Potential Cortical and Computational Biases In Representational Similarity Analysis

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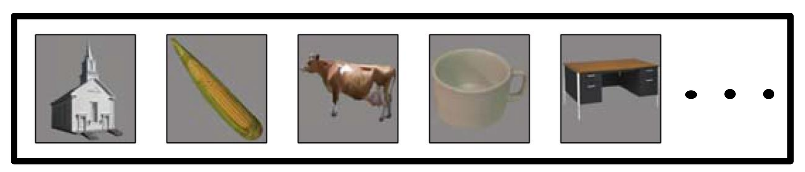
Background

Representational similarity analysis (RSA) is a valuable tool to observe and model complex patterns in cortical information processing (Kriegeskorte 2008). It has gained substantial traction, e.g., in studying the link between computer vision models and biological vision (Leeds 2013, Khaligh-Razavi 2014) and has been used successfully across species, recording modalities, and cortical regions. (Kriegeskorte 2008, Devereaux 2013)

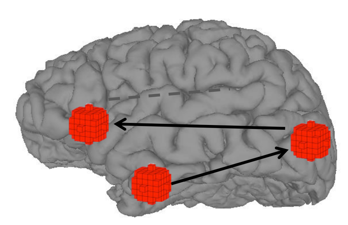
Our present work employs RSA to identify semantic models of visual object perception in the brain. In doing so, we find evidence that **models with strongly skewed responses are most commonly matched to local cortical encodings. Simulations indicate RSA is more sensitive to near-matches between skewed representations** compared to models with more evenly distributed behavior**.** We also study RSA's robustness to adjustments in significance testing assumptions

Methods: fMRI data, semantic models, RSA

- Participants shown photos & words of 60 real-world objects, 6x each, passive viewing
- BOLD signals recorded with slow event-related design (2 sec TR, partial coverage) for 5 subjects (Leeds 2013)



- 515-voxel sphere of responses at each location across the cortex (radius=5 voxels)



- Ratings of 218 semantic questions (models) recorded for 60 objects above and 940 additional objects (Sudre 2012)

Rating: Disagree-neural-agree scale of 1-5

- Identity
- Emotion
- Action
- Location

Can it fly?

Would you find it in a house?

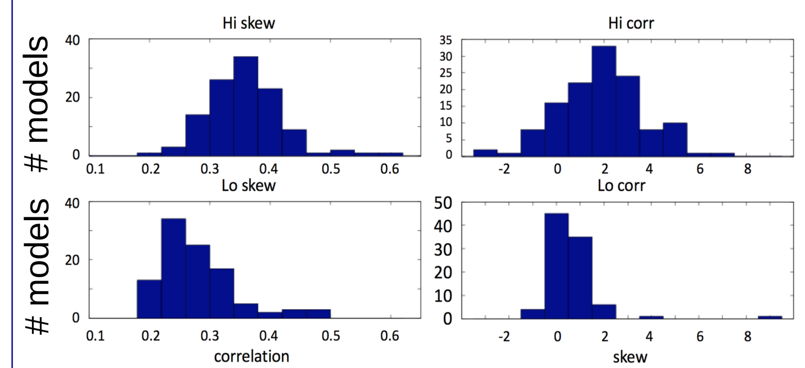
Is it friendly?

- RSA Distance matrix computations:
  - Cortical data: $D^{searchlight}_{x,y,z}(s^i, s^j) = 1 - r(v(s^i), v(s^j))$
    - $D_{x,y,z}$ – matrix for searchlight at cortical location (x,y,z)
    - $\mathbf{v}(s^i)$ – voxel responses for stimulus s^i (Leeds 2013). $r(\cdot,\cdot)$ is Spearman correlation
  - Semantic data: $D^{semantic}(s^i,s^j) = |rate(s^i)-rate(s^j)|$
    - $rate(s^i)$ – subject rating of stimulus s^i
- **fMRI vs model comparison:** Spearman correlation between elements of neural and model distance matrices
- **Significance testing:** Object ratings randomly permuted 100 times and used to compute 100 distance matrices and distribution of searchlight vs. permuted-model correlations (mean kurtosis=3). Z score computed from mean and standard deviation of permuted correlations. FDR significance threshold q<0.005 (p<2e-5, Z>3.5).

