Brain State Classification in a Social Hierarchy Game

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abstract

Support vector machine (SVM) analysis was used to classify the cognitive states of subjects who played a two person hierarchy/social exchange game using functional magnetic resonance imaging (fMRI) data. Forty-four participants (22 pairs) played 30 rounds of the game while being scanned in two 3T Siemens Trio scanners. During the game one player at a time played the role of the dominant player (α) the other, the submissive player (β). Several different events could happen during the game play such as the α player endowing a high or low amount of points to the β player or the β player challenging the α player to try to reverse the roles. The goal of this study was to examine the feasibility of predicting game-related events using classification models of the fMRI data. In addition to classification, general linear modeling was utilized to examine the neuronal correlates of the game-related events.

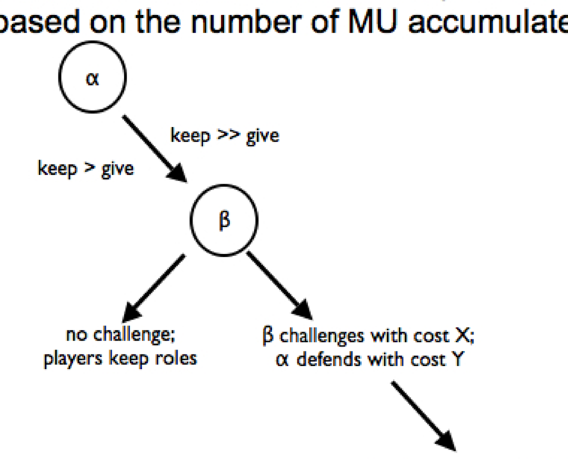
Results from classifying the α player endowing at high vs. low levels suggest that combining data across subjects leads to higher classification compared to predicting within individual subjects.

General linear modeling showed BOLD response to receiving a high or low endowment in the bilateral insular cortex. Activity in the caudate was only observed in response to a high endowments.

methods

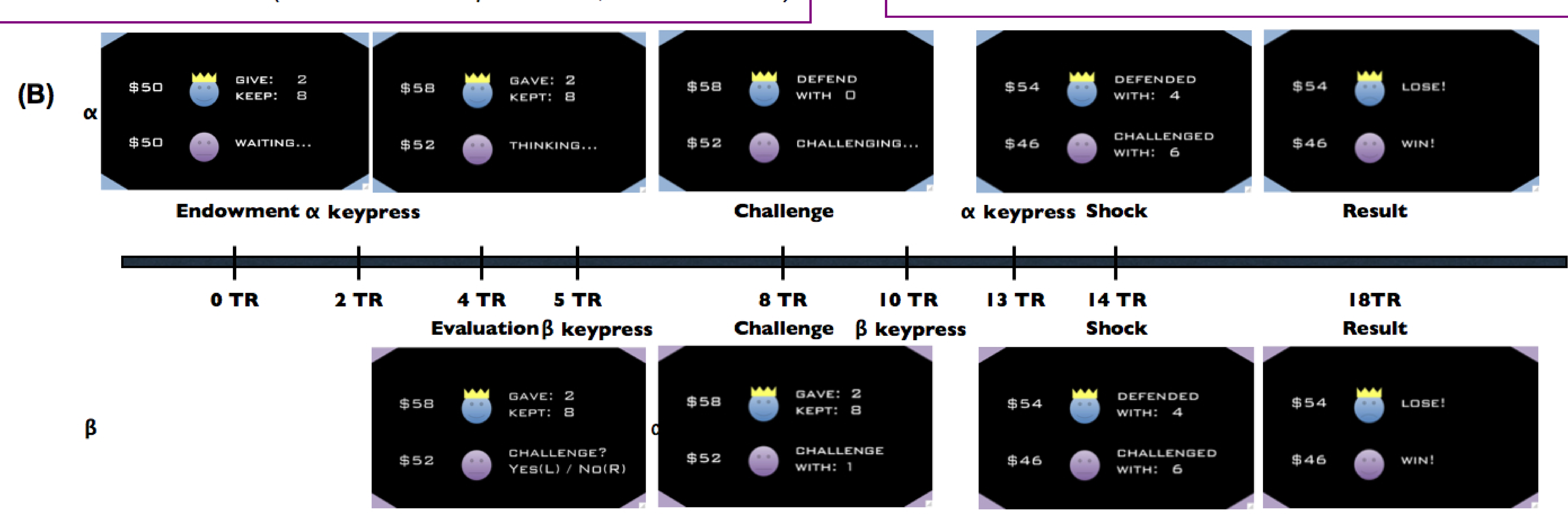
Fourty-four participant, played a social hierarchy game, outlined in figures (A) and (B). At the beginning of the first round, one subject was assigned the role alpha (α) and the other, the role beta (β). Each was initially given 50 monetary units (MU). In addition, 10 MU were allotted per player, per round. α was given the opportunity at the beginning of each round to endow β with MU. For this version of the game, endowments were restricted between 0-4 MU. Endowment values were revealed to β, and β was allowed to challenge for the α role in the next round. If β decided not to challenge, the roles were kept the same, and α remained α for the next round. If β decided to challenge, β selected a challenge amount (1-10 MU), and α selected a defense amount (0-10 MU). Challenge and defense amounts were revealed together after the respective decisions of β and α. If β challenge > α defense, β became the α for the next round and made the initial endowment. If α defense > β challenge, the roles were kept the same and α remained α for the next round. At the end of each round, the MU totals were recalculated, and revealed. Participants were paid between $25 and $50 USD, based on the number of MU accumulated over the course of 30 rounds

