MVPC

Coutanche (2013): Representatonal strength (RS):

Correlation-based classifier:

- 8 natural categories: faces, houses, cats ...
- provides RS timeseries.

Searchlight: arctanh(r(RS_seed, RS_searchlight))

Significance (clusterwise control):

- permute RS values in seed. (i.e., not projecting the neuroimaging data onto different bases, but shuffling the RS time-series), repeat searchlight n times
- save size of largest cluster saved from each perm. 50'th largest cluster saved from null. yields $p < 0.05$ cluster threshold.
-

Coutanche, M. N., & Thompson-Schill, S. L. (2013). Informational connectivity: identifying synchronized discriminability of multi-voxel patterns across the brain. Frontiers in Human Neuroscience, 7, 15â€“15.

MVPC

Coutanche (2013)

Limitations

- the original RS in seed reflects noise and signal
  - i.e., discriminability might reflect global noise signal across brain, such as noise.
  - note: not a problem for contrasts between conditions (e.g., face vs. house in high vs. low distraction conditions)*
- Important modulatory signals need not represent exogenous information represented in the seed
  - eg., endogenous attentional signal for "color" need not support decoding of "red" vs. "green".

Standard assumption: same noise across conditions.

"Multivariate Pattern Dependence"

Anzellotti (2017)

Cross-validated analysis:

1. Training set: unsupervised dimensionality reduction in seed and target (PCA)
2. apply transform to testing data
3. predict seed PC's from target PC's via multiple linear regression
4. r(y, ypred) for each seed component
5. weighted mean of correlations (by proportion variance explained)
6. Statistical Significance: sign flipping permutation test (SnPM)

Anzellotti, S., Caramazza, A., & Saxe, R. (2017). Multivariate pattern dependence, 1â€“20.

"Multivariate Pattern Dependence"

Anzellotti (2017)

Advantages:

- Seed and target can be in different representational space

Limitations:

- Bases are not (necessarily) functionally-relevant
- Noise (...could be mitigated with a contrastive approach)

Anzellotti, S., Caramazza, A., & Saxe, R. (2017). Multivariate pattern dependence, 1â€“20.

New Approach

Overview

1. Multivariate stimuli (orthogonal binary dimensions)
2. Representational strength via logistic regression
    - yields `nSamples * nFeatures` matrix
3. ZCA transform: Remove correlation between features.
4. Permuted seachlight analysis (250 iterations)
    - Shuffle the **labels**, project seed onto resulting bases
    - *Cross-validated* searchlight decoding (SVR)
5. Significance: Sign-flipping permutation test

New Approach

Improvements

Orthogonal Feature Representations:

- We can differentiate signals selectively modulating individual features, from those modulating all features at once (e.g. noise / engagement) (ZCA transform)

Robust to Differences in Representational Space:

- Searchlight need not be in same representational space as seed (SVR: voxel-space of each searchlight)

Shuffling labels

- Our hypothesis about information content changes
- Noise remains synced*

* We assume that noise is similarly decodable across all hypotheses/bases.

