Iterative LASSO: An even-handed approach to whole brain MVPA

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Introduction

- A large body of the most historically relevant work in cognitive neuroscience has emphasized **functional localization**.
- However, the focus on *reliability*, *specificity*, and *locality* of neural activity may reveal only a fraction of the full neural representation of these concepts and processes[1], overlooking what is **distributed and idiosyncratic**.
- We consider whether **Face**, **Place**, and **Object** recognition are processes whose neural bases are specific, reliable, and localized systems, or if they have important aspects that are distributed and idiosyncratic.

Iterative Lasso

Lasso[3] is an example of regularized regression:

$$\arg\min_{\beta} \sum_{i=1}^{n} (\bar{y}_i - X_i\beta)^2 + \lambda h(\beta)$$

It is standard regression with an additional penalty:

$$h(\beta) = \sum |\beta_j|$$

This forces a *sparse* solution. But that means many informative voxels may not be discovered. That is, **Lasso has a low hit-rate**.

If Lasso is run **iteratively**, each time excluding voxels that have already been discovered, more of the activity contributing to neural state can be recovered.

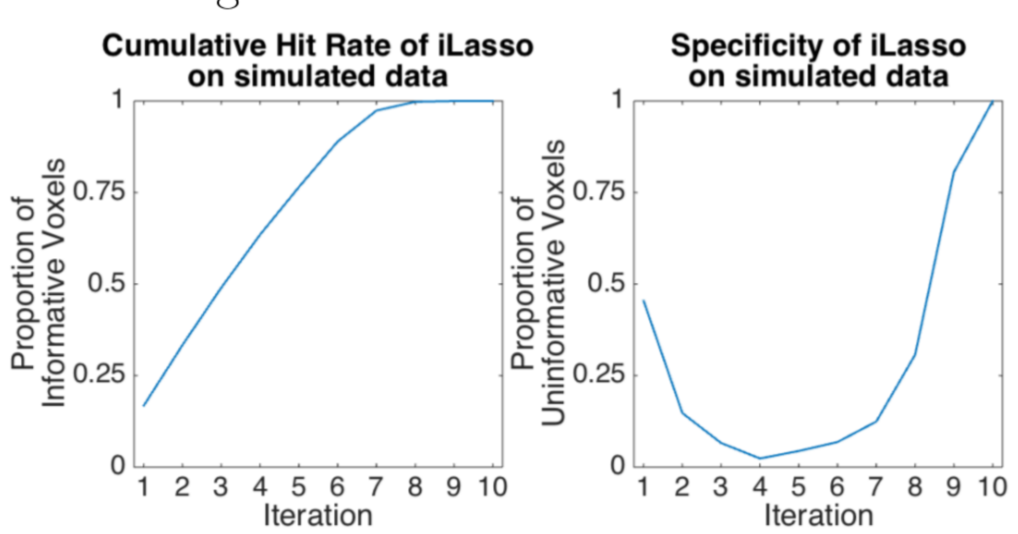

Figure 1: Specificity of Iterative Lasso

Lasso for fMRI analysis

Lasso achieves a sparse solution by selecting voxels that each provide *unique* information. If several voxels are very informative but are correlated, Lasso will select one and ignore the others. By running Lasso iteratively, these correlated voxels can be identified.

Data

- fMRI data from 10 Ps.
- Ps viewed each of 30 celebritiy **Faces**, 30 famous **Places**, and 30 common **Objects** in random order.
- On each trial, the picture stayed on the screen for 5s.
- After it disappeared, Ps rated how much they liked the celebrity, how much they would like to visit the location, or how often they encountered the object in everyday life.

We attempt classification based on each of the 5 (2s) TRs following stimulus onset.