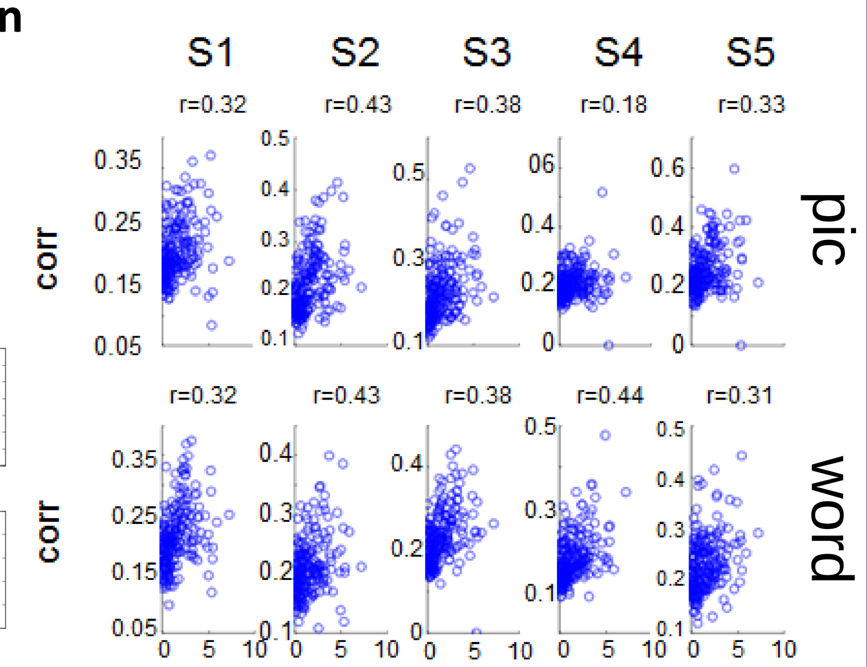
Results: model and biological skew

Model skew and cortical matches

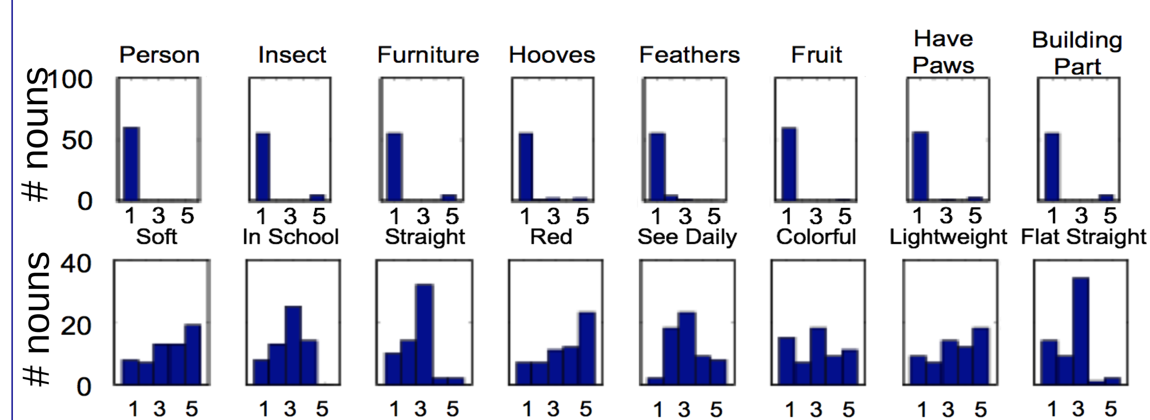
- **We observe a connection between the skew of a semantic model's rankings and the magnitude of its correlation with voxel representations**



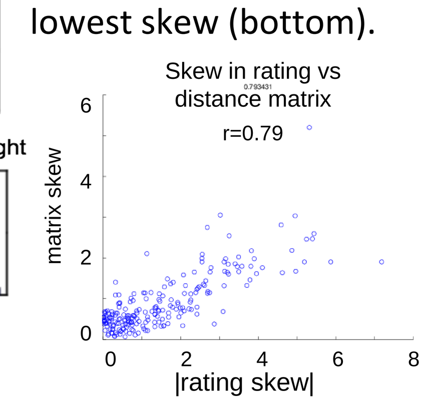
(Left) Distribution of max cortical correlations for models with skew above 1 (top) and below 1 (bottom) **(Right)** Distribution of skews for models with max correlation above 0.3 (top) and below 0.3 (bottom)



Skew vs max cortical correlation (q<0.005) for each semantic model while viewing picture (top) and word (bottom) stimuli. Correlations above each plot.

