Localizing functional regions of interest based on responses to dynamic naturalistic stimuli

DARTMOUTH · CCN Center for Cognitive Neuroscience at Dartmouth

Samuel A. Nastase, J. Swaroop Guntupalli, James V. Haxby, Yaroslav O. Halchenko

Department of Psychological and Brain Sciences, Dartmouth College, Hanover, NH, USA

http://www.pymvpa.org http://NeuroDebian.net

Introduction

Functional regions of interest (ROIs) are typically localized by contrasting responses to several classes of controlled stimuli (e.g., faces, houses).[1] However, the stimulus features driving these localized responses may also be embedded in rich, naturalistic stimuli, albeit in a more complex way. Dynamic movie stimuli have been shown to drive neural responses that are consistent across participants and encode extensive perceptual and semantic information.[2,3]

Hypothesis: If stimulus features driving functional localization are embedded in naturalistic stimuli, a classification algorithm should be able to assign voxels to functional ROIs based on their response profiles to a movie stimulus.

Data

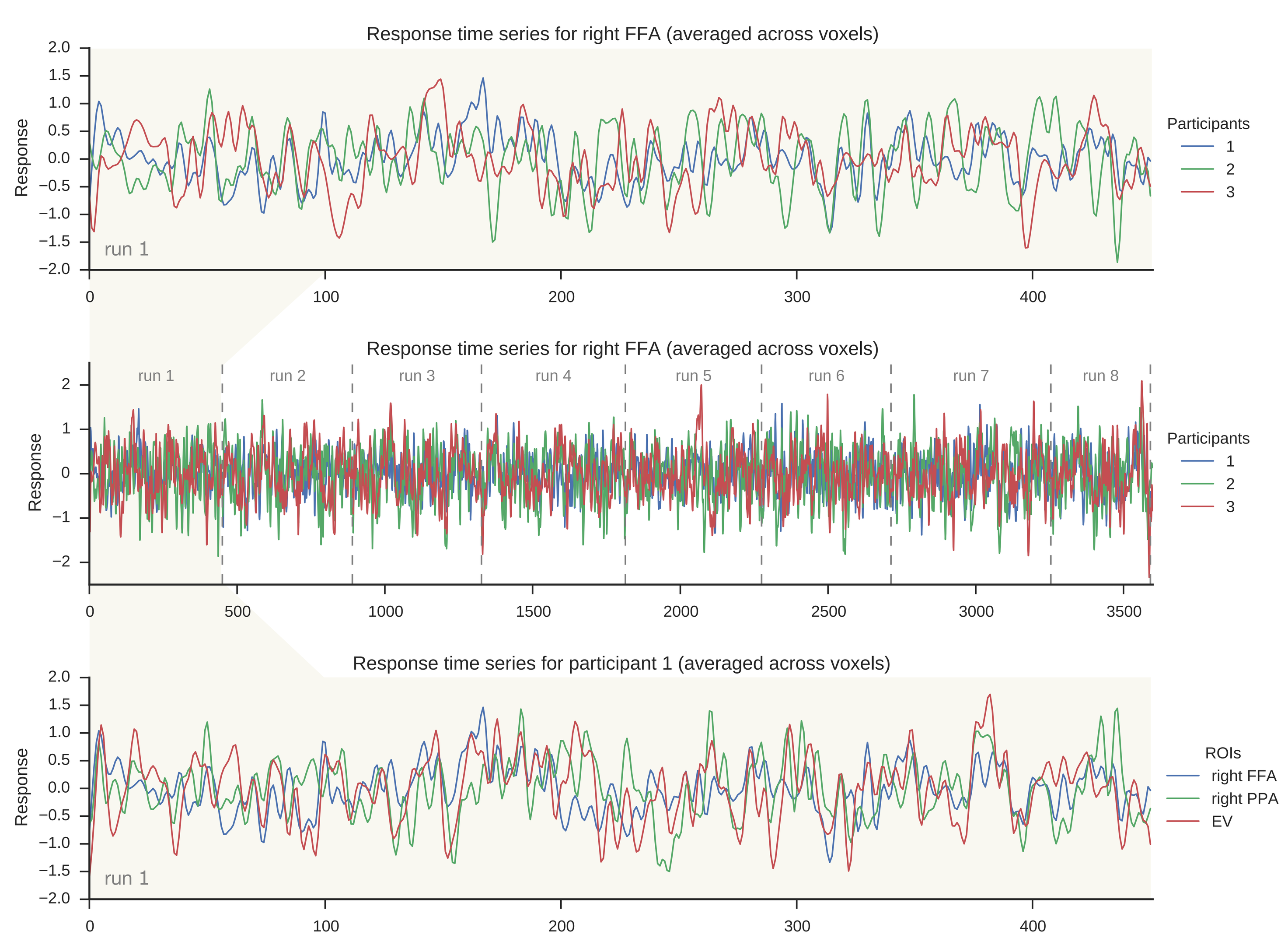
fMRI data collected during naturalistic stimulation and functional localizers were obtained from two extensions of the *studyforrest* project[4,5] (publicly available from openfmri.org, datalad.org, and studyforrest.org):