Iterative Lasso Procedure

repeat
  for all cv **do**
    $\beta_{iter,cv} \leftarrow \texttt{Lasso}(X_{cv}, y_{cv})$
    $prediction \leftarrow X_{cv} \cdot \beta_{iter,cv}$
    $performance_{cv} \leftarrow \texttt{dprime}(y_{cv}, prediction)$
  end for
  $iter \leftarrow iter + 1$
until $\texttt{mean}(performance.) < chance$
for all cv **do**
  $v* \leftarrow \texttt{any}(\beta_{\cdot,cv})$
  $X^*_{cv} \leftarrow X_{cv,v^*}$
  $\beta^*_{cv} \leftarrow \texttt{Ridge}(X^*_{cv}, y_{cv})$
end for

Face, Place, and Object ROIs

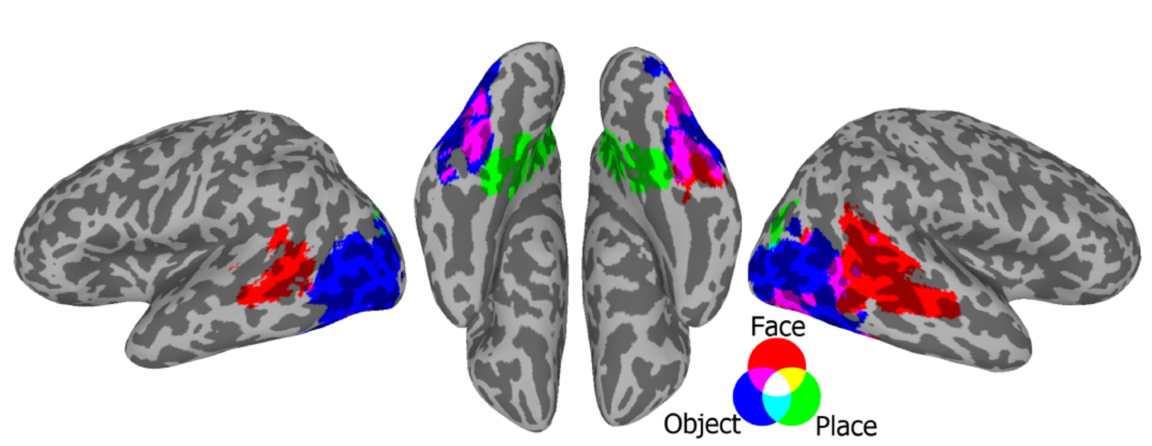

Figure 2: ROIs defined by Julian et al. (2012)[2]

Performance

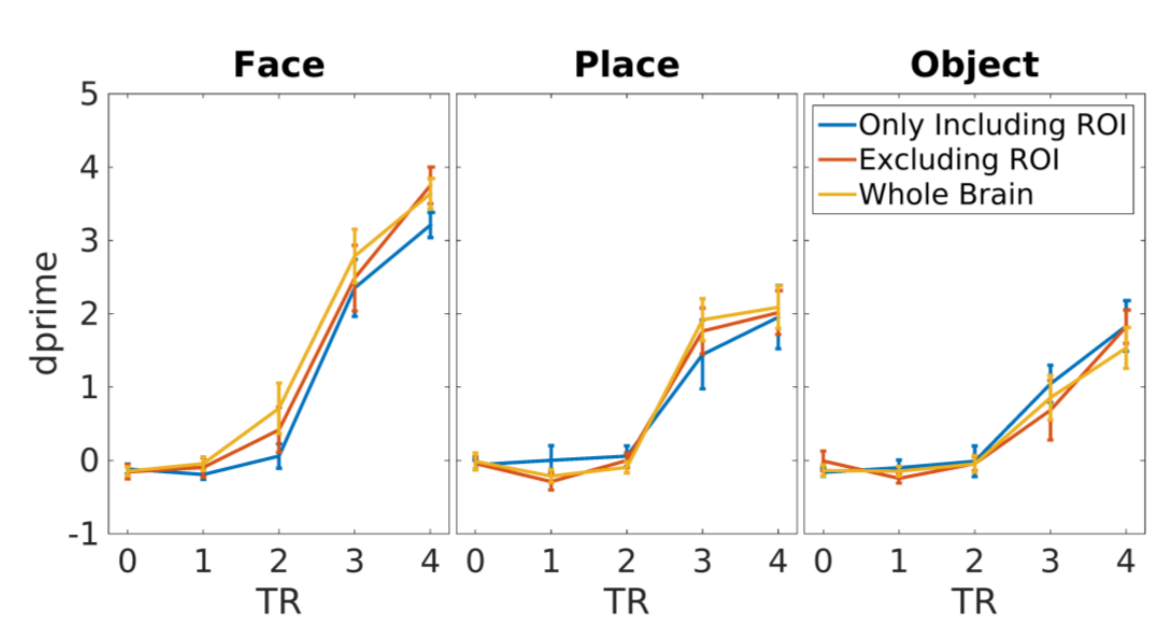

Figure 3: Classification performance. TR 0 is stimulus onset.