(A)



The presentation of stimuli, assuming a full round including challenging, is illustrated below in (B). If β had not challenge, the next round would begin after the onset of the evaluation screen. (*N.B. TR refers to repetition time, in this case 2 sec*)

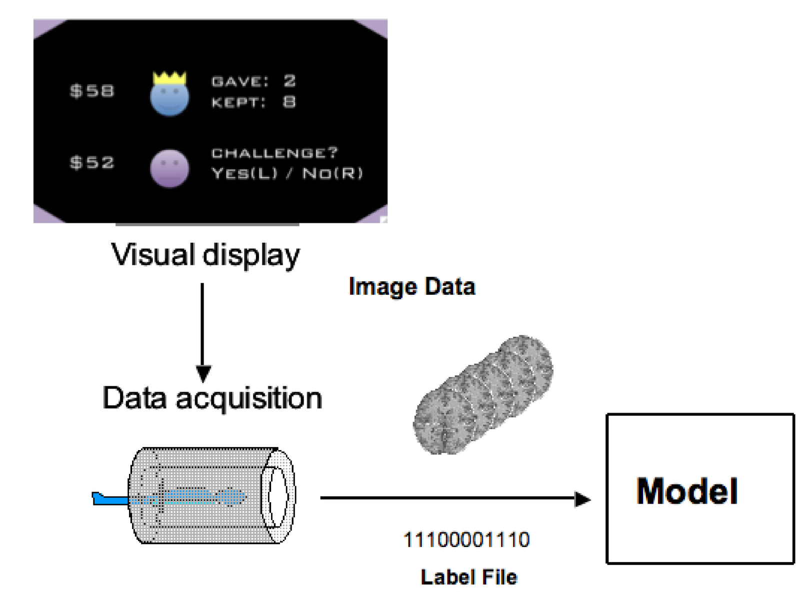
(B)



Scanning was performed on 44 subjects with two 3.0 Tesla Siemens Trio scanners. First, high-resolution T1-weighted scans were acquired using an MPRage sequence (Siemens). Subjects then played the hierarchy game while undergoing functional imaging. Functional run details: echo-planar imaging, gradient recalled echo; repetition time (TR) = 2000 ms; echo time (TE) = 30 ms; flip angle = 90°; 64 x 64 matrix, 37 4 mm axial slices, yielding functional 3.3 mm x 3.3 mm x 4.0 mm voxels. Slices were hyperangulated 30° relative to the AC-AP axis.

The data were analyzed using AFNI (Cox, 1996). Motion correction to the first functional scan was performed using a six-parameter rigid-body transformation. The average of the motion-corrected images was co-registered to each individual's structural MRI using a 6-parameter affine transformation. The images were then spatially normalized to the Talairach-Tournoux template (Talairach and Tournoux, 1988) by applying a 6-parameter affine transformation, followed by a nonlinear warping using basis functions. Images were then smoothed with an 4 mm isotropic Gaussian kernel and bandpass filtered in the temporal domain.

