Whole-brain Sparse Penalized Discriminant Analysis for Predicting Choice
Logan Grosenick1*, Brad Klingenberg2**, Stephanie M. Greer3, Brian Knutson3, Jonathan Taylor2
1Neuroscience Institute, Stanford University 2Department of Statistics, Stanford University 3Department of Psychology, Stanford University

INTRODUCTION
Predicting Behavior Using FMRI
Despite growing interest in applying machine learning to neuromaging data, few studies have gone beyond classifying sensory input to using brain data to directly predict behavioral output. Further, classifiers are rarely fit to whole-brain data across time and in general do not yield easily interpretable models. Here we use an interpretable classifier [1] to predict on a trial-by-trial basis whether a subject will buy a product or not, using only whole-brain BOLD data collected over several time-points prior to and during choice.

Approach
We have developed a classification method—sparse penalized discriminant analysis (SPDA)—that increases both classification accuracy and spatiotemporal interpretability relative to other popular classifiers fit to FMRI data within ROIs [1].

Here we extend SPDA to run on whole-brain FMRI data across multiple time-points, and add a Laplacian penalty that can be used to include spatial and temporal priors. We apply our method to previously-acquired data [2] collected from subjects engaged in a purchasing task.

Goals:
• Accurately predict choice on a trial-by-trial basis.
• Build an interpretable model that automatically selects only task relevant variables from whole-brain data.
• Compare SPDA performance to that of another popular classifier (linear SVM) on whole-brain data.
• Confirm previous findings for SHOP task [1,2]
• Analyze multiple presentations of the same product.

METHODS: SPDA Classifier
\[
\hat{\beta} = \arg \min_{\beta} (\theta(g) - X \beta)^2 \quad (\text{s.t. } N^{-1}||\theta(g)||_2^2 = 1)
\]

[Diagram showing the SPDA classifier process]

• Generalization of the Elastic Net [3] using optimal scoring and adding a Laplacian penalty
• Fast implementation using coordinate-wise descent [4]
• Iteratively adds variables to an “active set” and uses early stopping
• Allows the incorporation of spatial priors to better constrain coefficient estimates

EXAMPLE: Noisy image classification

METHODS: SHOP Task

<table>
<thead>
<tr>
<th>Class</th>
<th>SPDA 1</th>
<th>SPDA 2</th>
<th>SPDA 3</th>
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<td>1</td>
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Fixate Product Price Choice

250 trials per class

Signal to Noise: 1/2

RESULTS: SHOP Data

Whole-brain results replicate previous ROI results in [1]

Across subjects:

Within subjects:

Whole-brain SPDA yields interpretable spatiotemporal model:

These results validate, without ROIs or thresholding, previous findings [1,2] concerning which brain structures are involved in purchasing decisions at particular stages of buying, and show an interesting first encounter effect in buyers.

Whole-brain SPDA:
• Automatic variable selection
• Interpretable coefficients in native data space (voxel by TR)
• Can include spatiotemporal priors (smoothness, connectedness)
• Accurate trial-by-trial prediction
• Works for N <= p
• Can use both regression and DA methods (BIC/crimcoefs)
• Can be extended to be robust/nonlinear

REFERENCES