Title: Classification of Threat v. Safety in the Human Brain

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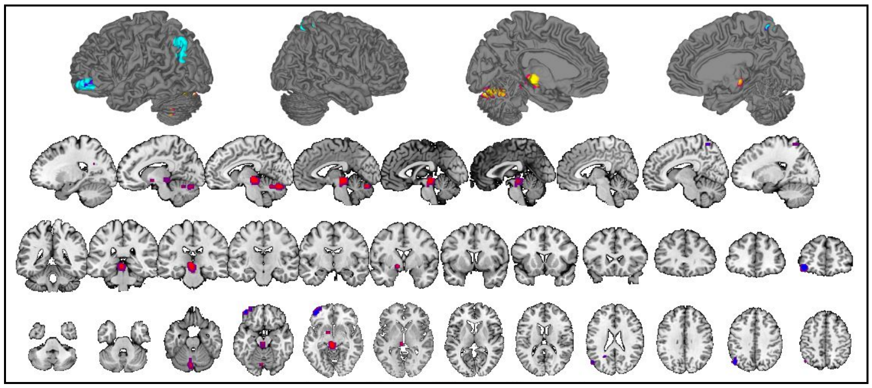
What: The goal is to improve classification accuracy of neural responses (fMRI images) to threat and safety. The ***training data*** are voxel (3 x 3 x 3mm) activations in the the brains of 68 human subjects who are learning that a tone (Class 1: CS+) will electrically shock them 33% of the time and another tone (Class 2: CS-) will never shock them. The ***test data*** are voxel activations in a subset of those subjects (N=23) who hear the same tones *again* after a short break. The ***baseline*** is a whole brain linear SVM classifier with 75% cross validated (leave one out) predictive accuracy (Figure to the right: Thresholded predictive weight map, bootstrapped 5,000 samples, FDR corrected p<0.05, voxel cluster size k=10).



Proposed Techniques:

1. Kernel methods are not typically used in neuroimaging due to interpretability issues. I propose to retrain the data using RBF SVM and compare accuracy as well as the support vectors (which are the most information brain regions) to baseline.
    - Using MATLAB predict toolbox developed by our lab.
2. Feature engineer the linear SVM to improve accuracy - We could add information such as physiological data (sweating responses) or survey data (state/trait anxiety scores).
    - Using a combination of MATLAB and python toolboxes for neuroimaging: PyMVPA, NiPy, Scikitlearn
3. Compare the accuracy of local vs. distributed classifiers. Does training on the whole brain produce better results than training selectively in predetermined brain regions implicated in threat processing? That is, are MULTIPLE threatt-related brain areas better than any ONE?
    - Can test best signature on other types of ‘threatening’ neural data (threatening images, shocks paired with other perceptual modalities like visual images, etc).
4. (Maybe) Apply deep learning to the data and compare results to supervised methods.

Timeline:

Nov. 1	Results from P1
Nov. 7	Results from P3
Nov. 11	Results from P2
Nov. 13	Comparison & analysis of results P1:3
Nov. 14 - on	Attempt deep learning approach