How Humans Perceive Emotion: Analysis of *Friends* fMRI Data

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This project was an exploratory study into how people respond to emotion and dialogue from an observer's point of view. Understanding how the brain processes emotion in a naturalistic setting can help us build artificial intelligence that is better at social interactions. Five participants watched four seasons of Friends while being recorded with fMRI. Every data point was labeled with the dialogue and emotion that a character was displaying. A linear encoding model was built to predict brain activity as a function of perceived emotion content. The model was tested using held-out data. It was hypothesized that the regions involved in emotion processing will be well predicted by character emotion. The results were inconclusive because three of the five participants had higher correlation in the orbitofrontal cortex and medial prefrontal cortex, which are thought to be involved in emotional processing, but the other two participants showed no correlation.

CCS Concepts: • **Applied computing** → **Imaging**.

Additional Key Words and Phrases: fMRI, linear model, emotion

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1 INTRODUCTION

Predicting emotional reactions and emotion perception is a rapidly growing area in NLP. Recently, there has been commercially applicable advances, such as predicting human-computer conversations [38] and better understanding the responses for news stories [35]. This field is also being used to better diagnose and treat different neurological disorders[7, 20]. While most people experience emotions, the scientific knowledge pertaining to human emotions is still limited.

According to the American Psychological Association (APA) emotion is a complex reaction pattern by which an individual attempts to deal with a personally significant matter or event. Perceived emotion is the emotion a person thinks someone else is feeling. There is currently no agreement with how many unique and independent emotions humans feel.

Ekman [5] argued there are six universal emotions: fear, anger, joy, sadness, disgust, and surprise. Using faces, he argued that regardless of age, culture, or sex, humans could narrow down all faces into the six categories. He viewed any other potential emotion as the combination of the six basic emotions. Plutchik [25] investigated stimulus events to determine the emotion generated and subsequently displayed in an overt behavior. He came to the conclusion there were eight emotions: fear, anger, joy, sadness, acceptance, disgust, expectation, and suprise. Cowen et al. [4] showed participants numerous videos and had them rate the video on different emotional scales and assign free response emotions. Then segmented the space and were able to derive 27 emotions to accurately describe most of the videos. Even though there is multiple theories on the universal emotions, they are mostly based on surveys and empirical data.

To attempt to solve this problem, similar research has been done successfully in the field of color perception. While every human has virtually the same color receptors, every language has their own subset of color categories for wavelengths at different frequencies [29]. This led to numerous theories of how humans perceive light. Anatomically studying cones in the eye, scientists have a good understanding of how vision is processed in the early stages, mainly segmenting light into three different categories of red, green, and blue [34]. Modifying the intensity combinations makes humans see different colors, this is the basis of all monitors and virtual colors. There were multiple hypothesis using surveys and experiments that *CIELAB* was the best model for color perception [10, 16] and color perception was non-linear [2]. It is known fMRI can give cortical insight, especially when measuring slower stimuli which overcomes the small signal-to-noise ratio. Using fMRI to correlate a stimulus with known color processing brain regions, it was confirmed that *CIELAB* is the best at modeling spatial difference between colors [1, 13, 21, 22].

To figure out which regions of the brain are attributed to emotion handling, researchers employ experiments with people having a neurodegenerative diseases or by measuring activation of BOLD responses given fMRI. Studying patients suffering from certain diseases, when compared to a control, had lower scores predicting emotion and a decrease in functional connectivity in different respective regions [9, 36]. Across multiple studies it's been found the ventral-limbic brain network including the amygdala, anterior cingulate cortex (ACC), medial prefrontal cortex (mPFC) and orbitofrontal cortex (OFC)[9, 24] play a key role in emotion processing. The OFC is expected to have higher BOLD during emotion processing because it connects many regions associated with memories and emotion processing, while serving to regulate rewards[30]. Functional neuroimaging have agreed with these finding [8, 11, 23]. For most those these studies the emotional stimulus for prediction was faces.

