A Project of Unkuestionable Koality by the ~~Un~~Koalified Koalantined Koalas of pod-195-capricious-koalas

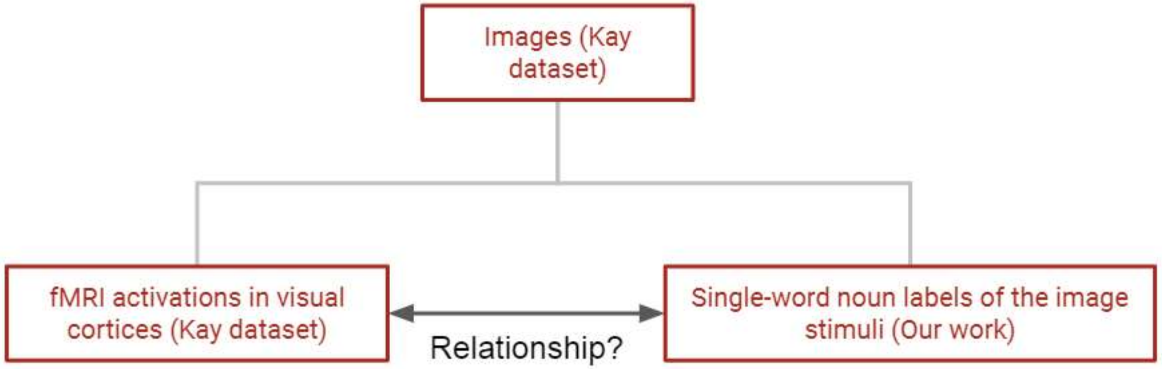
Wenxuan Guo, Sumayyah Khan, Wesley Leong, SungMin Park, Rohan Saha

Background

- Human visual cortex has been shown to encode objects in a hierarchical way, representing from low level features such as lines, bars, and edges to high-level features invariant to illumination, size, etc.
- Basic levels of object categories (e.g. tigers) have invariant features such as shape, so V4 representations might have certain semantic information.

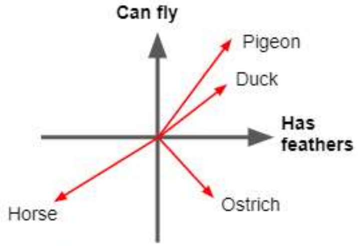
Research question(s)

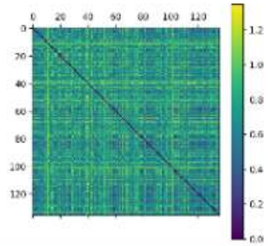
- Does V4 cortex of the visual pathway encode semantic distinctiveness of objects?
- Does it contain more semantic information than lower level visual cortices?



Methods

Comparing Representational Dissimilarity Matrices (RDM)





Word vector RDM

Our project scope

Images (Kay dataset)

Manual labelling of images (eg. “zebra”)

Compute **z-scored** fMRI activation patterns for each image (Kay dataset)

Data exclusion
1. Unidentifiable or Ambiguous object
2. Multiple objects

Represent words as **vectors** (Word2Vec)

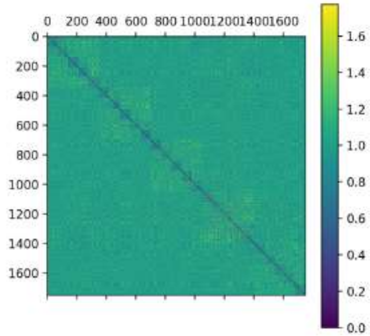
Compute stimulus-wise dissimilarity between word vectors using cosine similarity

PCA on voxel responses (90% variance)

Compute stimulus-wise dissimilarity between fMRI activity using correlation distance

Spearman ranked correlation

Weird phenomenon: small dark blue squares along the identity line indicate strong correlation (low dissimilarity) between stimulus pairs *within* each block of the experiment; 5 big yellow squares low correlation (high dissimilarity) within each of the 5 scanning sessions.
Hypothesis: artifact either of fMRI preprocessing or movement (we didn't have time to get into this too much)