(C)



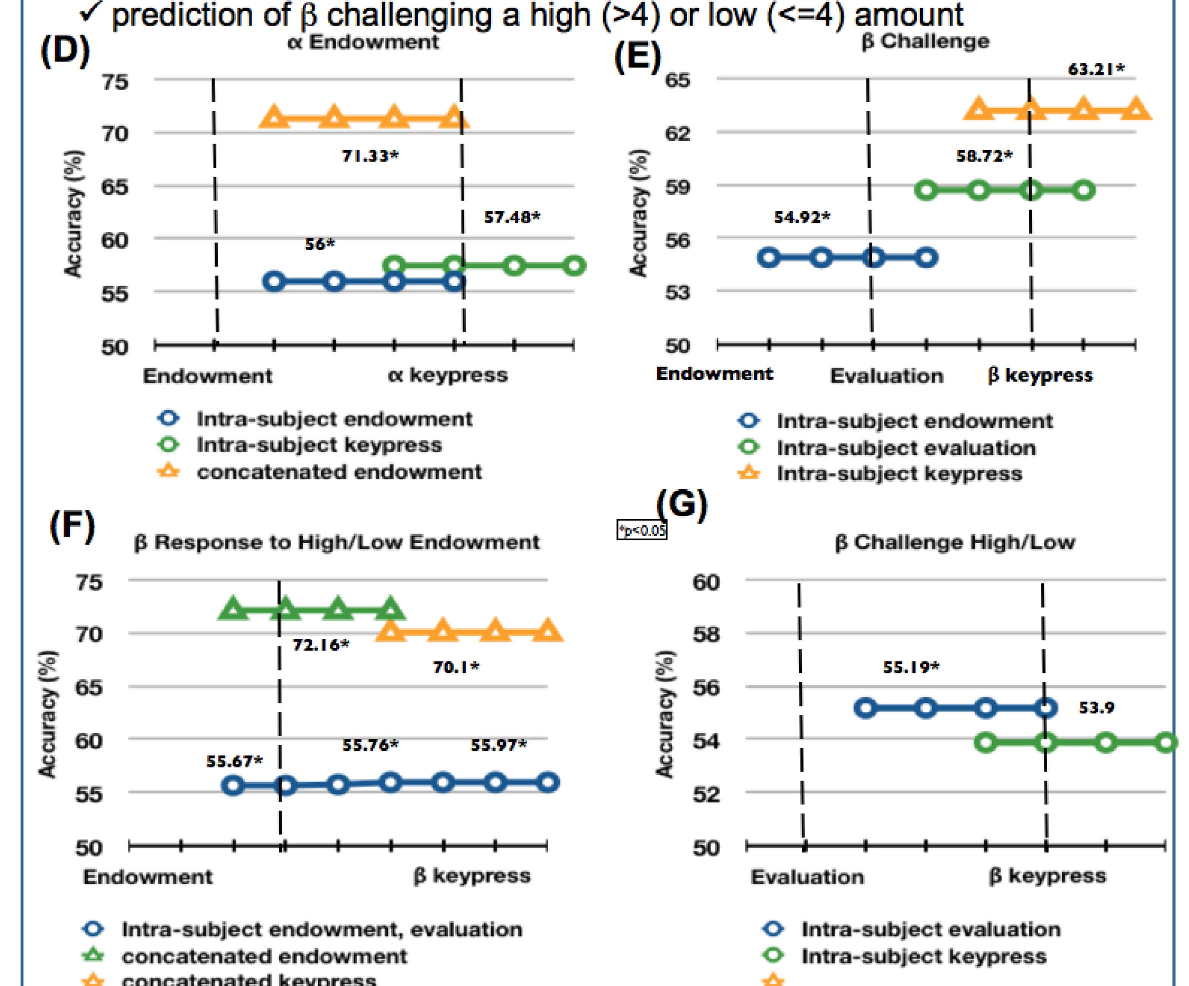
The support vector machine (SVM) algorithm within AFNI, *3dsvm*, was used for multivariate classification of whole brain volumes (LaConte, 2005). Label files containing 1s and 0s corresponding to two classification states were created for β challenging or not challenging, α endowing a high or low amount, β receiving a high or low endowment, and β challenging with a high or low amount. Label files were created to model the hemodynamic response, a 1-2 second lag time at the onset of the stimuli, and duration of 6-8 seconds. Significant time points before and after each of the 4 events were identified and used to create a time-locked schedule for training and testing of the models. The label files were split into 1/4ths, and models were built on 3/4ths of the data, and tested on the remaining 1/4th. Models were built and tested on each of the 4 possible 3/4th:1/4th splits for each subject for each event. Total correct and incorrect classifications were summed for each of the 4 splits for each subject per event and a final prediction accuracy was obtained. Large volume data sets were concatenated from multiple subjects to test the prediction of accuracy of models built on more time points. Subjects with little variance concerning the event were not included in the analysis, eg. Subject 001-1 always endows high when α.

