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 (ref), 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 ideosyncratic.

Iterative Lasso

Lasso (ref) is an example of regularized regression:

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

It is standard regression with an additional penalty:

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

Seeks best solution using *fewest* voxels. But that means many informative voxels may not be included in the solution. 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.
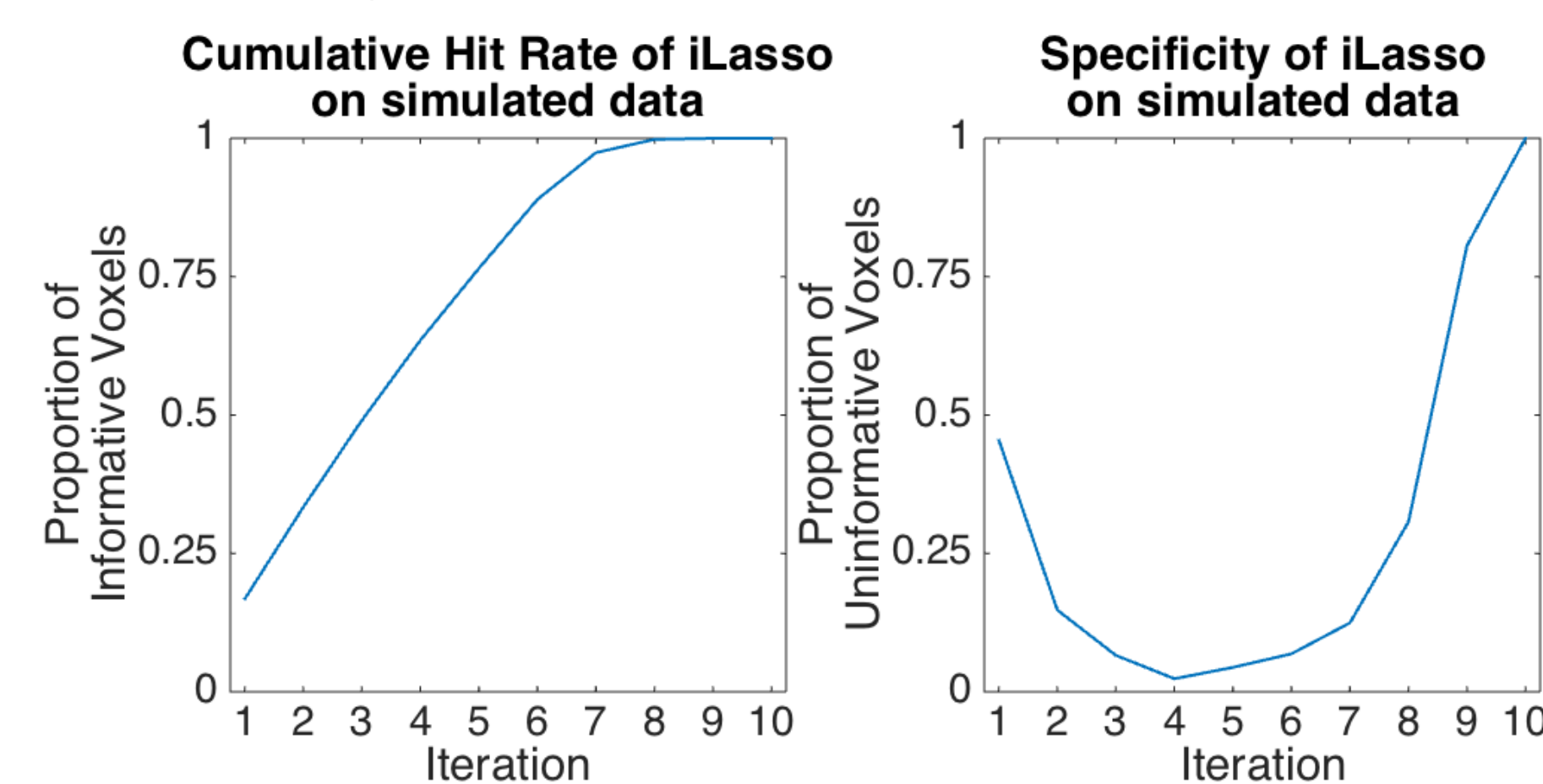