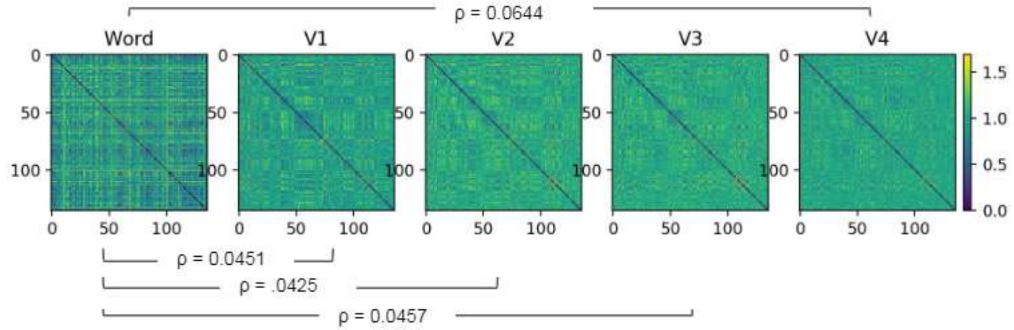


fMRI RDM

Courtesy of Kay/Gallant

Results

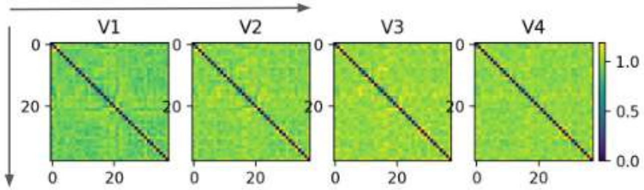
1) Spearman's rank correlation between the RDM of word vectors and the RDMs of different regions of visual cortex:

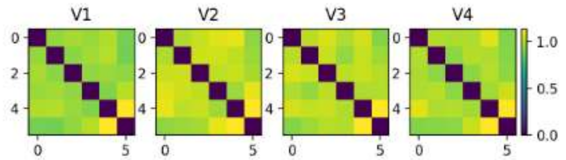


2) Qualitative analysis of the RDMs of some word labels associated with multiple stimulus images (frequent occurrence of these objects in the stimuli):

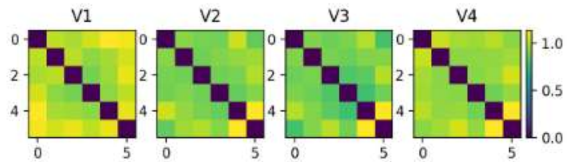
Oh, **Man**

Both x, y axes: all the stimuli images labelled as **"man"**





A **Zebra** never changes its stripes



Cry me a **River**

If more semantic representation is encoded in V4 than early visual cortex, we should be able to find that V4 RDM has lower dissimilarity (more green) than V1-3 RDM of the stimuli that have the same word label. These three examples show that this is not the case.

Conclusion & Discussion

1) Our analyses failed to find any evidence of semantic representation of images in V4 visual cortex. Further study on the correlations between semantic information and visual cortex requires careful design of the stimuli.

2) Numerous possibilities why we did not find expected results:

A. V4 does not encode the same kind of semantic information that Word2Vec is encoding.
B. Word2Vec doesn't actually represent visual semantics.
C. No way to tell what the subject was actually looking at during the experiment (no fixation point during manual labelling).
D. The relationship between semantic information and visual cortex representation is non-linear.
E. Temporal sequence of the stimuli influence visual cortex activation in a way unrelated to semantics.

NEUROMATCH ACADEMY

Final Project
Pod 009-Keen Bullfinch

POD 009-KEEN BULLFINCH

The Rolling Neuro-Stones Project
Mentor: Gunnar Blohm
TA: Katherine Overman

Utilized Dataset: Kay, K.N.; Naselaris, T.; Gallant, J. (2011): fMRI of human visual areas in response to natural images. CRCNS.org. http://dx.doi.org/10.6080/K0QN64NG

Robert Nokolai

Gustavo Juantorena

Daniel Triana

Question: What is the response amplitude per voxel given the mean spatial frequencies of the natural images in the dataset?

Experimental Method: For our project we wish predict the response amplitude of the voxels given the mean spatial frequencies of the natural images in the data set. We use a Generalized Linear Model (GLM) whose output is the predicted voxel response for every ROI using the spatial frequency information of every image. To address over-fitting, we utilize an L2 regularizer with our linear regression model.

