Machine Learning for fMRI

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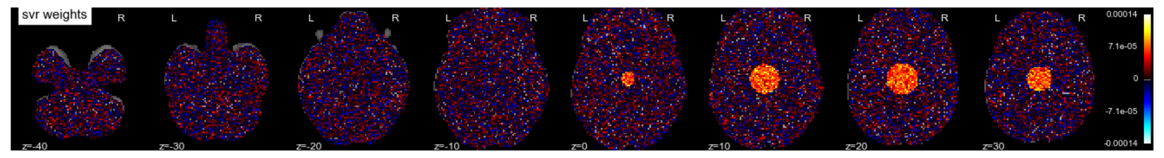
INTRODUCTION

Analyzing massive amounts of fMRI data to obtain interesting new insights is a challenge. Traditionally, neuroscientists have used a simple but computationally demanding technique called searchlight analysis. New machine learning approaches such as support vector regression have yielded great success as well. The goal of this project is to compare the performances of the two approaches on different types of data. We simulated fMRI data with local linear activation, two covarying regions, and two regions mediated by a third. Owing to differences in the two techniques, we expect to find differences in reconstruction accuracy, especially in mediation data.

METHODS

Our neurolearn library can:

1. Simulate fMRI signals
2. Run massively parallel searchlight analysis on fMRI data
3. Run whole brain machine learning algorithms on fMRI data



An example fMRI simulation showing a sphere of 'activated' voxels in the center of the brain

We used the simulator to make the following activations: one local region with linear activation, two covarying regions, and two regions mediated by a third.

Searchlight analysis measures local correlations. For every voxel in the brain, the searchlight algorithm selects all the neighboring voxels within a radius and runs multivariate regression on them to predict some brain state (emotional affect, in our case) given their activations. When applied to the entire brain, the searchlight technique yields a heat map of the areas most correlated to the brain state being studied.

For the whole-brain machine learning algorithm we chose support vector regression because it is supported by a large body of existing research

The fMRI data simulator is another important component. It performs 3D matrix operations using a combination of methods from numpy and nilearn.

CODE

Parallelizing the searchlight algorithm

1. Load simulated fMRI data and call the searchlight analysis method
3. Select voxels in spheres of radius r around each voxel
4. Save coordinates of voxels that lie within those spheres
5. Split job into n jobs and run on Discovery
6. When all jobs finish, reassemble data and transform to three dimensions
8. Save as a nifti file and notify user by email

Dependencies

NumPy

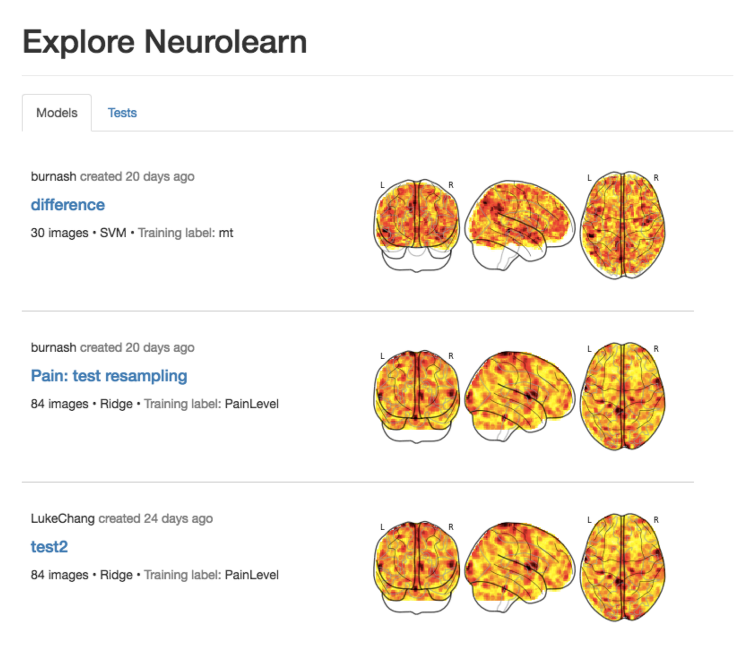
nilearn

matplotlib

pandas

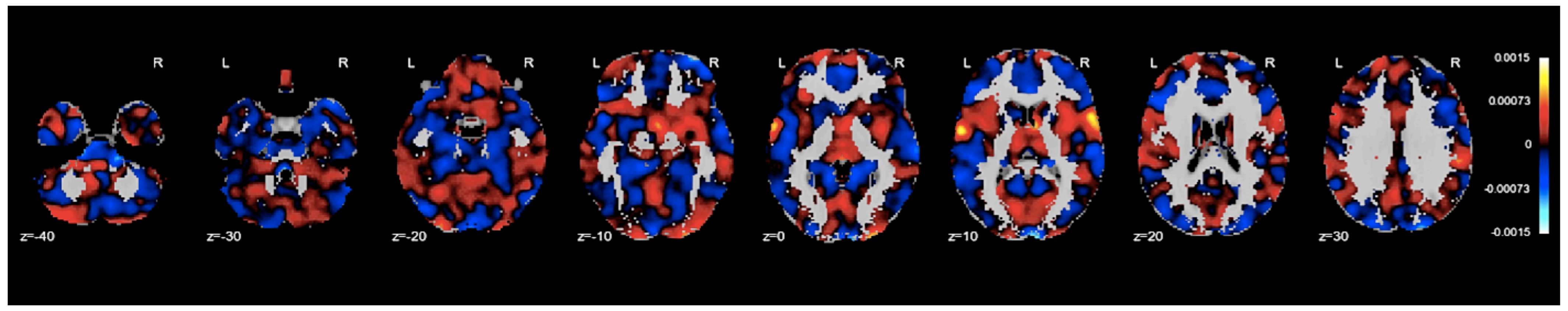
$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