- 15 right-handed participants (mean age 29.4 years, 6 female)
- 3T fMRI, 2.0 s TR, 3.0 mm isotropic voxels (resliced to 2.5 mm)
- 3,599 time points (TRs) of audiovisual movie-viewing (*Forrest Gump*, German language) divided into 8 runs
- 123,910 voxels (SD = 2,718) per participant in whole-brain mask for a total of 1,858,654 voxels across participants

Six functional ROIs were obtained by contrasting responses to conventional localizer stimuli presented in a block design[5]:

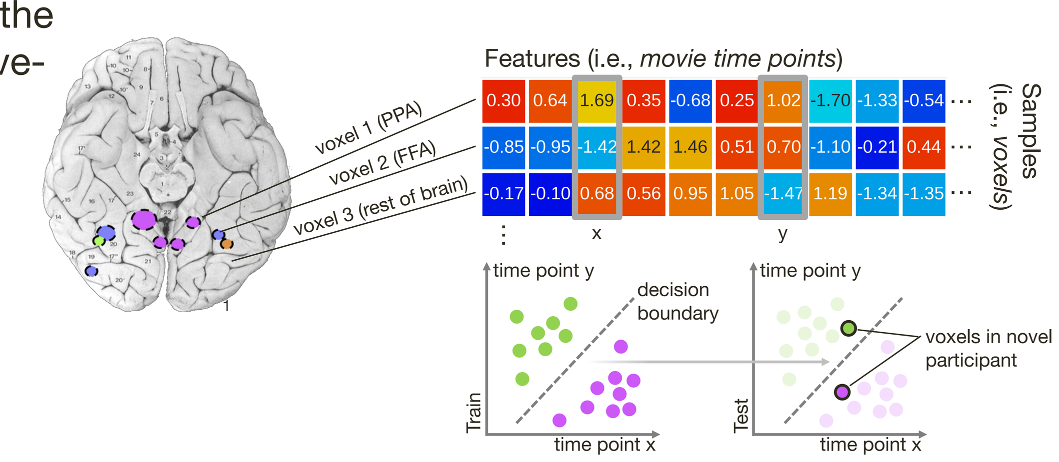
ROI	Total voxels	Mean ± SD voxels	Omissions
Early visual cortex (EV)	4,851	323 ± 167 (per participant)	2 (out of 15)
Lateral occipital complex (LOC)	3,809	254 ± 124	1
Occipital face area (OFA)	801	53 ± 43	4
Fusiform face area (FFA)	2,285	152 ± 73	1
Extrastriate body area (EBA)	1,869	125 ± 64	0
Parahippocampal place area (PPA)	4,434	296 ± 105	0
Rest of brain	1,840,605	122,707 ± 2,523	0

Movie data were motion-corrected, whole-brain masked, normalized to a study-specific group template, detrended (3rd-order polynomial), low-pass filtered (cutoff: 0.1 Hz), and z-scored per voxel (within runs):