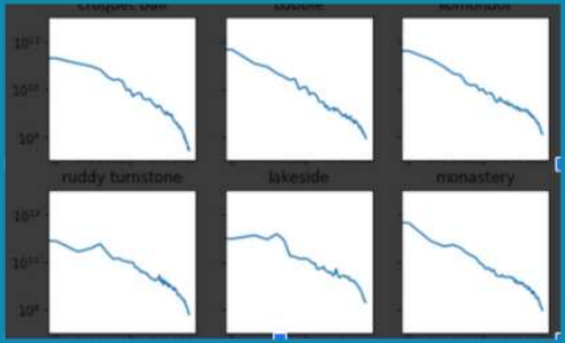
SPATIAL FREQUENCIES

Selected Feature

Refers to the quantitative measure of a periodic pattern across space. In mathematics, physics, and engineering, spatial frequency is a characteristic of any structure that is periodic across position in space. Normally is expressed as the number of cycles per degree of visual angle.

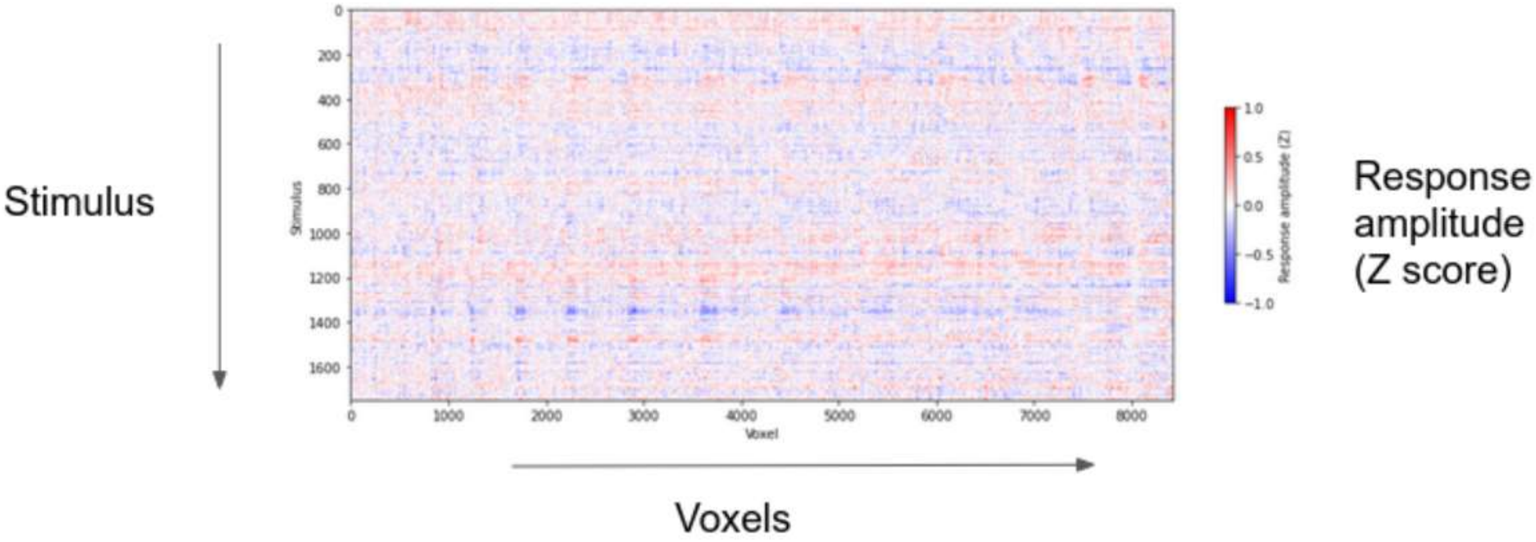
The spatial-frequency theory of vision is based on two physical principles:

- Any visual stimulus can be represented by plotting the intensity of the light along lines running through it.
- Any curve can be broken down into constituent sine waves by Fourier analysis.



