A Connectome-based Predictive Model of Affective Experience During Naturalistic Viewing

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Abstract:

Our thoughts and actions are guided by our ongoing affective experience. Affective states are often measured using self-report ratings, which are labor intensive to collect and can also disrupt ongoing cognition if obtained while performing a task. In this study, we aim to 1) derive a continuous and non-intrusive measure of affective experience based on dynamic functional connectivity (FC), and 2) characterize the interaction between brain regions underlying changes in affective states. We trained a connectome-based predictive model to predict subjective ratings of valence, arousal and dominance from fMRI data of participants watching a TV episode. All three models achieved reasonable accuracy (valence: r = .486, p = .018; arousal: r = .519, p = .002; dominance: r = .602, p = .008). FC edges within and between multiple large-scale functional brain networks reliably contributed to model predictions, suggesting that affective states are encoded in the interactions between brain regions. Taken together, our work presents a promising approach to probe affective experience based on brain imaging data.

Keywords: valence, arousal, dominance, connectome-based predictive model, functional connectivity

Introduction

Affective experience guides perception[1,2], cognition[3,4], decision making[5,6], and social behaviors[7,8]. For example, when people experience low arousal negative emotions (e.g., sadness), they are more likely to behave in an antisocial manner in economic games[7]. Unsurprisingly, measuring affective experience improves our ability to explain and predict human behavior[8,9]. Affective states are often measured using behavioral ratings along affective dimensions (e.g., valence, arousal) or emotion categories (e.g., joy, anger, fear). Obtaining continuous measures of these ratings while participants perform a task is labor-intensive. Moreover, repeatedly probing participants' affective state during a task is disruptive to performing the task and can in turn bias their behavior.

The goal of the current study is to two-fold. The first is to compute a continuous, non-intrusive measure of affective experience derived from time-varying functional connectivity data while participants watch a dynamic visual-audio stimulus. The second is to characterize the interaction between brain regions that contribute to ongoing affective experience. While prior studies have identified specific brain areas where activity correlates with the experience of different affective states[10,11], we know less about how these brain regions interact with each other and the rest of the brain. By examining how whole-brain functional connectivity tracks with dynamic changes in affective experience, we advance our understanding of how affect is encoded in the brain.

To that end, we trained a connectome-based predictive model (CPM) on time-varying functional connectivity data from an open dataset of participants watching a TV episode (n = 17). The CPM was trained to predict behavioral ratings of valence, arousal dominance collected from a separate group of participants (n = 125). For each affective dimension, we then examined the functional connectivity edges that most reliably contributed to model predictions.

Results

Model Predictions Track Self-Report Affective Experience

We trained a support vector regression (SVR) model to predict moment-to-moment (i.e., at every TR) behavioral ratings of valence, arousal, and dominance from dynamic functional connectivity (Figure 1*A* and *B*). The model was trained on the *Sherlock* dataset[12] and tested within the same dataset using a leave-one-subject-out cross-validation procedure. We calculated the Pearson's correlation between model predictions and behavioral ratings. The resulting *r*-values were then Fisher's z-transformed, averaged across cross-validation folds, and then transformed back to an average r-value as a measure of model performance. Mean squared error (MSE) and R^2 were computed as additional measures of model performance.

To assess statistical significance, we compared model performance against null distributions generated by computing the correlation between phase-randomized behavioral ratings and model predictions

(1000 permutations). We assumed a one-tailed significance test, with P = (1 + number of null r values ≥ empirical r)/(1 + number of permutations). Across all three affective dimensions, model performance was significantly higher than null, indicating that affective experience can be predicted from patterns of functional connectivity (valence: mean r = .486, MSE = .765, R^2 = .235, p = .018; arousal: mean r = .519, MSE = .734, R^2 = .267, p = .002; dominance: mean r = .602, MSE = .646, R^2 = .354, p = .008; Figure 1*C*)