Researchers have tried to use neuroimaging with an functional magnetic resonance imaging (fMRI) scanner to provide additional statistical evidence of certain emotion models to varying degrees of success. They have tried music [14, 15] [32] and text [6] as stimuli. However, a relatively unexplored stimulus is a more naturalistic setting. It has been shown in the past to do well on other language processing tasks, but remained elusive at predicting perceived emotion. By providing more context with multi modalities, emotion perception may be more active because it is dealing with a lot of modalities that activate it: music, facial emotion, dialogue, body posture.

Without considering naturalistic stimuli, there is a lot of research at the intersection of language-models and fMRI. However, it is unknown what fMRI can provide over alternatives like word-embeddings. Schwartz et al. [31] fine-tuned a model of **BERT** to better predict brain activity, however this shift did not improve or hinder the performance on other NLP tasks. Ramakrishnan [28] compared a different language model, *GPT-2*, with fMRI and surprisingly found the word2vec model, which is based on context, better predicted word abstractness than the brain activity.

The paper aimed to answer three questions. Is there any merit to the six universal emotions? For an NLP task can fMRI provide additional information compared to word embeddings? With a noisier multi-modal stimulus, is it possible to still get high correlations for the voxels?

We propose using a linear model to establish a correlation between perceived emotion and different regions of the brain under the stimuli of naturalistic scenes. We expect that emotions should be good indicators of emotion processing regions, the more natural stimuli will create a higher correlation than previous studies, and a high correlation would imply fMRI data provides additional information than just using the stimuli.

2 RELATED WORK

A few studies have shown inconclusive or spread results of using fMRI data to predict emotions. Using a subset of Ekman's emotions, Kesler et al. [12] conducted a similar experiment showing participants under fMRI different facial expressions. They found it was possible to detect when a face was non-neutral; men showed a different neural response depending on the emotion; and the frontal lobe had the most activity. Skerry et al. [33] had participants read stimuli describing situations that would cause a particular emotion under fMRI. A classifier was then used to try to correlate regions of interests with basic emotions. It was found that Ekman's universal emotions failed to capture the activity in the subcortex regions. Furthermore, it appeared they were equally as predictive as word-features.

Given that fMRI and text have produced similar results, this paper used the Multimodal Multi-Party Dataset for Emotion Recognition in Conversation (MELD) [27] which has been used previously to test different language models. Throughout the history of the dataset, multiple models have been tried against it to predict emotions using varies amounts of context with varying results.

bc-LSTM+Att [26] was hierarchical classification that was based on a LSTM-RNN model where utterances-level text, audio, and video were combined to achieve a weighted f-1 of 56.44. **DialogueRNN** [19] took into account speakers, global contexts and historical emotions into an RNN model and achieved a weighted f-1 of 57.03. **KET** [39] was knowledge enriched transformer utilizing self-attention and external commonsense knowledge and achieved a weighted f-1 of 58.18. **BERT+MTL** [18] tuned a BERT model and exploited a multi-task learning (MLT) of emotion and speaker information to achieve 61.90. **CoPMPM** [17] utilized RoBERTa as a Context Embedding Module in addition to a Pre-trained Memory Module to account for different speakers style and achieved a 66.65.

In the five years of the dataset, there was only a 10% improvement and a best accuracy of 66% in emotion prediction. This leaves an opportunity for brain activity to provide alternative and additional information.

3 METHODS

3.1 Data Collection

3.1.1 Stimulus and fMRI data.

Six participants were asked to watch four seasons of the television series *Friends*, made available by the Courtois Neuromod group (data release `cneuromod-2020`). This data is available upon request at https://docs.cneuromod.ca/en/latest/ACCESS.html#downloading-the-dataset.We used five participants' data watching the first season in our experiments. The episodes were split into two segments, with each segment roughly 11-13 minutes long and presented in a separate run. Each episodes' subtitles were aligned to the specific stimuli by applying the UPenn Forced Aligner [37] on the audio portion of the recording. Timestamps for each word were generated including the start and end time with respect to the stimuli.