MODEL

Initial Data



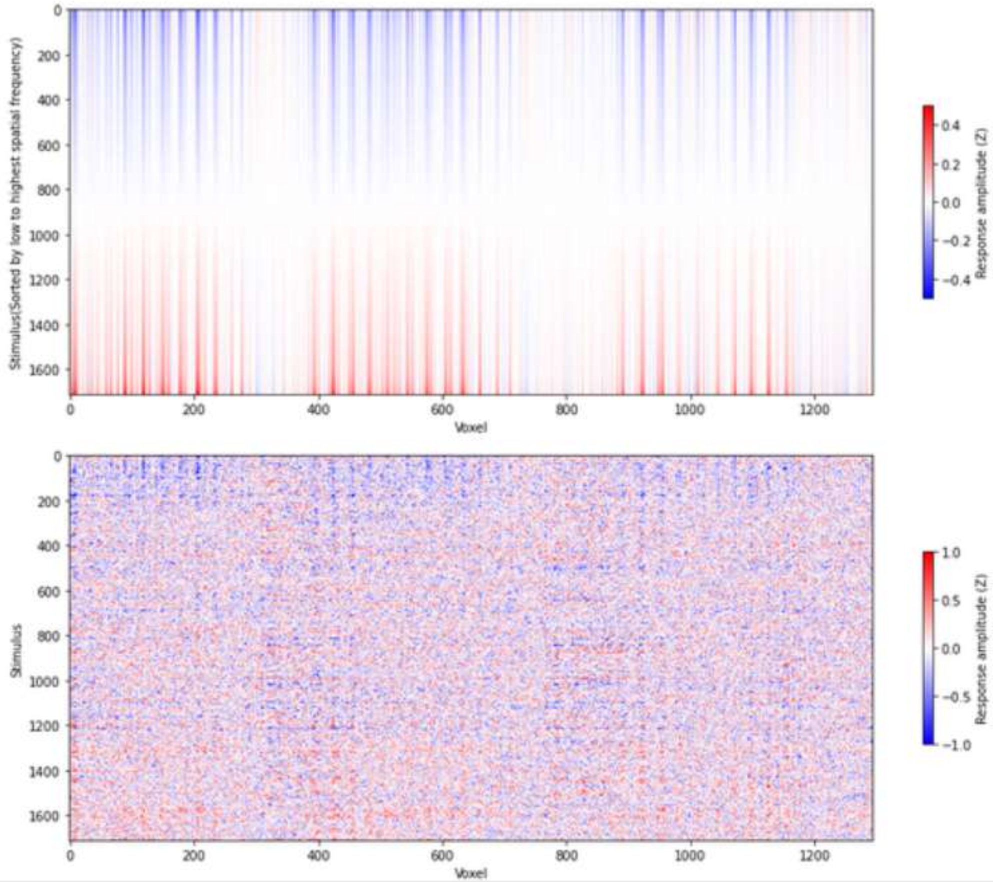
- **Given the characteristics of the Data Set and the output expected, we've decided to use a Generalized Linear Model (GLM)**
- **To address the overfitting problem of our model, we use an L2 Regularizer (Ridge-regression) sklearn.linear_model.Ridge class**