Classifying voxels into functional ROIs

Two algorithms were used to classify all voxels in the brain according to functional ROI labels using leave-one-participant-out cross-validation. We can also append voxel coordinate features to incorporate anatomical information into the classifier. Due to highly unbalanced class frequencies, we evaluate classifiers using recall and precision.



$$recall = \frac{true\ positives}{true\ positives + false\ negatives}$$

$$precision = \frac{true\ positives}{true\ positives + false\ positives}$$

Gaussian naive Bayes (GNB)
Assumes independence between features (movie time points)
Prior is ratio of class frequencies

Accuracy: 92.01%, 94.54%

Recall: 61.73%, 64.08%

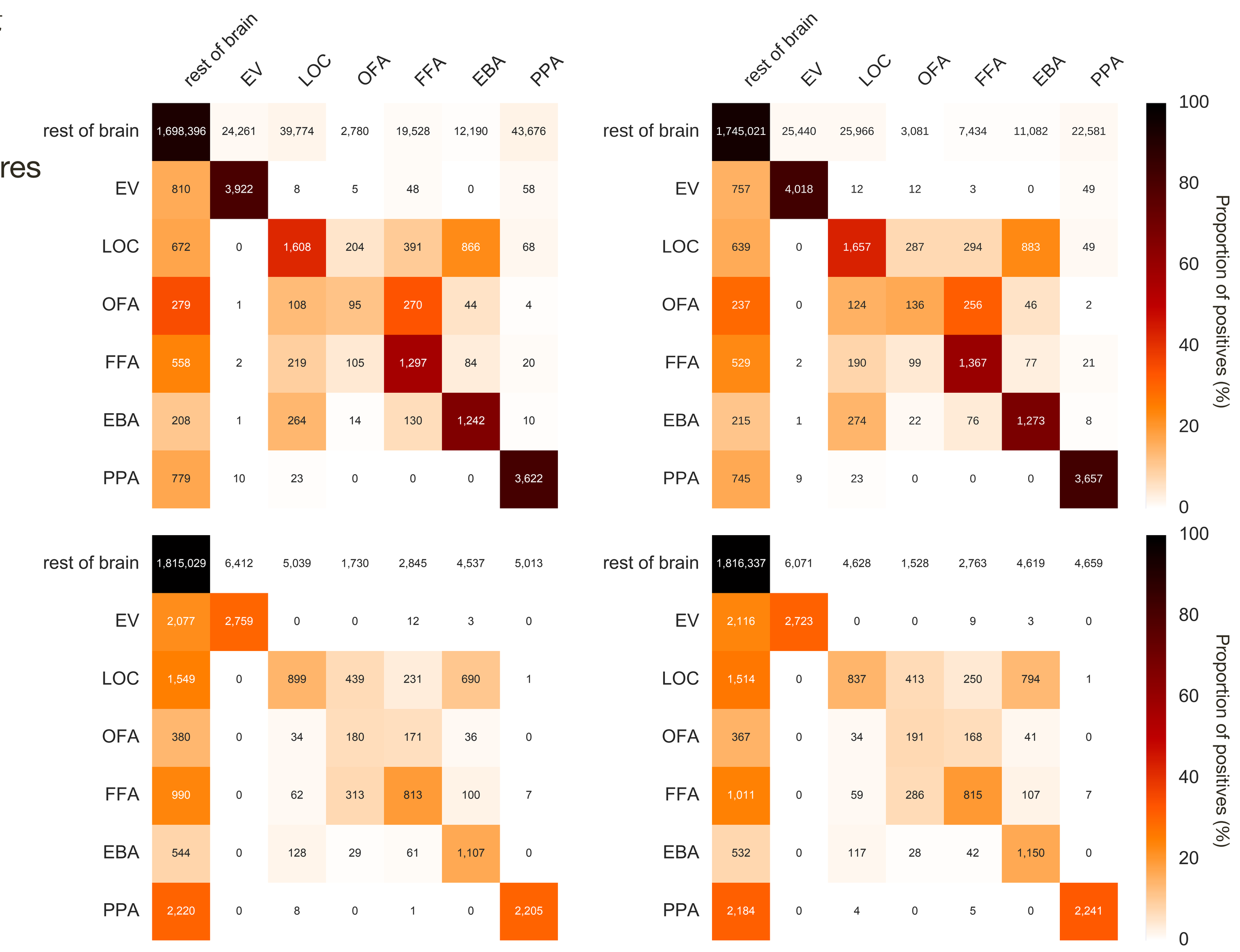
Precision: 20.39%, 22.99%

Stochastic gradient descent (SGD)
Hinge loss and L2 regularization approximates linear SVM
Samples are weighted according to class frequencies