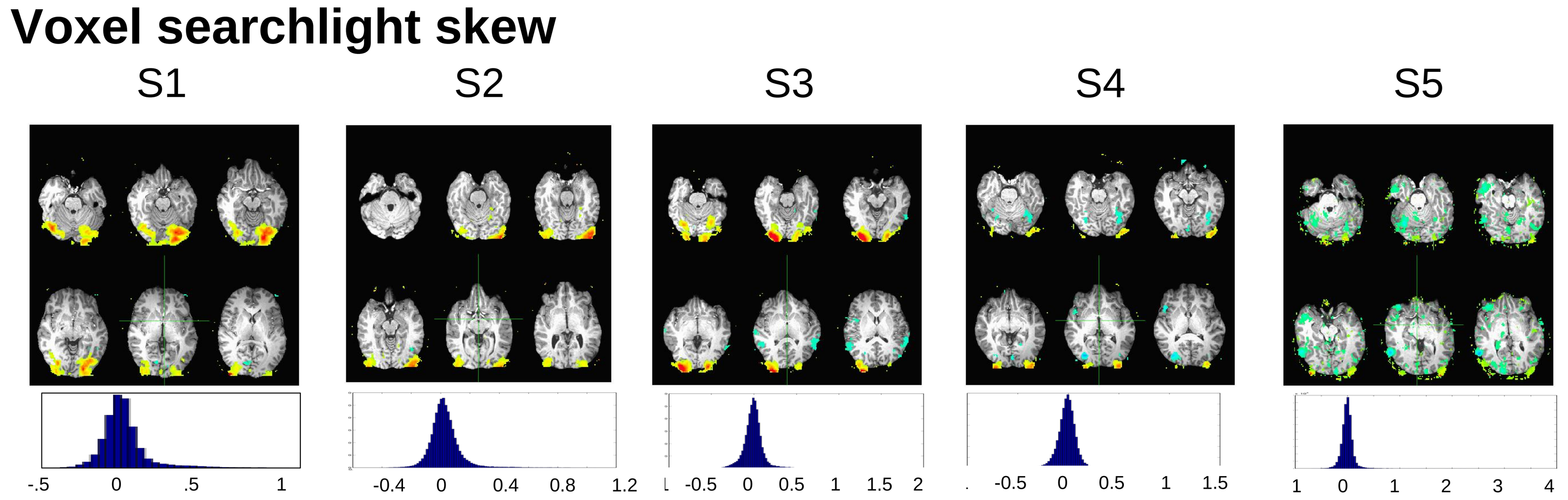


Distribution of ratings for eight features with highest (top) and lowest skew (bottom).



- Low skew models: continuous-valued property, or most nouns neutral (3)
- High skew models: object-category, typically most nouns "non-member" (1) and few nouns as "full-member" (5)

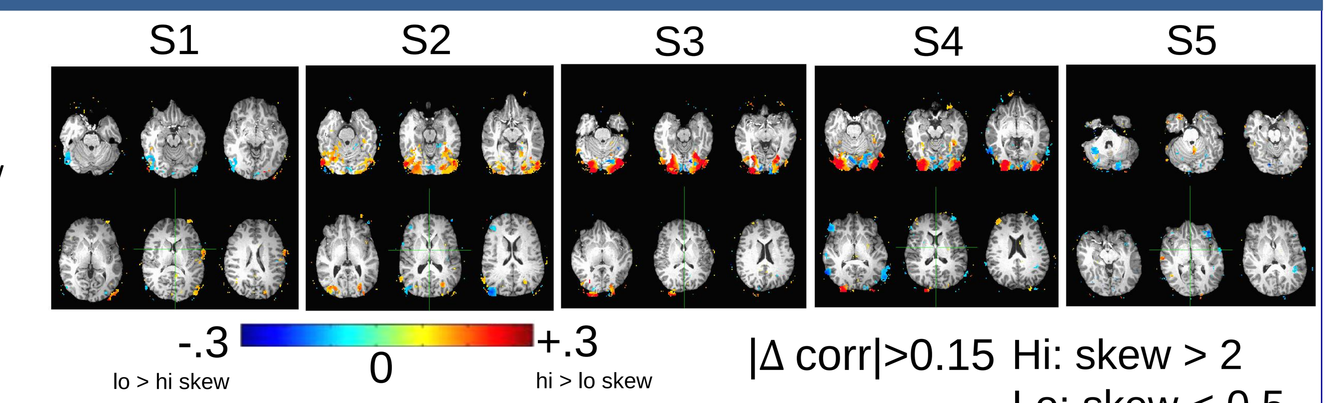
Voxel searchlight skew



Spatial location of searchlight skews across ventral cortical slices. Full distribution of skew values shown below each set of slices.