y = Voxel response amplitude
X = Spatial frequency of the images

STIMULUS VS. VOXELS

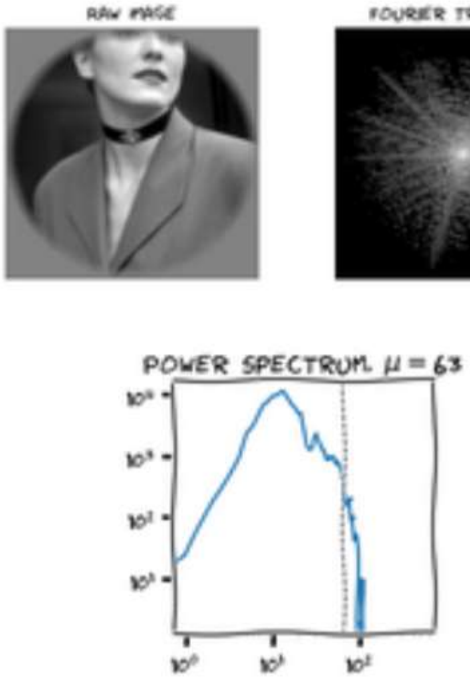
Region of interest: V1

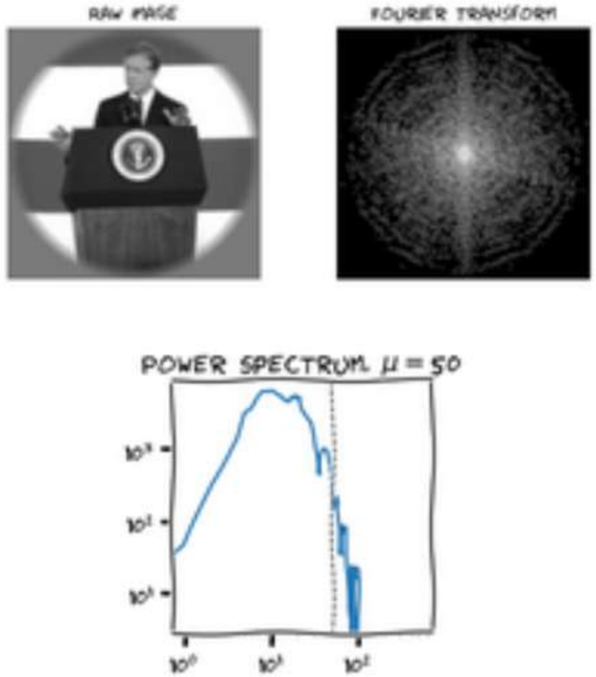
The stimulus are sorted by low to highest spatial frequency



FOURIER TRANSFORMATION OF THE IMAGES

Power Spectrum





OUR EXPERIENCE

Our favorite part of the project was the collaboration and the chance to really get to know our peers.

The project was challenging for all the members of the team. None of the team-members has previously worked with fMRI datasets.

The most time-consuming part of the project was to define the scientific question that we wanted to address.

The time-constraints were the more challenging aspect. We believe in our hypothesis and that we could results with more time.

The mentorship of Gunnar Blohm was invaluable to us establishing our priorities and to narrow the possible approaches and methodologies that we could use.

Our first approach involved using advanced third-party machine learning tools that were quite foreign to the group.

Overall, this was a great experience that resulted in learning new skills, personal development, and having a good time.

Color Memory Representations in Primary and Extrastriate Visual Cortex (V1, V4)

neuromatch academy

Isaac Menchaca (U.C. Riverside), **Kathryn O'Nell** (University of Oxford), **Kevin Wayne Rusch** (University of London), **Czarinah Micah Rodriguez** (U.C. Berkeley)

Questions

- How are color memory representations implemented in the visual stream?
- What is the relationship between V1 and V4 with regards to color memory?
- Can we recover color representations from V4 and V1 given recolorized naturalistic images?

Literature Review

- Humans can identify colors under a large array of illuminations.
- In order to solve this underconstrained problem, we incorporate color memory (CM).
- CM information is fed back from V4, doesn't always make it to V1.

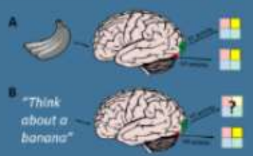


Figure 1. Participants presented with grayscale images of objects with identifiable color content, color was recoverable from both V1 and V4 (A). However, when participants were asked to think about the same objects, color was recoverable from V4 but not V1 (B).

Methodology

Colorization Process

- Generated three colorized versions of the dataset:
  - Deep AI Image Colorization API by Sorgsvartvras.
  - deOldify @ render factor 8 and deOldify @ render factor 13.
- Picked best (i.e. most straightforwardly colored) version of each picture for total of 1150 viable images.
- Clustered HSV color values for each pixel of each image, nucleus of largest cluster picked as dominant color.

Classification Process

- We predicted the RGB color values of each image from V4 and V1 voxel activations.
  - We ran a linear model with a lasso regression.
  - Initial trial-and-error showed elastic net, ordinary least squares, and ridge approaches yielding worse results.
- We then randomized pairings between images and voxel activations in order to create a bootstrapped distribution of expected root mean squared errors given the biased color content of our image set.

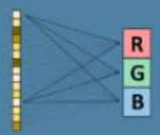


Figure 3a. Schematic of regularized net. Lasso regression minimized the number of non-zero weights.