New Approach

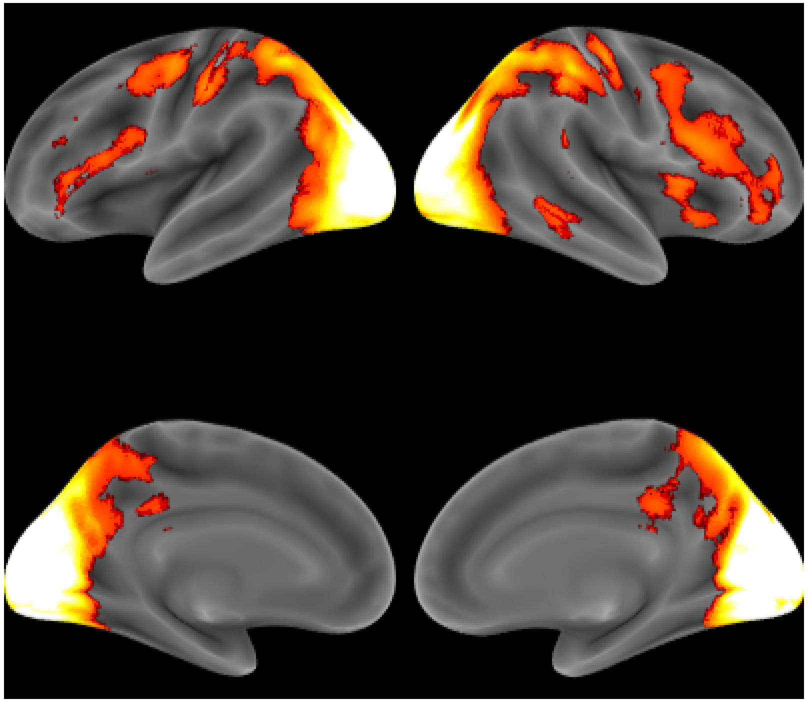
IPS Seed

Identified IPS voxels via logical conjunction between OTC connectivity map and Neurosynth map (*"attention"*)

* We assume that noise is similarly decodable across all hypotheses/bases.

New Approach

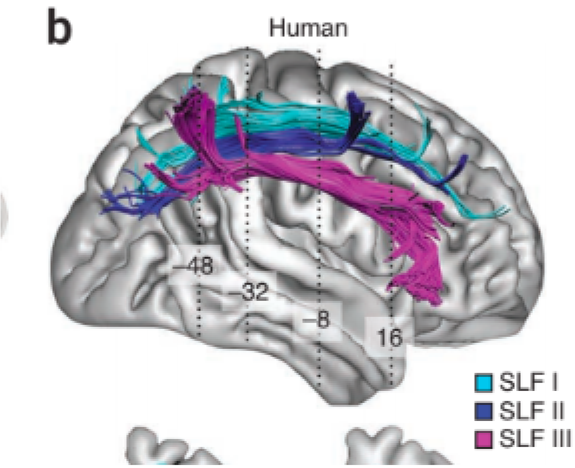
Searchlight Results

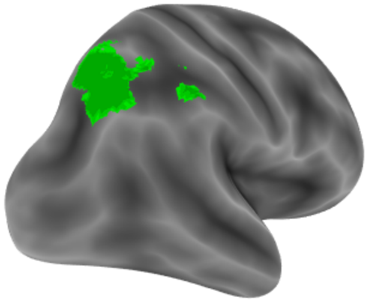


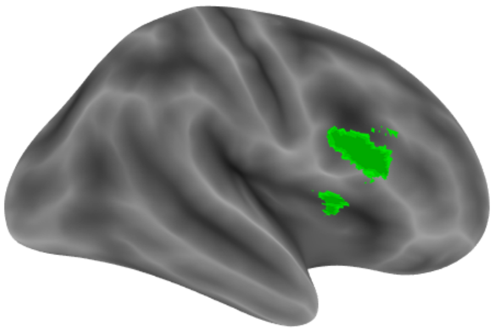
Voxelwise FWE < 0.01

* We assume that noise is similarly decodable across all hypotheses/bases.

New Approach: ROI's







Thiebaut de Schotten, M., Dell'Acqua, F., Forkel, S. J., Simmons, A., Vergani, F., Murphy, D. G. M., & Catani, M. (2011). A lateralized brain network for visuospatial attention. Nature Neuroscience, 14(10), 1245–1246. https://doi.org/10.1038/nn.2905