- Most searchlight object responses not highly skewed
- Cortical skews less extreme than semantic models
- Highest skews in early/mid vision regions

Results: Locations of model-cortical matches

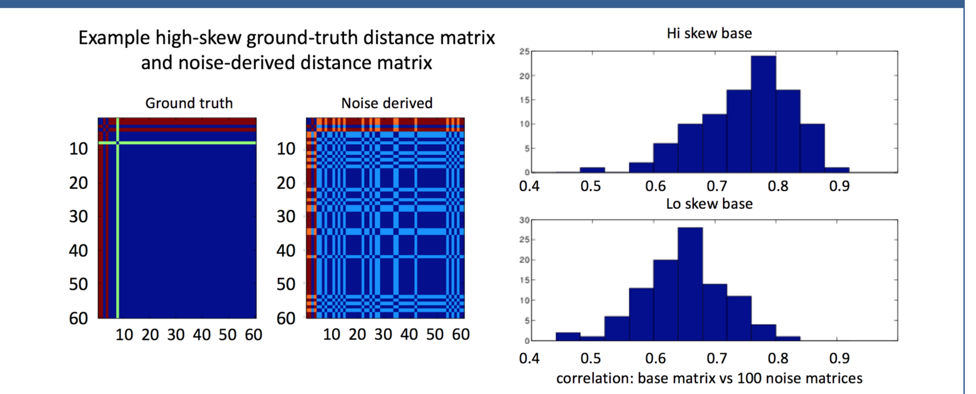


- Top model-cortical matches in high skew cortical searchlights
- Low skew models more commonly match medium-skew searchlights

Simulation: noise effects in RSA

Methods

- Initialize 2 "ground truth" rating vectors (1) high-skew ("has paws?") and (2) low-skew ("hard inside?")
- Create 100 copies of each rating vector and add Gaussian noise.
- Generate distance matrix for each rating vectors
- Compare "truth" and "perturbed"



Distribution of correlations for noisy versus ground-truth representations of sixty objects based on high skew ground-truth ratings (top) and low skew ratings (bottom).

Results

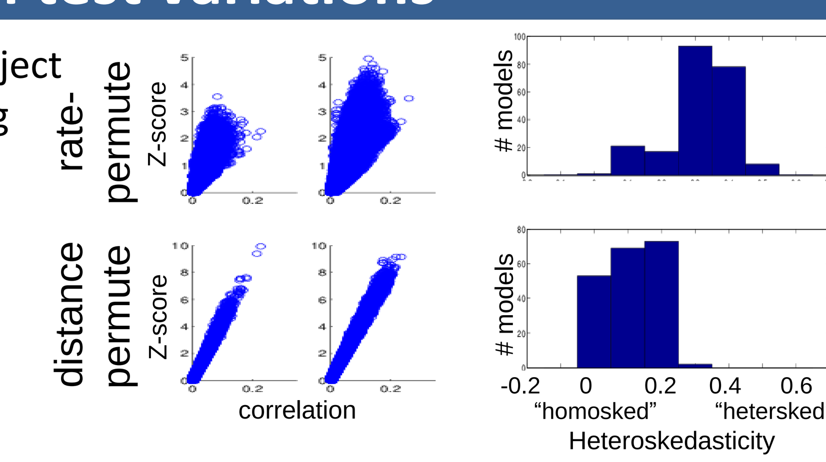
Substantially higher post-noise correlations when ground-truth representation has higher skew

Permutation test variations

We assess statistical impact of permuting object ratings (Kriegeskorte 2008) versus permuting distance matrix entries (without preserving distance structure).

Variance of Z- scores increases with higher model-cortical correlations.

Higher variance between correlation and Z-scores when permute object ratings rather than distance matrix entries



(Left) Comparison of correlation values and Z scores based on permutation of object scores (top) and distance matrix entries (bottom) for two example semantic models. (Right) Distribution of Z-score-to-correlation variance (heteroscedasticity) based on Breusch-Pagan test (Breusch 1979)

Discussion

- **High skew (object-category) models have higher RSA matches with the brain** than do low skew models (property ranges)
- Early/mid-visual regions have high-skew object representations
- **Skewed distributions show greater robustness to Gaussian noise**, expected while studying neuroimaging data
- High RSA correlations strongly vary in statistical significance

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Acknowledgements

This work was supported in part by funds to Daniel Leeds from the Fordham University Faculty Research Grant. Valuable poster layout assistance provided by William Charles **Carnegie Mellon University** Shared data from labs of Michael Tarr (Leeds et al. 2013) and Tom Mitchell (Sudre et al., 2012)

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