Figure 3b. Predicted colors from V1 and V4 activations.

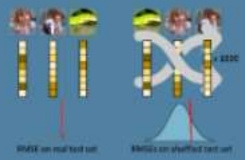


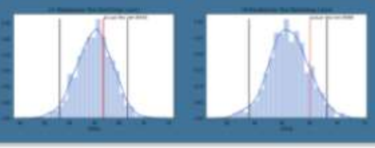
Figure 3c. Lasso net root-mean-square error compared to RMSE distribution from shuffled image-voxel pairings.

Results

While the first two questions proved too broad to answer with this project, we did arrive at a reasonable answer to the third question:

Can we recover color representations from V4 and V1 given recolorized naturalistic images?

No -- our models were unable to achieve the desired effect. Our RMSE spanned the entire range of colors.



Future Aims

Kay-Gallant dataset contained recolorization uncertainty due to mixed color content. For future experimentation, we suggest:

- Utilizing images focused on strong canonical hue (e.g. banana).
- Accounting for shape bias in color representations (e.g. Blue with horizontal line due to sky and bodies of water).
- Utilizing a more complex model to improve performance for high dimensional voxel features (e.g. Neural Network).

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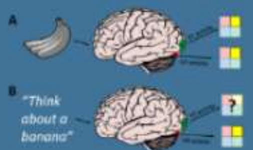

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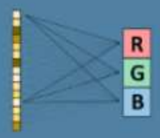

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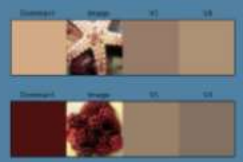

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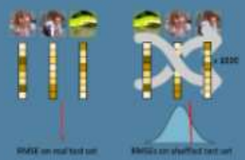

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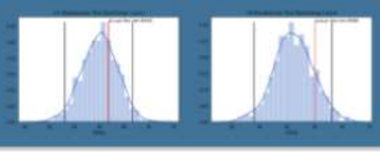