Accuracy: 98.08%, 98.15%

Recall: 46.28%, 46.67%

Precision: 34.11%, 34.79%



No voxel coordinates — With voxel coordinates

GNB with lateralized ROIs

Accuracy: 91.86%, 94.90%

Recall: 47.75%, 58.92%

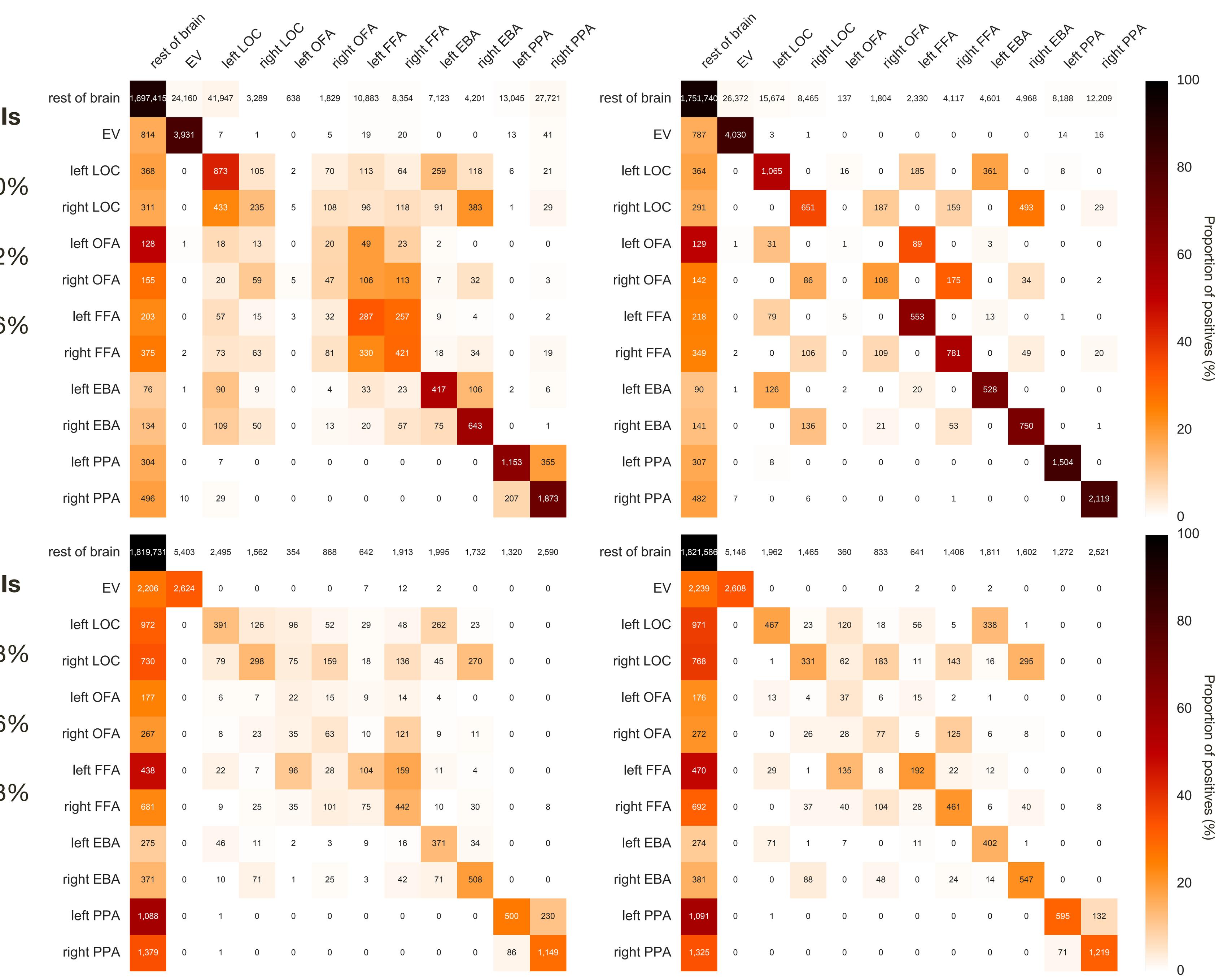