Figure 1: False Alarm Rate

Lasso for fMRI analysis

Lasso achieves a sparse solution by selecting voxels that each provide *unique* information. Is 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.
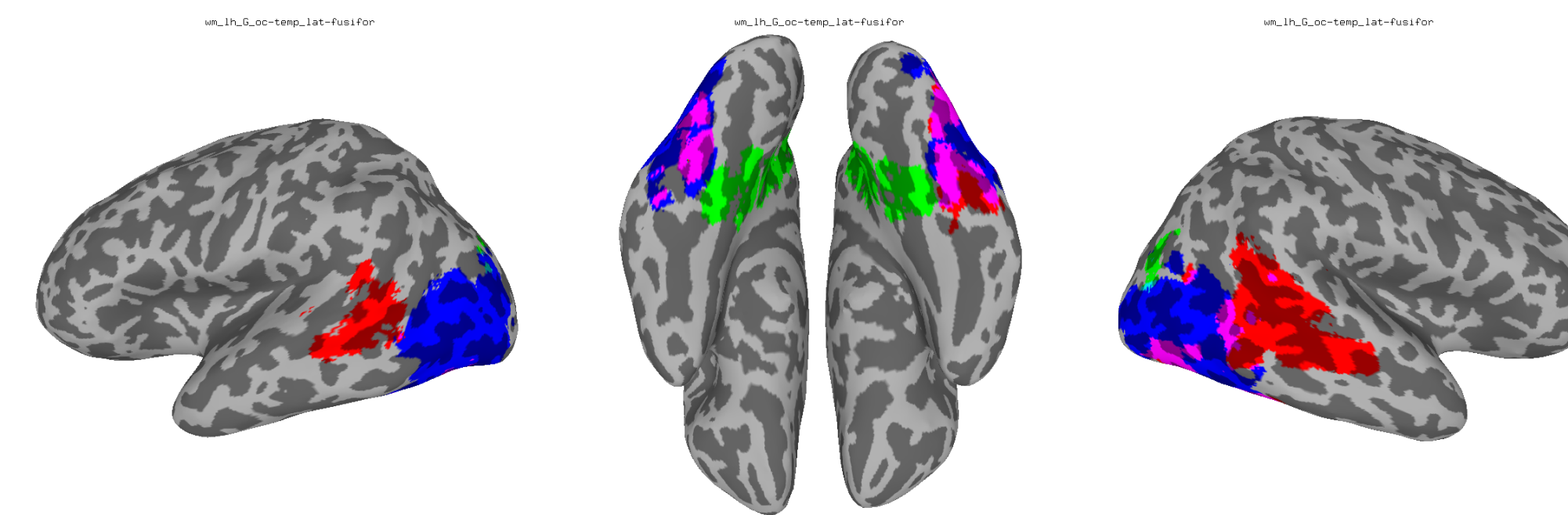
Data and ROIs