Each fMRI scan consts of a sequence of voxel-responses acquired at a fixed repetition time (TR = 1.49s) with a voxel sixe of 2x2x2mm. The fMRI dataset used the Courtois NeuroMod template space (MNI152NLin2009cAsym).

3.1.2 Emotion Ratings.

We combined the EmotionLines dataset by Chen et al. [3] and it's offspring MELD dataset by Poria et al. [27]. Each dataset assigned one of Ekman's six basic emotions with a default neutral emotion to every phrase. This was achieved using five scorers from Amazon Mechanical Turk. The main difference between datasets was the MELD dataset used a majority model and kept only one emotion, while EmotionLines had the information of the combined votes for each emotion. By combing datasets, we had access to phrases grouped by season, episode, and dialogue_id corresponding to speaker and seven universal emotions on a soft-scale. The timing of each phrase was mapped from its corresponding scene in the aligned subtitles.

3.2 Data Preparation

3.2.1 Vectorizing. Using a seven vector to represent the emotion corresponding to each phrase, we partitioned the phrases into chunks so all the phrases in a chunk were at least partially present in the stimulus of the chunk. The chunks had a duration of 1 TR which corresponds to the period during the fMRI phase. All phrases were included in the chunks which overlapped with the start and end time

3.2.2 Downsampling. Occasionally multiple phrases overlapped within a TR. To account for this, we followed a similar methodology of Ramakrishnan [28] and downsampled the stimulus emotions by normalizing the summation of all emotion vectors present ($\vec{e}_p$) in chunk(C_i) by the total number of votes ($|C_i|$). This can be described as:

$$\vec{e}_i = \frac{1}{|C_i|} \sum_{p \in C_i} \vec{e}_p \tag{1}$$

3.2.3 Stacking. When there is neural activity, it requires energy and resources to be sent to that area in the brain. This means the activity is coupled with neurovascular activity. Blood oxygen level dependent (BOLD) signal is a non-linear combination of blood oxygenation and volume, meaning brain activity can be monitored. BOLD signals linger for around 8 seconds after a stimulus occurs. In our research, since the TR = 1.49 seconds, we take into account $\frac{8}{1.49} \approx 5$ of the previous chunks ($[\vec{e}_{i-4}, \cdots, \vec{e}_i]$)to predict the fMRI response at B_i.

To account for delayed response of the BOLD signal from different stimuli we temporally stacked the emotions from multiple chunks within each episode. This created an embedding space $E \in \mathbb{R}^{T \times S}$ where T denotes the number of chunks with s previous chunks labeled with Ekman's 6+1 basic emotions and a voxel-response matrix of $B \in \mathbb{R}^{T \times D}$ where D is the dimension of the mask. For this experiment $T = 1833, S = 7 \times s = 35$, and $D = 94521$.

3.3 Predictive Model

We consider the problem of correlating voxel activity with stimulus perceived emotion. To achieve this, we learned the $E \longrightarrow B$ mapping for each subject. The mapping was a linear model with $L2$-regularization logistic regression.

3.4 Evaluation

To validate the model, we used 4-fold cross-validation. For one round of validation, a fourth of the dataset (E, B) was held out while the remaining three fourths was used to train the linear model. The estimated emotion label weights W were used to predict responses in the held out data. By multiplying the held out emotion labels by the weights, this generated predicted brain responses. From there a correlation (see equation below) was established between the predicted voxels and expected voxels. Each individual voxel response in the predicted and expected was zscored, multiplied together, and averaged over all validation points. This was repeated with every fourth of data and averaged.

$$\textsc{corr}(W \times E, B) = \textsc{mean}(\textsc{zscore}(WE) \times \textsc{zscore}(Y))$$

4 RESULTS

Using the Pycortex modeling software, we were able to visualize the predictive power of the model (see Fig 1. and Appendix. Flattened fMRI) Color is a measure of the correlation between emotion and brain activity. The scale of correlation for the images was from [-0.2,0.2] where red indicates a higher correlation and blue corresponds to noise respectively.