Whole-brain Solutions

Voxels identified with a positive weight in more than 5 out of 10 cross validation runs in any subject are plotted on a common brain. Values indicate number of subjects for whom that voxel was selected.

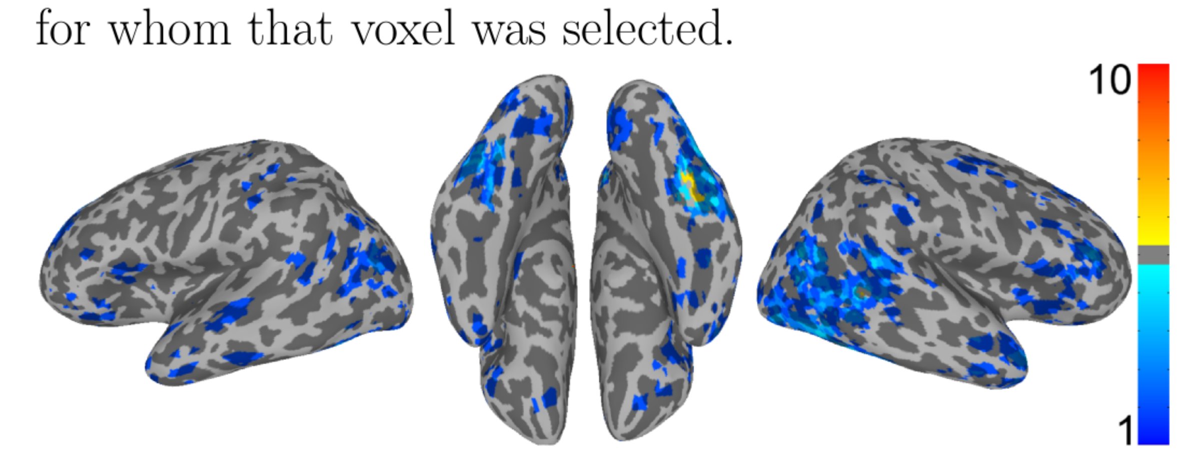

Figure 4: Face Solutions

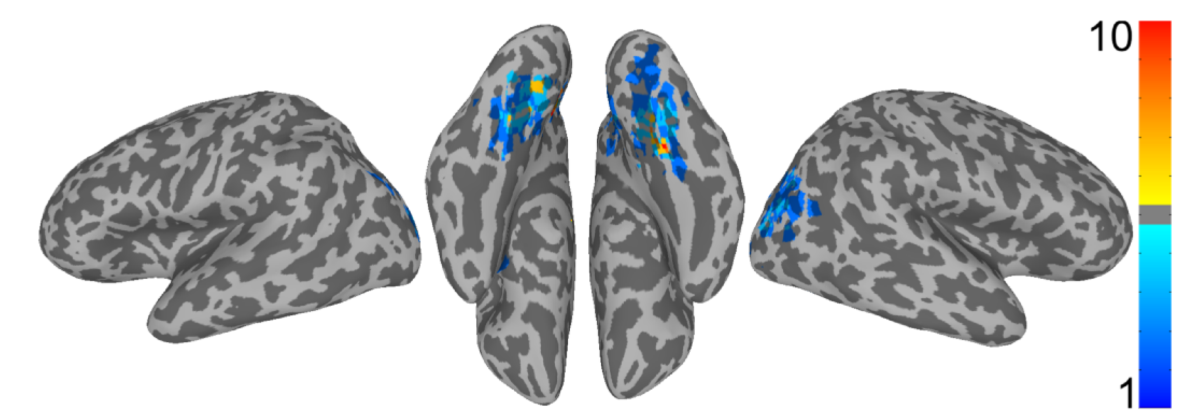

Figure 5: Place Solutions