Separate general linear models (GLM) were specified and estimated for each of 26 subjects. All visual stimuli and motor responses were entered as separate regressors that were constructed by convolving punctate events at the onset of each stimulus or motor response with the fixed hemodynamic response function implemented within AFNI. Fixed-effects associated with individual rounds were pooled across behaviorally defined categories and compared using a t-test.

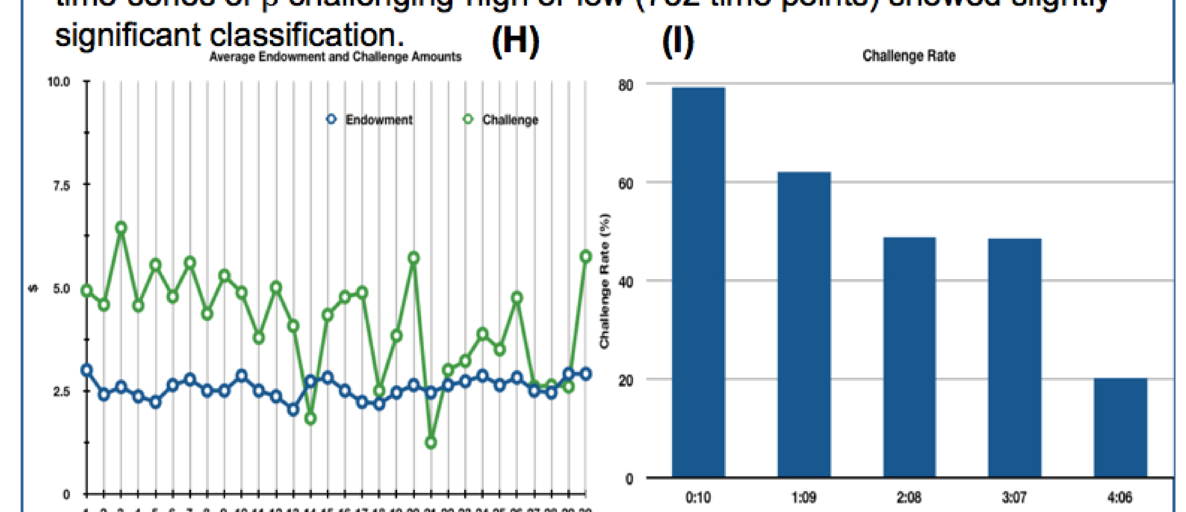
results

SVM

- ✓ prediction of α endowing a high (>2) or low (<=2) amount
- ✓ prediction of β challenging or not challenging
- ✓ classification of β brain state following high or low endowment
- ✓ prediction of β challenging a high (>4) or low (<=4) amount



