Predicting Distributed Patterns of Neural Activity During Color Perception

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Following recent advances in multi-voxel pattern analyses of fMRI data (Mitchell et al. 2008; Kay et al. 2008), we attempted to develop a general predictive model of particular subjects' cortical activity during a color perception task. This was accomplished by training a computational model to learn the relationship between stimulus variation along the three axes of the CIE LAB color space and variance in BOLD signal in bi-lateral ventral temporal and occipital cortices.

design

Task: Stimuli (shown below) were borrowed from Simmons et al. (2007) and Beauchamp et al. (1999). Subjects fixated on the dash in the center of the wheel, and determined whether the wedges were sequentially ordered from lightest to darkest.

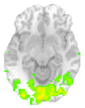
Stimuli came from 10 color shades (e.g., dark red, light brown).

From each run, all images associated with a particular shade were averaged to yield a single image for that shade for that run. This resulted in 50 averaged images (10 categories, 5 runs). All analyses were performed on averaged images.

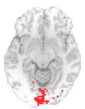
methods

Voxel Selection, Training, and Testing

(Data were preprocessed and analyzed using AFNI and the MVPA toolbox for MATLAB)



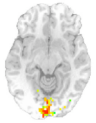
(a) We first restricted the analysis to those voxels that responded more to visual stimuli than fixation.



(b) The analysis was then further constrained to those voxels within the previous subset exhibiting the greatest correlation between stimulus variation in color space and BOLD signal in the training data set.

L - 50
A - 60
B - 40

f(x)

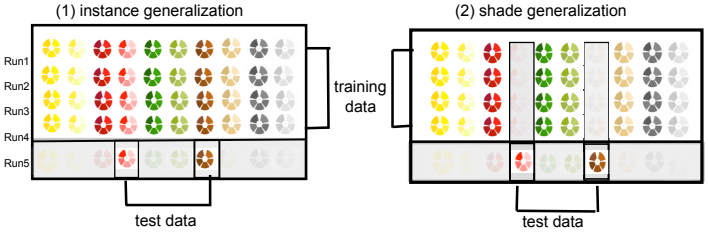


Stimuli were represented by the LAB values of the center wedge.

Multiple regression was used to obtain the maximum likelihood estimates of the coefficients for each dimension of color space at each voxel.

The activity at each voxel was modeled as a weighted sum of these three dimensions, giving a predicted multi-voxel pattern for any input point in the CIE LAB color space.

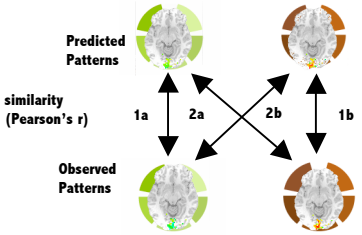
Training sequences



This procedure was repeated for all comparisons, for all runs.

methods (cont)

Testing procedure (adopted from Mitchell et al. 2008):



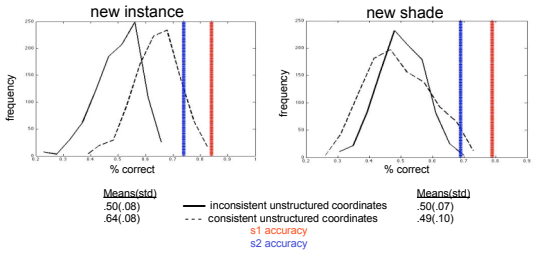
Decision rule:
If sim1a +sim1b > sim2a+sim2b then correct

results

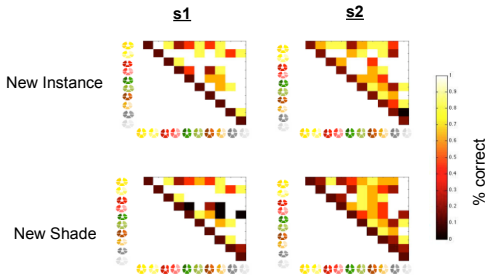
accuracies (% correct) for each subject and training procedure

	New instance	New Shade
s1	84%	79%
s2	74%	68%

empirical chance distributions for 1000 iterations of scrambled LAB coordinates



neural confusability matrices



Correlation [*r*] between s1 and s2 confusability matrices

New Instance	New Shade
0.43 (p =.003)	0.53 (p < 0.001)

results (cont)

The model was also trained and tested using local data from spheres containing ~30 voxels (Kriegeskorte et al., 2006)

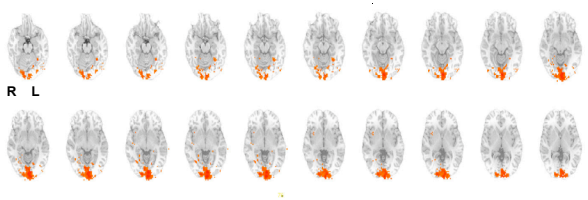


Figure: Voxel neighborhoods in ventral temporal and occipital cortices exhibiting performance above 68% in generalizing to new shades in s1

discussion

The model was able to predict a neural signature for entire color shades (e.g., dark red) that were not included in the training set. Interpolation and extrapolation to novel shades was possible because it learned the relationship between variation along the axes of a continuous space (capable of characterizing any color) and BOLD signal.

Like other recent work, this approach facilitates predictive generalization to novel sub-classes of stimuli (e.g., color categories), yields comprehensible models linking brain activity to stimulus components, and is robust against the employment of process-irrelevant information (e.g., stimulus specific associations) in classification.

Information regarding the color content of the stimulus appears to be available throughout ventral temporal and occipital cortices, particularly in subject 1.

Future work might adopt a similar methodological approach with a design optimized for detecting these effects and specific anatomical hypotheses about the computations performed in each region.

references

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(2) Beauchamp MS, Haxby JV, Jennings JE, DeYoe EA (1999) *Cereb Cortex 9*: 257-263.
(3) Kay, K.N., Naselaris, T., Prenger, R.J. & Gallant, J.L. (2008). Identifying natural images from human brain activity. *Nature, 453, 353-355.*
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(5) Mitchell, T.M., Shinkareva, S.V., Carlson, A., Chang, K.M., Malave, V., Mason, R.A., and Just, M.A., (2008). *Science*, 320.
(6) Princeton MVPA toolbox, http://www.csbmb.princeton.edu/mvpa/
(7) Simmons WK, Ramjee V, Beauchamp MS, McRae K, Martin A, Barsalou LW (2007) *Neuropsychologia 45*: 2802-2810.

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