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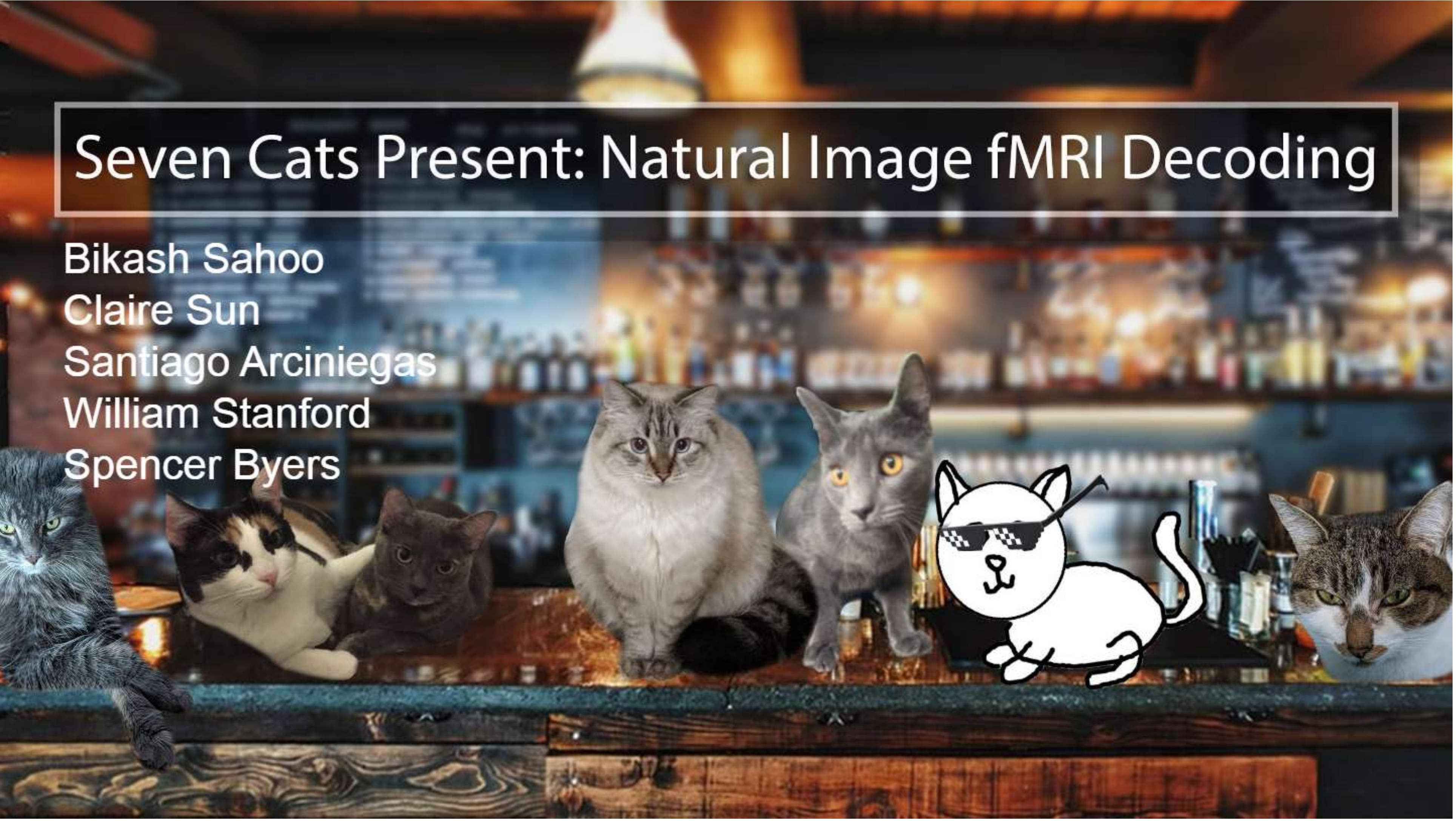
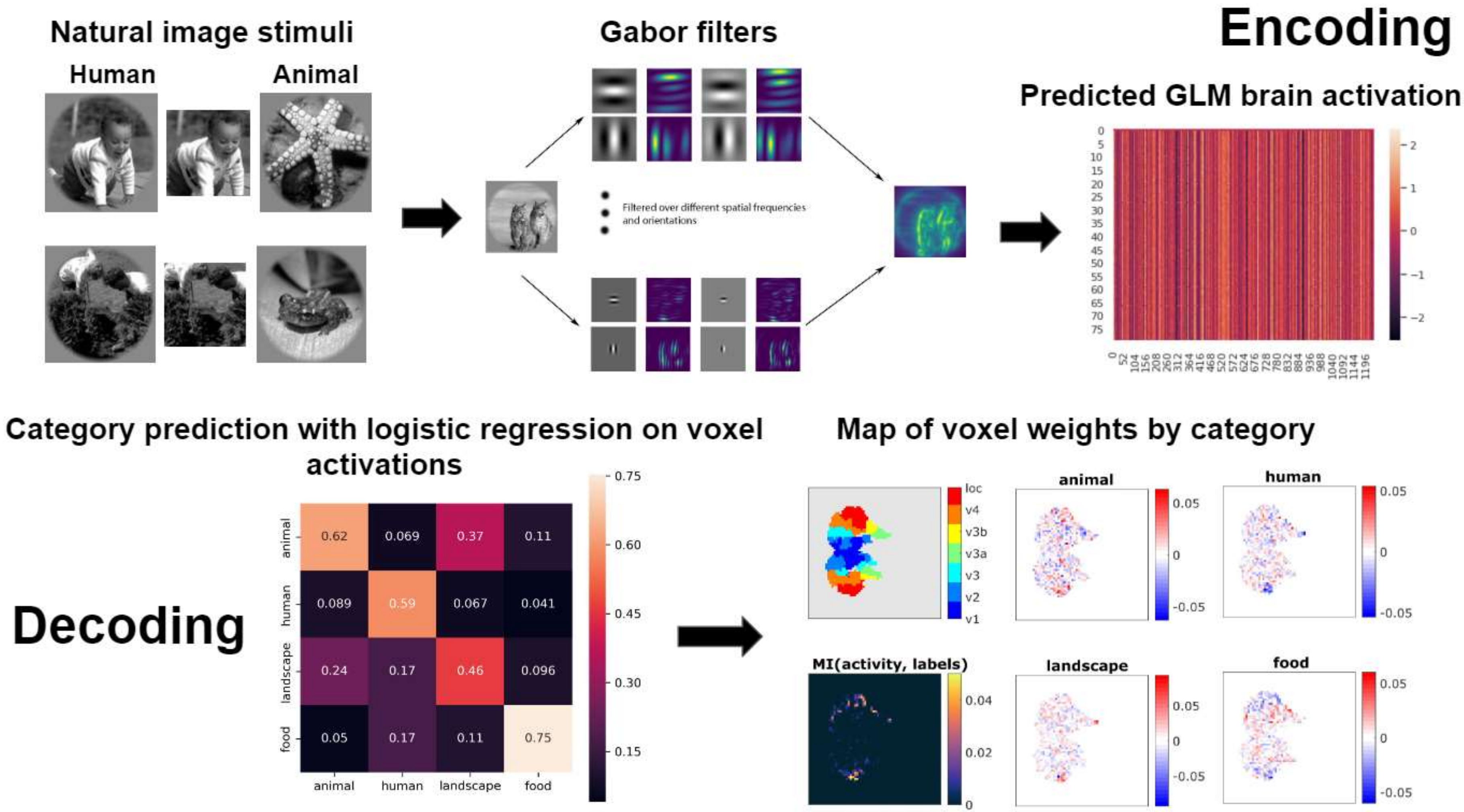