The neurolearn library



The neurolearn library powers www.neurolearn.com, a web app for fMRI analysis

RESULTS



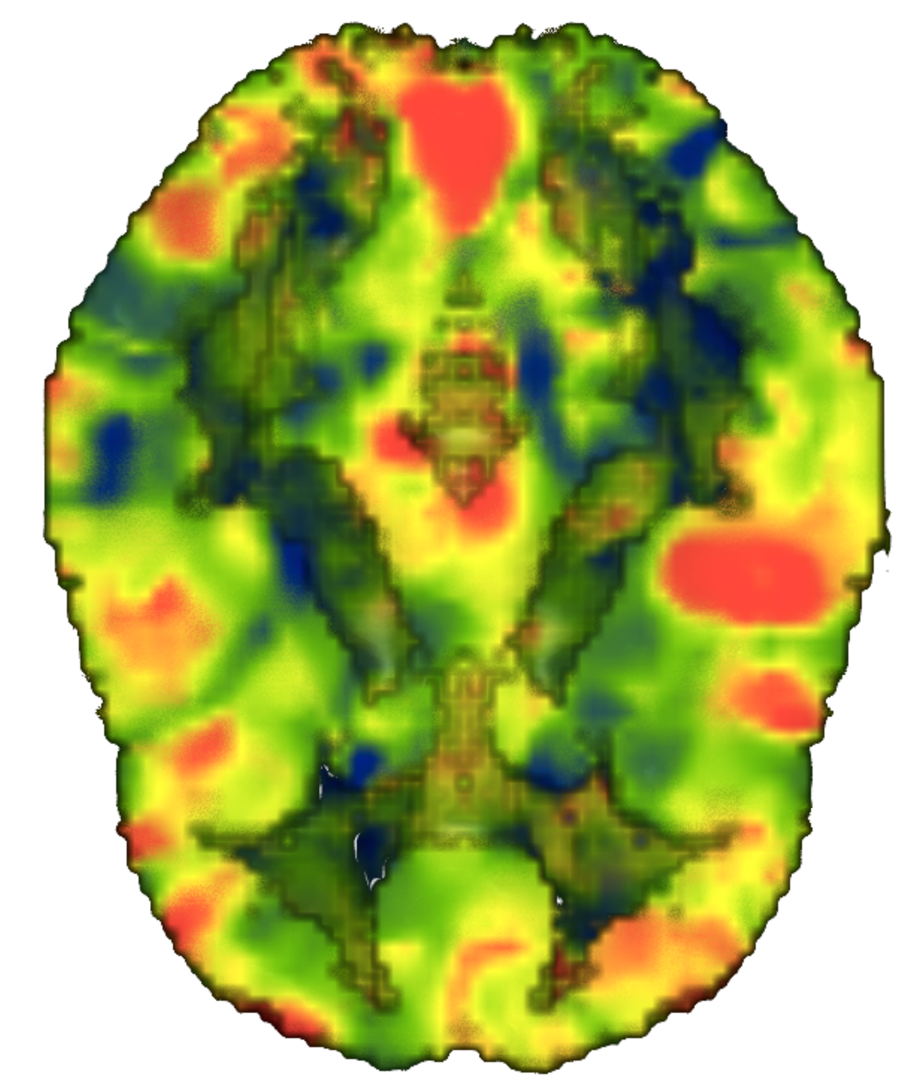
Slice visualization of coefficients for support vector regression model trained on pain dataset (84 subjects)

Algorithm

The data we are analyzing has dimensions 91 x 109 x 91, meaning we must perform nearly a million multivariate regressions. Furthermore, the number of variables in these regressions increases by a power of 3 with the radius. Parallelizing the code as described lowered the computation time from 10 days to a few hours.

Data

Our algorithm replicates results from Professor Chang's 2015 pain study (one example shown on right). We have not finished enough runs to make claims about the comparative performance of searchlight and whole brain techniques. Qualitatively, the linear and covarying region activations have given similar results. Mediation analysis is ongoing.



A correlation coefficient colormap representing brain activation vs. negative emotional affect (84 subjects)

CONCLUSIONS

The searchlight parallelization decreases computation time by a factor of 50-100, making a comprehensive study of its behavior feasible. Both the parallel searchlight and simulator are already part of the neurolearn library and available for public use.

We are running our code on a wide variety of simulated data to better understand how the searchlight compares to full-brain machine learning techniques.

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CITATIONS

1. Chang LJ, Gianaros PJ, Manuck SB, Krishnan A, Wager TD (2015) A Sensitive and Specific Neural Signature for Picture-Induced Negative Affect. PLoS Biol 13(6): e1002180. doi:10.1371/journal.pbio.1002180
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