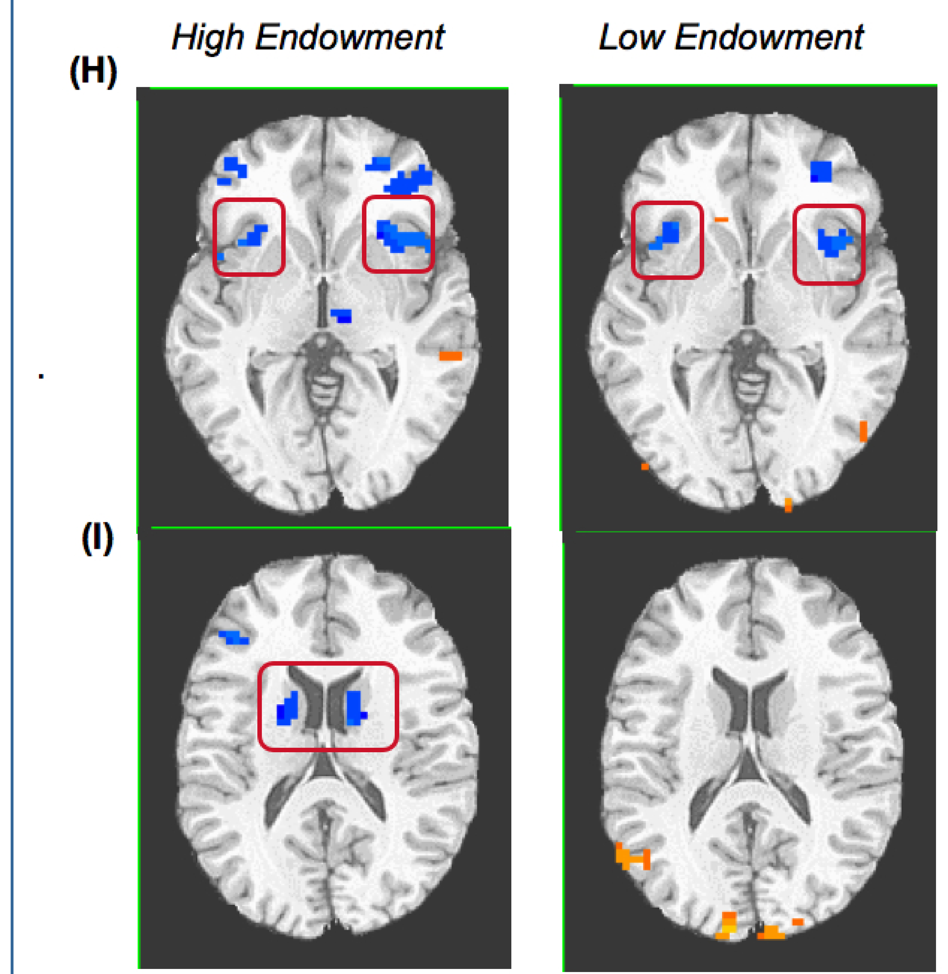
Successful classification of whole brain states implementing the SVM algorithm allowed for an increased prediction accuracy for α endowing a high (>2) or low (<=2) amount (t-test, $p<0.05$) and β challenging or not challenging (t-test, $p<0.05$) prior to the keypress, when the decision is logged. Also, there was successful classification for β receiving a high or low endowment (t-test, $p<0.05$) and on one time-series for β challenging with a high (>4) or low (<=4) amount (t-test, $p<0.05$). For α endowments (D), modeling implemented 1-4TRs following the onset of the endowment screen (1632 time points) and 2TRs prior to and following the keypress (1484 time points) show relatively constant classification on an intra-subject basis. A concatenated data set for the same keypress series (415 time points) shows significant improvement. Intra-subject models implemented for β challenging (E) show increased classification accuracy from 1-4TRs following the endowment screen (2156 time points) and following the evaluation screen (2304 time points), through 2TRs prior to and following the keypress (2044 time points). Intra-subject modeling on the same endowment, evaluation, and keypress time-series showed constant classification for β receiving a high or low endowment (F) on 1336, 1336, 1288 time points, respectively. Models built on concatenated data for the endowment and keypress time-series (both 388 time points) had higher classification accuracies. A model built from the evaluation time-series of β challenging high or low (732 time points) showed slightly significant classification.



The percentage of endowment offers that elicited a challenge from β as a function of the endowment split offered by α is shown in (H). There is an increased likelihood of eliciting a challenge as the endowment to β is decreased. The average endowment and challenge amounts per round over 22 games are depicted in (I).

GLM

Results from the general linear model in response to the revelation of high and low offers to β reveal BOLD response in the bilateral insular cortex (H). High offers showed BOLD response in the left and right caudate (I). These regions of activation are consistent with the findings from social interaction and exchange games (King-Casas, 2005; Sanfey, 2003).



summary

Support vector machine (SVM) algorithms were implemented to build models on fMRI data collected from subjects playing a social hierarchy game. These models were used to successfully classify whole brain states corresponding to time-locked events within each round of the game: β challenging or not challenging in response to an endowment (D) , α endowing a high or low amount to β (E), β receiving a high or low endowment (F), and β challenging with a high or low amount (G). Models built from concatenated data sets had higher classification accuracies than intra-subject models, as more time points are included in the concatenated data set models. Also, in general, time series closer to the event in question have higher classification accuracies.

General linear modeling revealed BOLD activity in the bilateral insular cortex in response to both high and low endowments being revealed to β. High endowments also elicited activity in the left and right caudate (H)

Further studies will include implementation and analysis on model building with concatenated data sets, as the classification is more accurate. These results will be used in conjunction with activation maps elucidated from the GLM to created region of interest (ROI) masks in hopes to optimize the SVM alogrithm.

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