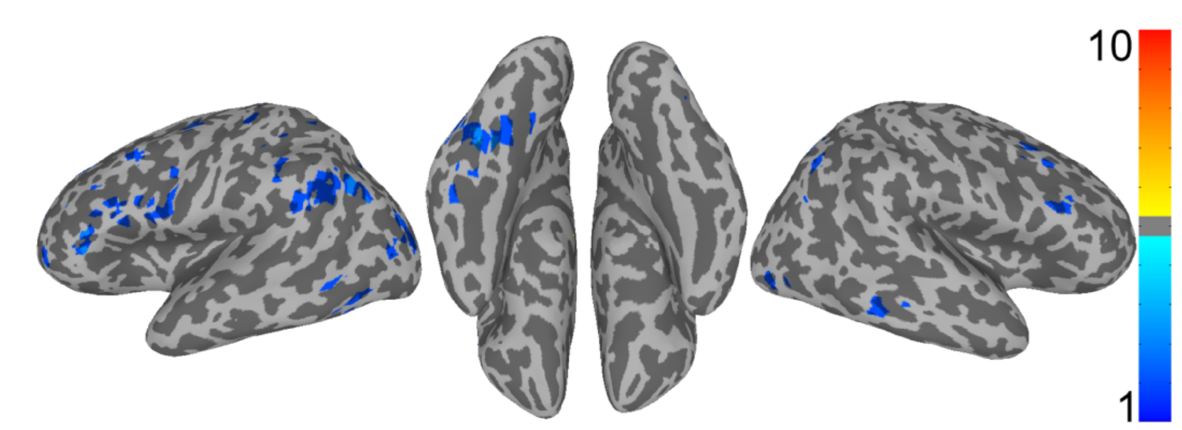

Figure 6: Object Solutions

Aggregate

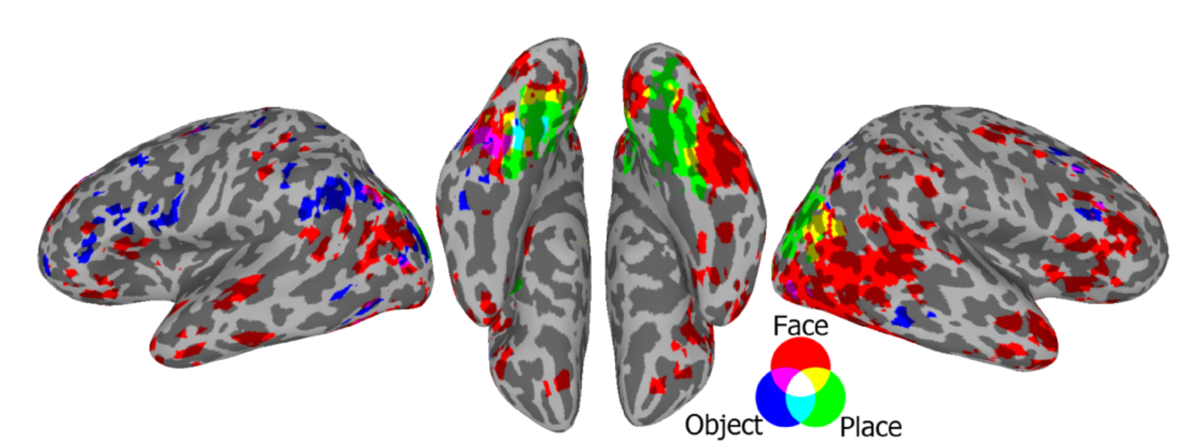

Figure 7: Combined Solution Map

Code for Iterative Lasso

The core code for doing analyses with iterative lasso can be found here:
`https://github.com/crcox/iterativelasso`
With your help, it will become a robust tool!

Where are the discovered voxels?