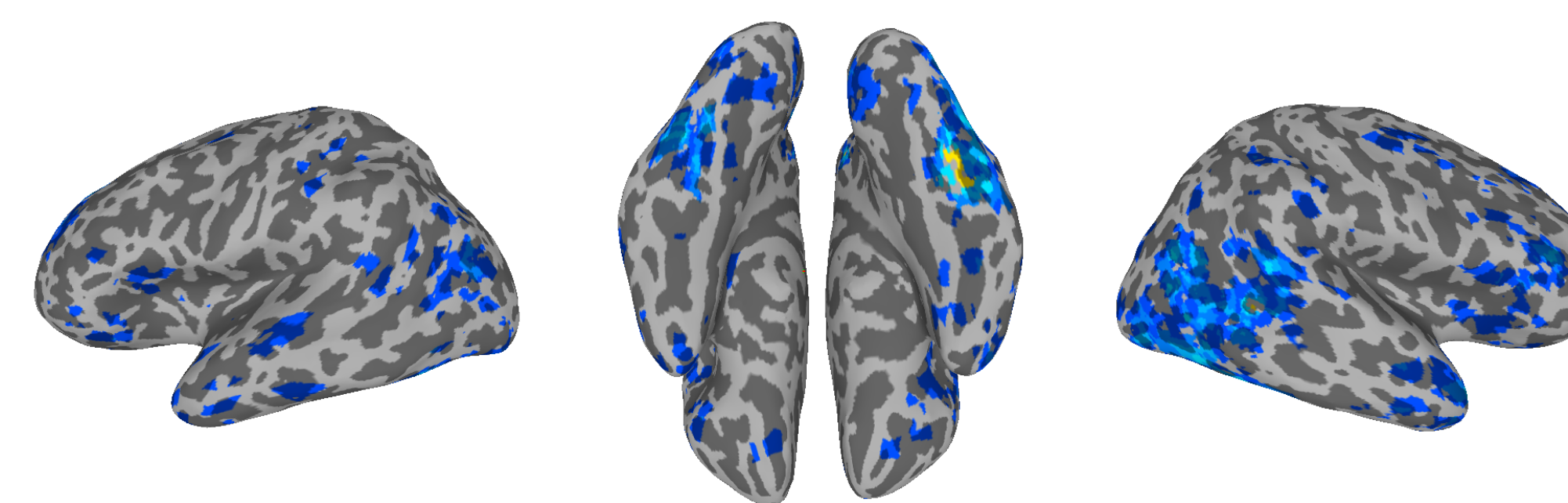Figure 2: False Alarm Rate

Solutions
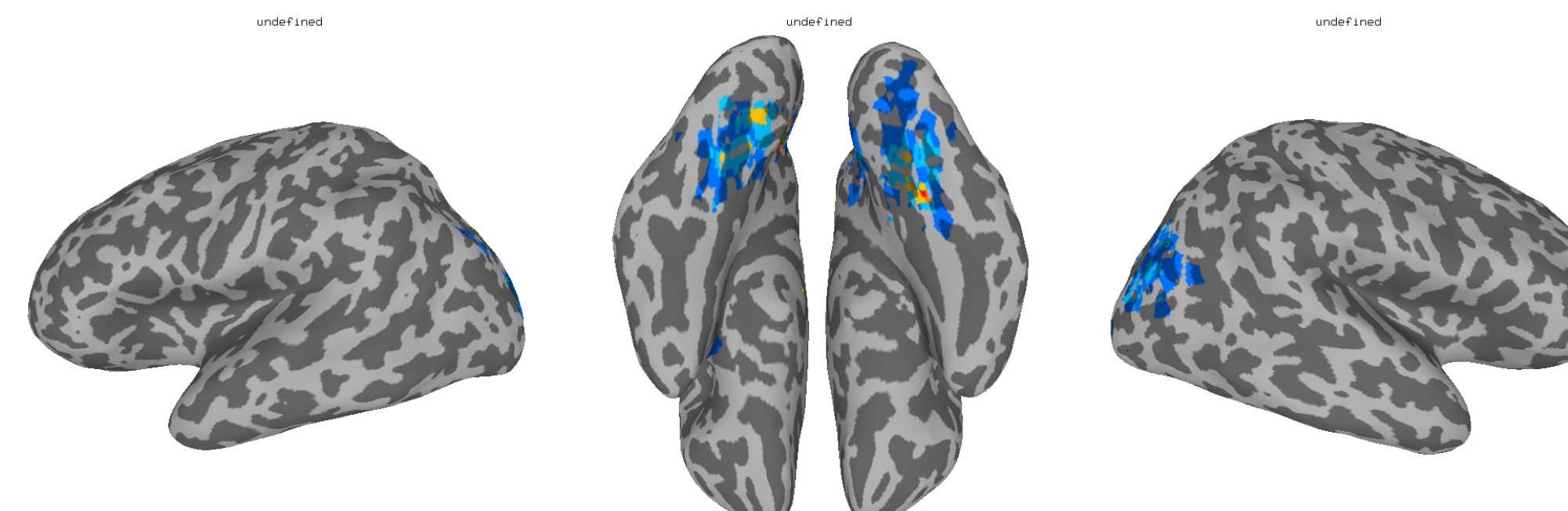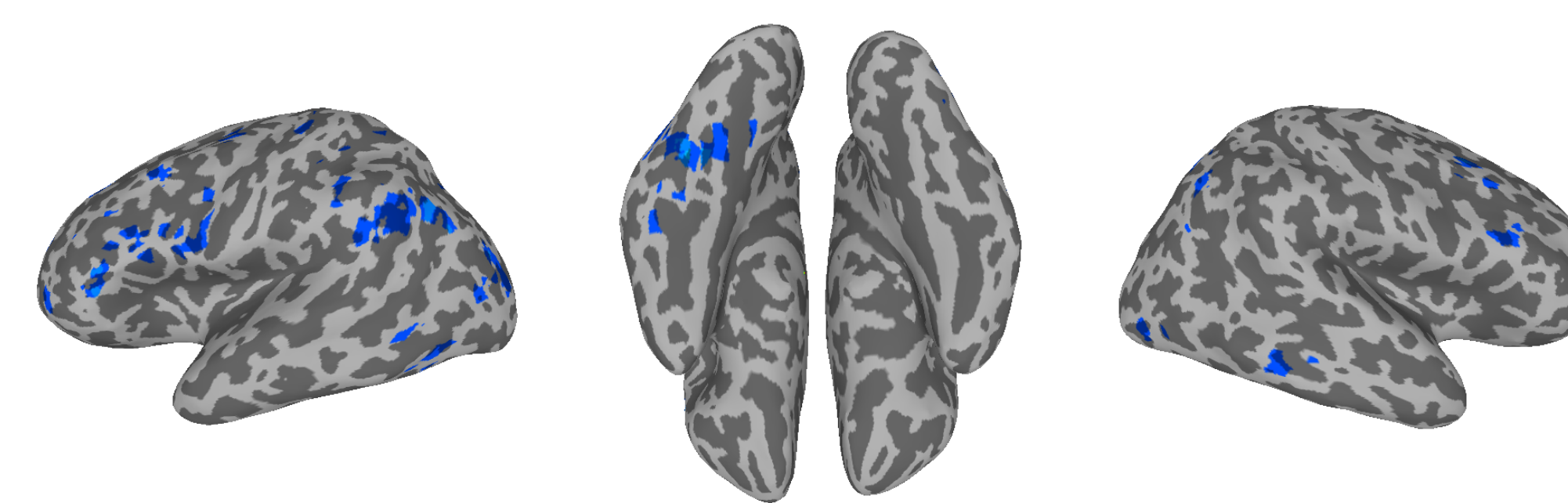