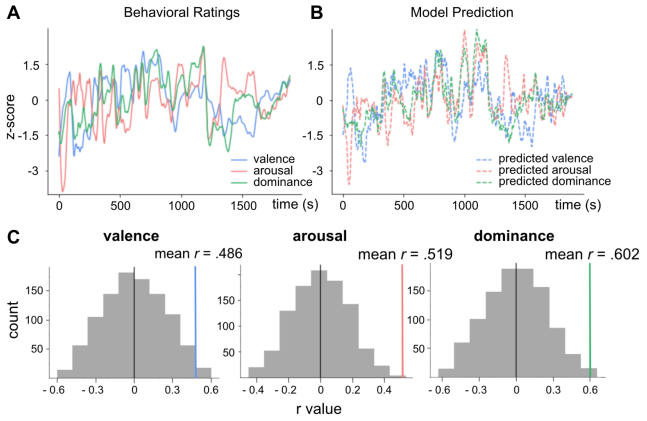

Fig. 1 Behavioral ratings (A), and model predictions (B) of valence, arousal, and dominance. All models are significantly better than null models (all p < .02, C)

Functional Connectivity Networks for Valence, Arousal, and Dominance

To characterize the anatomy of the predictive networks, we visualized the functional connections (FC) consistently retained in the feature selection step in every round of within-dataset cross-validation. For the valence network, a set of 330 FCs was consistently selected (250 positive, 80 negative); For the arousal network, 653 FCs were selected (395 positive, 258 negative); For the dominance network, 517 FCs were selected (280 positive, 237 negative) (Fig.3).

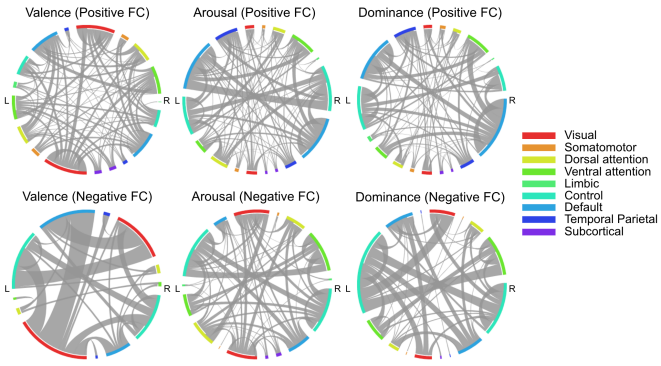

Fig. 2 FC networks for valence, arousal and dominance

The results suggest that affective states are encoded by more than the subcortical and limbic networks commonly associated with emotional experience[13]. Other networks, especially the default and control networks are also substantial involved via connections with other networks.

Conclusion

Using naturalistic viewing data from an open fMRI dataset, we built a CPM to predict the experience of three affective dimensions (valence, arousal and dominance) from dynamic functional connectivity patterns. Our models achieved a reasonable predictive accuracy (mean r > 0.48 for all models), and reveal the involvement of brain regions across multiple large-scale functional brain networks. An important limitation of the current work is that we trained and tested on affective states experienced while viewing the same stimulus. Even though we utilized a leave-one-subject-out cross validation procedure, the model remains susceptible to overfitting to features of the stimulus. Future work will train similar models on multiple datasets to assess generalizability of the model. Nevertheless, the current work presents a promising new approach to measure affective experience based on brain imaging data.

Materials and Methods

Behavioral Data Analysis

Behavioral ratings of were acquired from Kim et al., 2020[11]. 125 participants watched the first episode of Sherlock. The video was paused every ~4.5 seconds, and participants were asked to rate the valence, arousal and dominance of the preceding segment. We averaged the ratings, convolved them with a HRF and applied a tapered sliding window of 30 TR (= 45s), with a step size of 1 TR and a Gaussian kernel σ = 3 TR.

fMRI Image Acquisition and Preprocessing

The preprocessed Sherlock dataset was downloaded from Princeton University's DataSpace repository[14]. Preprocessing steps followed slice timing correction, motion correction, linear detrending, high-passing filtering (140-s cut off), coregistration, and affine transformation to the MNI space. The functional images were resampled to 3-mm^3 voxels.

Whole-Brain Parcellation

We followed Yeo et al.[15] for whole brain parcellation. Cortical regions were parcellated into 114 ROIs based on a 7-network cortical parcellation. Subcortical regions were parcellated into 8 ROIs from the Brainnetome atlas[16] (bilateral amygdala, hippocampus, basal ganglia, and thalamus).

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