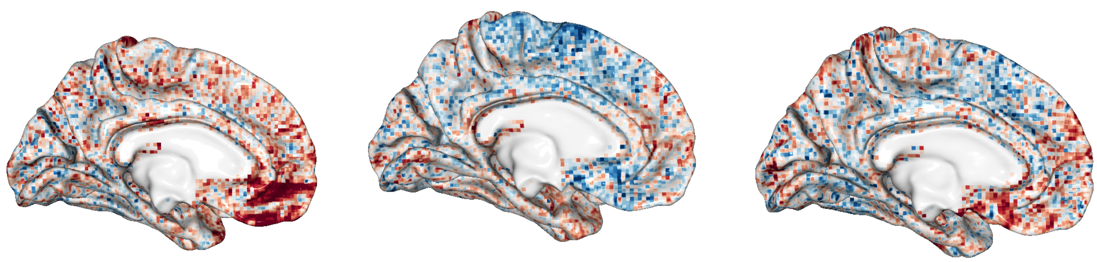

Fig. 1. Correlation between voxel and emotion for three participants. Image created with Pycortex (https://gallantlab.github.io/pycortex/).

It was found in three participants, the region near the orbitofrontal cortex, pictured in dark red, was highly correlated with perceived emotion and the prefrontal cortex, pictured with lighter red, was correlated with perceived emotion. The orbitofrontal cortex and prefrontal cortex are both involved in emotional processing, which is what we expected. However, this result was not seen in the other two participants. It may be the case this is a spurious correlation. Pertaining to the subcortical regions which are also related to emotion processing, they were not robust.

5 SURPRISES

Throughout working on this project, we encountered a few surprises. Attempting to find a dataset that had labeled *Friends*' perceived emotion, we found the *emoryNLP* dataset. This was similar to MELD and EmotionLines but had slightly different phrases and emotions assigned. This dataset had very little correlation with respect to predicting brain activity. This was confusing because a very similar dataset produced a wildly different result. This also lead into a surprise within the results. As shown in Appendix. Flattened fMRI the correlation varied across participants. It is unknown why some people reacted differently to perceived emotion.

Also when comparing the MELD dataset's timing to the subtitles original timing, they appeared to be the same. This almost made sense because the stimuli removed the title sequence But what didn't make sense, when investigated further the subtitles aligned very differently to the stimuli, even when accounting for the missing title sequence. This is why we had to use the UPenn Forced Aligner to create accurate timings.

The biggest surprise in the dataset, also turned out to be the most subtle and time consuming. For season one, the *Neuromod* fMRI dataset started by showing participants episodes 2-6, then episode 1, and then episodes 7-24. This was hard to catch because before we tested on all the data, we used the first few episodes to see if there was any correlation. However, given that were were trying to correlate emotion labels from episode 1 to episode 2's brain activity, we always got no correlation. We thought the problem may be the new timing alignment of the Penn 2 Forced Aligner, so we spent a lot of time double checking. Then we considered trying different down sampling techniques to see if that improved correlation, it did not. Finally, the mistake was fixed but all the trials leading up to this point provided no evidence and had to be rerun.

6 CONCLUSIONS AND FUTURE WORK

In conclusion, the results were inconclusive. While we cannot confirm fMRI data encodes additional data that can't be combined using the stimulus and context, it does appear that Ekman's six emotions may not be able to predict brain activity. This is consistent with previous literature that has attempted similar goals. There is some uncertainty due stimulus being more complex which may have caused the perceived emotions to not predict BOLD signals.

In the future, multiple modifications can be tried. One that was brought up, was to try and use only one scorer so the perceived emotion was consistent across all phrases. This means that the envisioned perceived emotion that a scorer attributed to a certain phrase was the same for all other phrases. To reduce the spurious correlation we could also incorporate other seasons. To improve correlation, we also could eliminate phrases which appear longer than 10 seconds because the BOLD response of feeling the emotion will have died down.

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A COURTOIS NEUROMOD

Three of the participants are native French speakers and three are native English speakers. All are fluent in English and watched English movies regularly.