Figure 3: Face Solutions

Figure 4: Place Solutions
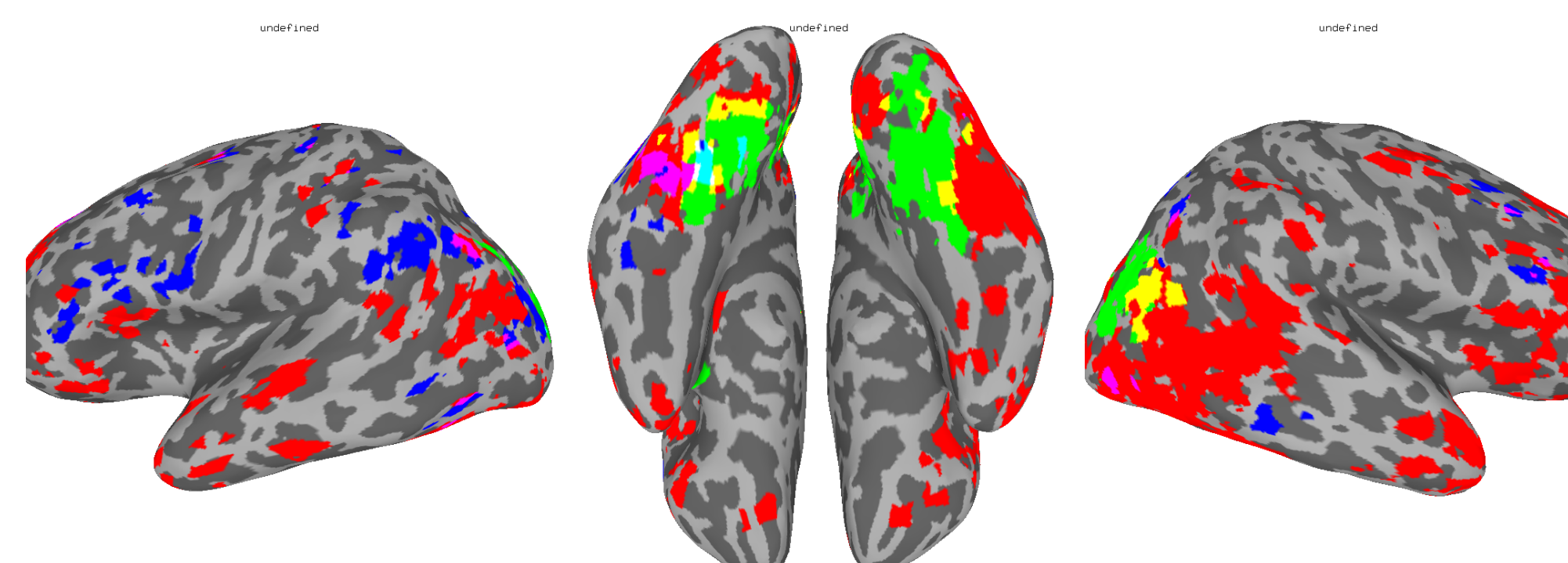

Figure 5: Object Solutions

Aggregate

Figure 6: Combined Solution Map

Alert Block Colours

You can similarly modify the colours for alert blocks (but try not to overdo it):

\setbeamercolor{block title}
{fg=black,bg=norange}

\setbeamercolor{block body}
{fg=black,bg=white}