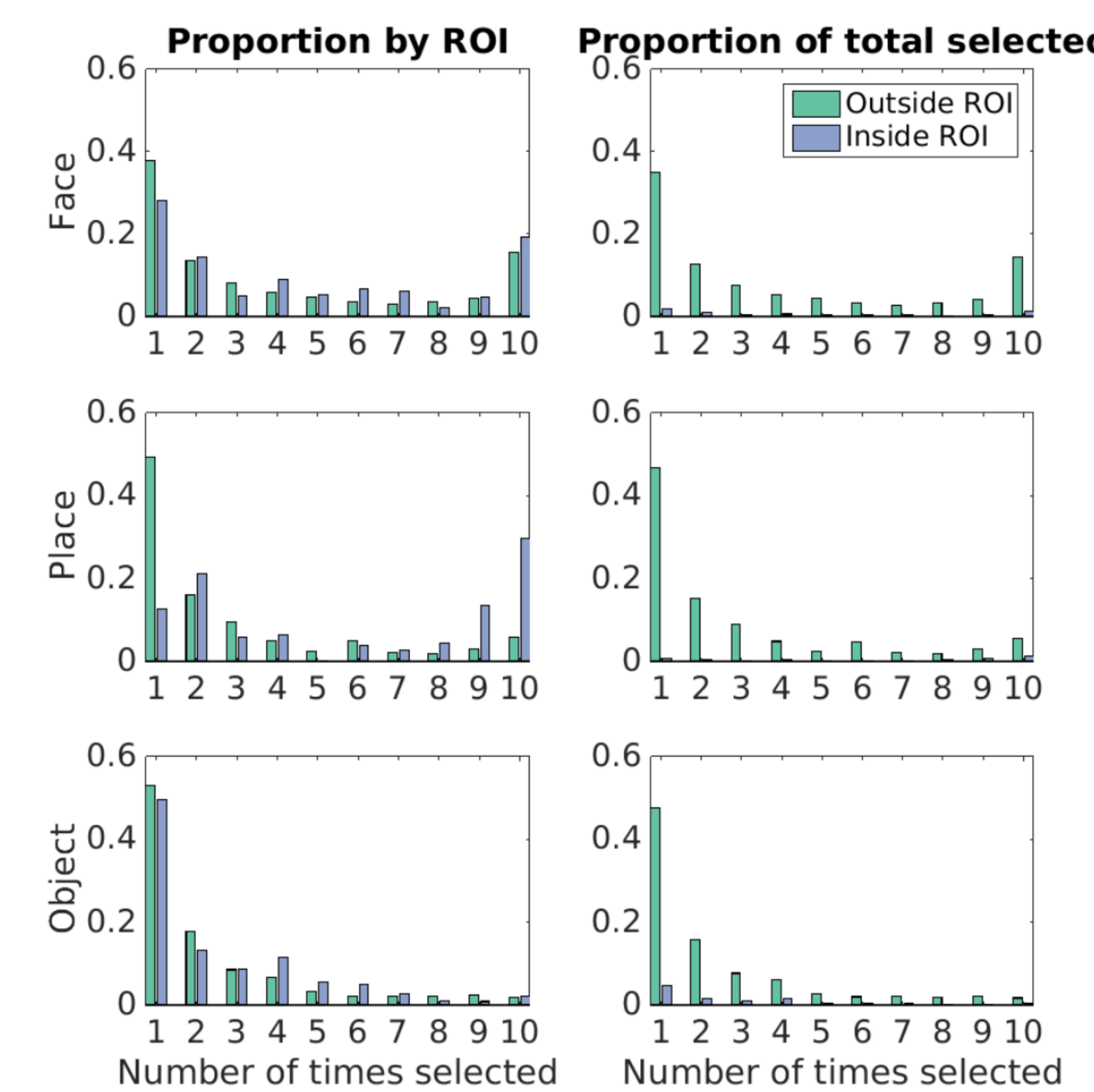

Figure 8: Proportion of voxels selected within and outside the prescribed ROIs.

Conclusions

- A whole-brain multivariate analysis (Iterative Lasso), with no built in assumptions about reliability, specificity, or localization nevertheless identifies much of the neural regions suggested by univariate analyses that do make such assumptions.
- On the other hand, Iterative Lasso also identifies many areas that lie far beyond the prescribed regions of interest.
- These “extra” areas appear to idiosyncratic to each subject.
- We know important information is represented beyond the ROIs, because performance does not drop when the ROIs are removed.

Iterative Lasso appears to be a relatively unbiased approach to whole-brain MVPA.

References

[1] Christopher Cox, Mark Seidenberg, and Timothy Rogers. Connecting functional brain imaging and parallel distributed processing. *Language, Cognition and Neuroscience*, pages 1–15, 2014.

[2] J.B. Julian, Evelina Fedorenko, Jason Webster, and Nancy Kanwisher. An algorithmic method for functionally defining regions of interest in the ventral visual pathway. *NeuroImage*, 60(4):2357 – 2364, 2012.

[3] Robert Tibshirani. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1):pp. 267–288, 1996.