B FLATTENED FMRI

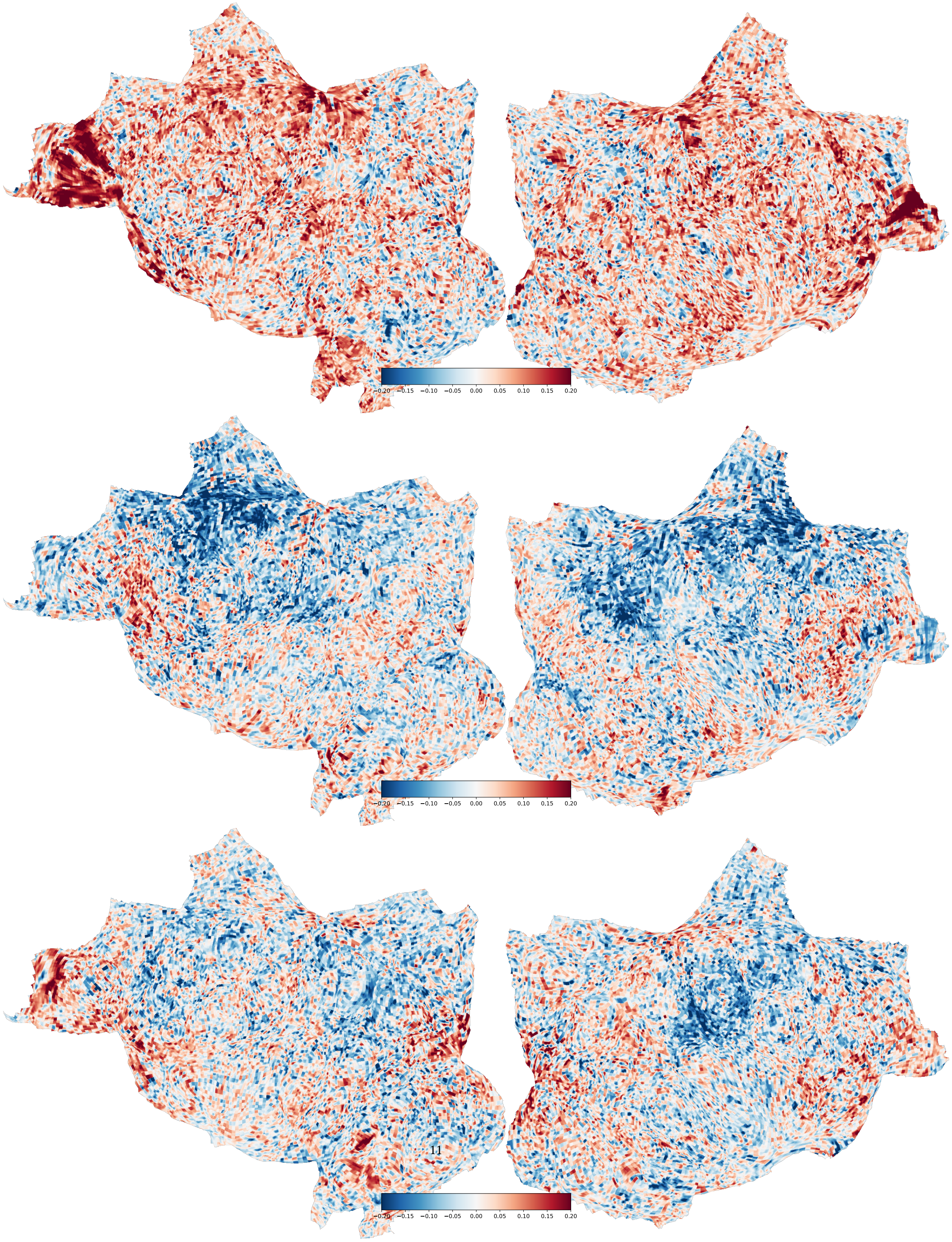

Fig. 2. Correlation between voxel and emotion for Participants 1,2,3. Image created with Pycortex (https://gallantlab.github.io/pycortex/).

