R FOP3 X L VVC: 0.1697677774914792 R_TF_X_R_a32pr: 0.171074742224633 R PeEc X L MT: 0.1718701148802075 _TE2a X L_TGv: 0.18943281353493696 R MI X L VMV3: 0.191268980932562 R 33pr X R_PH: 0.19445604046699702 Top 10 negatively correlated FC features: R_a32pr X L_LIPv: -0.30794332707259 R_MI X R_MBelt: -0.294660576819098 R VMV1 X R s32: -0.29455442628612466 R_F0P4 X R_MBelt: -0.2801476538159778 R_V3CD X L_7m: -0.2791657550889988 R_F0P2 X R_STSda: -0.2758326196562335 L STV X L VVC: -0.27244479988299947 R FOP2 X R PI: -0.2712490248267335 R_A1 X R_F0P4: -0.2695676228262036 R_52 X R_F0P4: -0.268666642819917

Table 2 - Top Ten Positively And Negatively Correlated Functional Connectivity to Part 1's SVM Model Accuracy

Discussion

- Our models from part 1 revealed a range of accuracies across subjects, showing individual differences in reward sensitivity. Glasser parcellated regions identified as most important features for the models were those identified in past literature as relevant in reward processing
- Our results from Part 2 failed to show relationship between individual differences in resting state fMRI and task-fMRI during reward processing.

Limitations & Future Directions

- The Glasser parcellation used in this study only reflected neocortical area.
- No data from subcortical regions like striatum or amygdala which are essential to reward processing

Future studies are needed to utilize machine learning with subcortical regions of the brain to understand how those regions impact reward processing and predict individual differences in reward sensitivity.

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