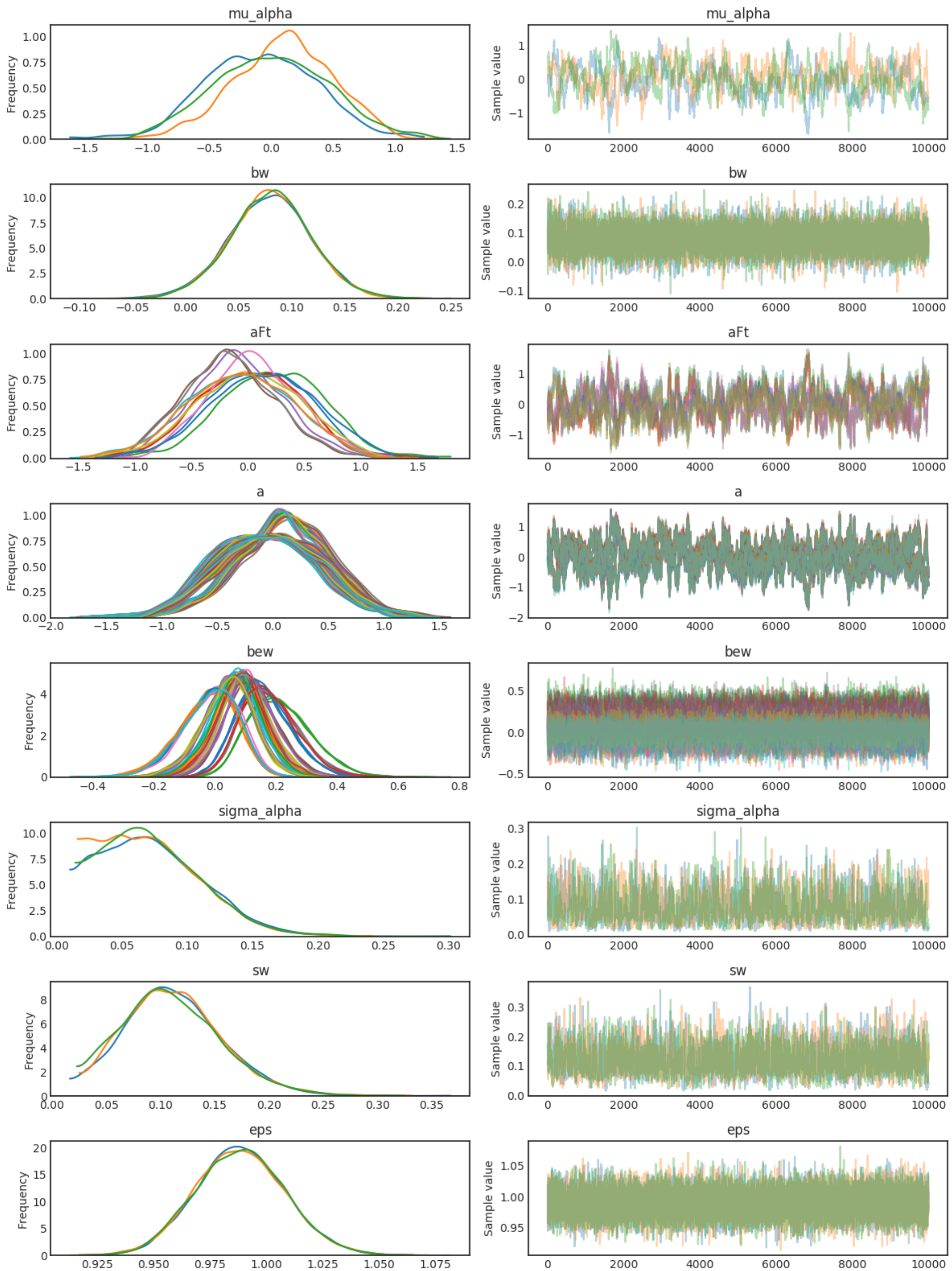
New Approach

Does attention modulate connectivity?

seed: Bilateral IPS target: RIFG

1. project IPS to bases (logreg, zca transform)
2. cross-validated prediction of IPS bases using rIFG voxels
3. for each feature and stimulus, calculate arctanh(r(y, ypred))
4. hierarchical regression:

```
arctanh(r) ~ w + visualFeatures + (1 + w|sub)
```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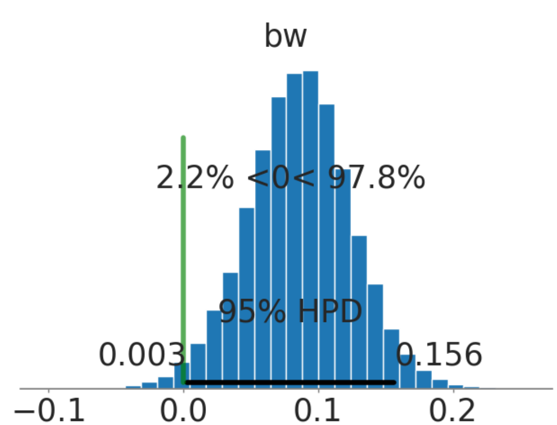
Sample value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