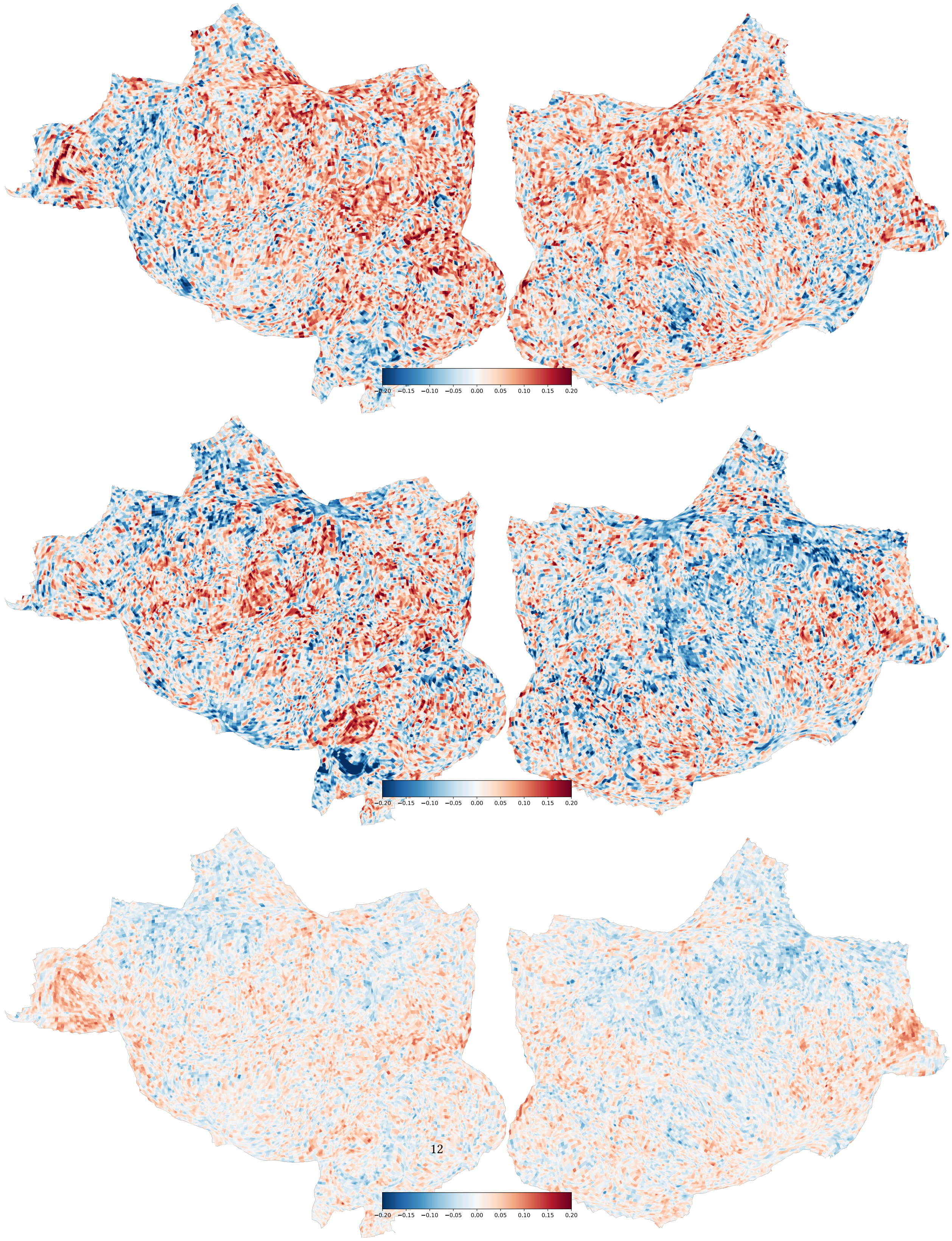

Fig. 3. Correlation between voxel and emotion for two Participants and a combination of all participants. Image created with Pycortex (https://gallantlab.github.io/pycortex/).