Precision: 13.50%, 17.96%

SGD with lateralized ROIs

Accuracy: 98.25%, 98.38%

Recall: 32.25%, 35.26%

Precision: 26.42%, 30.38%



No voxel coordinates — With voxel coordinates

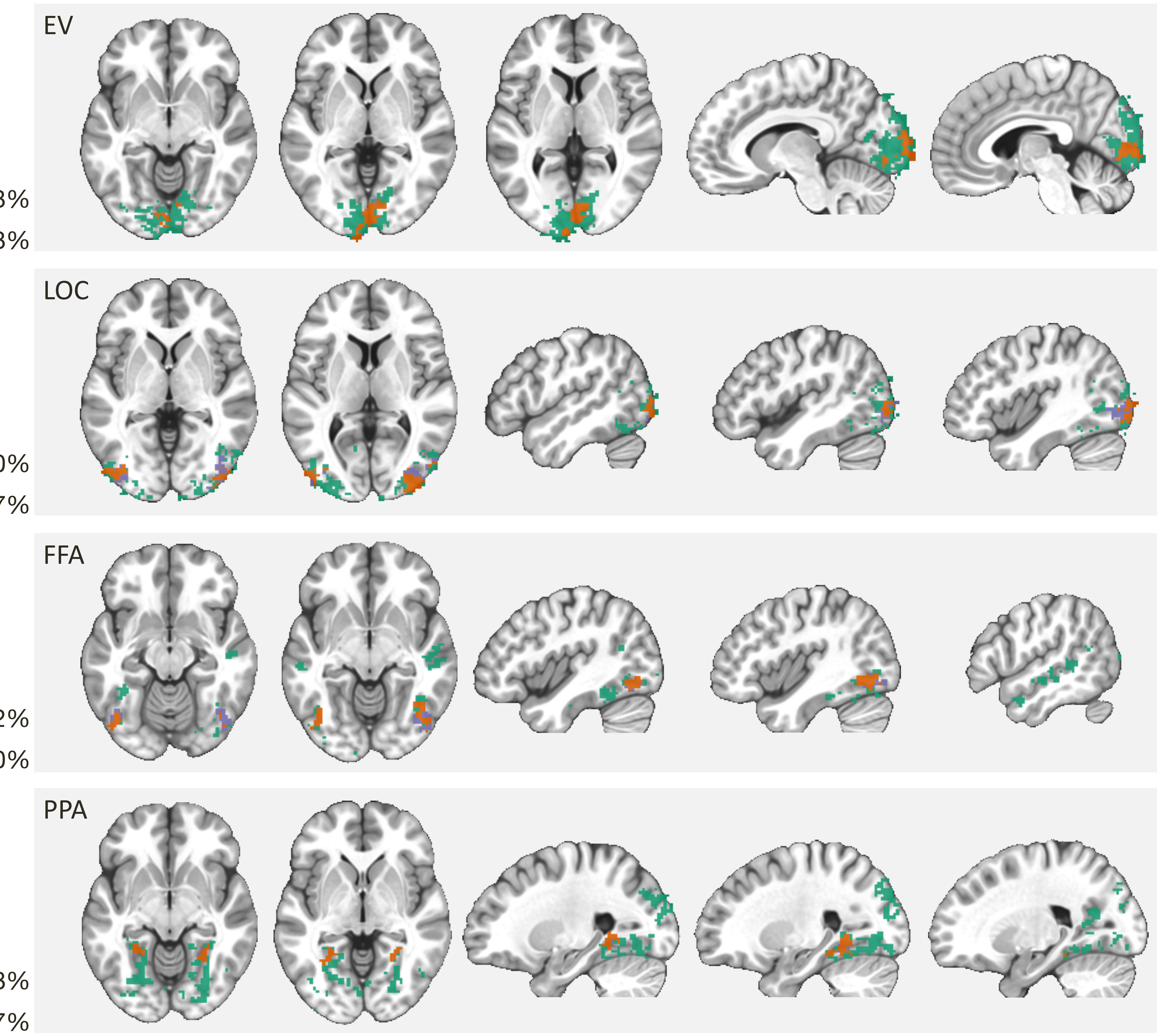
Mapping classifier predictions onto the brain

Classifier predictions for each functional ROI can be mapped onto the brain. False positives indicate voxels that were misclassified as belonging to a particular ROI based on their response profile.

- True positive (hit)
- True negative (correct rejection)
- False positive (false alarm; Type I error)
- False negative (miss; Type II error)

GNB classification (with voxel coordinates) in a representative left-out participant

Overall performance:
Accuracy: 94.54%
Recall: 64.08%
Precision: 22.99%



EV — Recall: 82.83%, Precision: 13.63%

LOC — Recall: 43.50%, Precision: 5.87%

FFA — Recall: 59.82%, Precision: 14.50%

PPA — Recall: 82.48%, Precision: 13.87%

Conclusions

Localized functional regions of interest can be recovered from neural responses to dynamic naturalistic stimuli in an automated fashion.

Classifier performance generalizes to novel participants without relying on anatomical features or anatomical alignment, but anatomical features improve classifier performance.

However, highly unbalanced class frequencies result in relatively low true positive rates and many false positives—overall classification accuracy is not a very useful evaluation metric in this context.

False positives (i.e., voxels with similar response profiles to the target ROI) are localized to potentially meaningful structures.

Unlike existing parcellation methods,[6] here we start with well-established functional areas as targets to remove ambiguity in prescribing a functional role to a given parcel; cross-validation to novel participants natively provides an assessment of the method's generalization across the population.

Future work may leverage more sophisticated (e.g., nonlinear) classification algorithms, incorporate additional multimodal features such as cortical surface curvature or structural and functional connectivity, and evaluate classifier generalization across scanning sites.

References:
1. Kanwisher, N. (2010). Functional specificity in the human brain: a window into the functional architecture of the mind. *Proceedings of the National Academy of Sciences of the United States of America, 107*(25), 11163–11170.
2. Hasson, U., Nir, Y., Levy, I., Fuhrmann, G., & Malach, R. (2004). Intersubject synchronization of cortical activity during natural vision. *Science, 303*(5664), 1634–1640.
3. Guntupalli, J. S., Hanke, M., Halchenko, Y. O., Connolly, A. C., Ramadge, P. J., & Haxby, J. V. (2016). A model of representational spaces in human cortex. *Cerebral Cortex*, *26*(6), 2919–2934.
4. Hanke, M., Adelhöfer, N., Kottke, D., Iacovella, V., Sengupta, A., Kaule, F. R., … Stadler, J. (2016). A *studyforrest* extension, simultaneous fMRI and eye gaze recordings during prolonged natural stimulation. *Scientific Data*, *3*, 160092.
5. Sengupta, A., Kaule, F. R., Guntupalli, J. S., Hoffmann, M. B., Häusler, C., Stadler, J., & Hanke, M. (2016). A *studyforrest* extension, retinotopic mapping and localization of higher visual areas. *Scientific Data*, *3*, 160093.
6. Glasser, M. F., Coalson, T., Robinson, E., Hacker, C., Harwell, J., Yacoub, E., … Van Essen, D. C. (2016). A multi-modal parcellation of human cerebral cortex. *Nature, 536*, 171–178.

samuel.a.nastase.gr@dartmouth.edu