Seven Cats Present: Natural Image fMRI Decoding
Bikash Sahoo
Claire Sun
Santiago Arciniegas
William Stanford
Spencer Byers

What was our question?

The human visual system is faced with the difficult task of reconstructing complex natural scenes and extracting relevant semantic information from them. How much structural and semantic information is represented at the various levels of the human visual system?

What approach did we take?

- Create encoding model to predict voxel activation from image features
  - Large Dataset -> PCA reduced, gabor filtered images-> GLM design -> predictions for voxels -> accuracy (MSE)
- Decoding model using a logistic regression to classify images based on their evoked voxel activity response


Natural image stimuli
Human
Animal
Gabor filters
Filtered over different spatial frequencies and orientations
Encoding
Predicted GLM brain activation
Category prediction with logistic regression on voxel activations
Decoding
animal
human
landscape
food
0.62
0.069
0.37
0.11
0.089
0.59
0.067
0.041
0.24
0.17
0.46
0.096
0.05
0.17
0.11
0.75
Map of voxel weights by category
loc
v4
v3b
v3a
v3
v2
v1
MI(activity, labels)

What did we learn?

1. How to collaborate via Google Colab!
2. How to build a GLM (and watch it run past the project deadline)
3. Multicategory classification (using logistic regression).
4. timeToRun(Python) > timeToRun(Matlab).
5. Industry is filled with rainbows and candy (I disagree - Claire, I don't like candy, but rainbows are cute. - Bikash).

Encoding Models and RSA: Bridging the Divide

By: Matthew Shinkle, Md Ashaduzzaman Rubel, Kimia Yaghoubi
Mentors: Alaa Ahmed, Michael Waskom
Pod: Dashing Catfish

neuromatch academy

fMRI--Two Common Approaches

Voxel-wise encoding/decoding
- Estimates voxel 'tuning'

Representational Similarity Analysis
- Captures 'representational geometry' of the brain

Question--Is there a fundamental relationship between these methods?

- Do encoding model weights reflect the representational geometry of the brain?
- Could RSA even be used to predict encoding model performance?

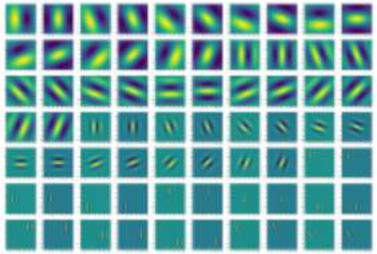
Kay Natural Images

1750 training images

120 validation images

fMRI responses for one

Gabor Features



- Vary in:
  - Spatial frequency
  - Size
  - Location
  - Orientation

Semantic Features


["bridge.n.01", "tree.n.01"]


["face.n.01", "hand.n.01", "man.n.01", "suit.n.01"]


["eagle.n.01", "face.n.07"]


["face.n.07", "monkey.n.01"]

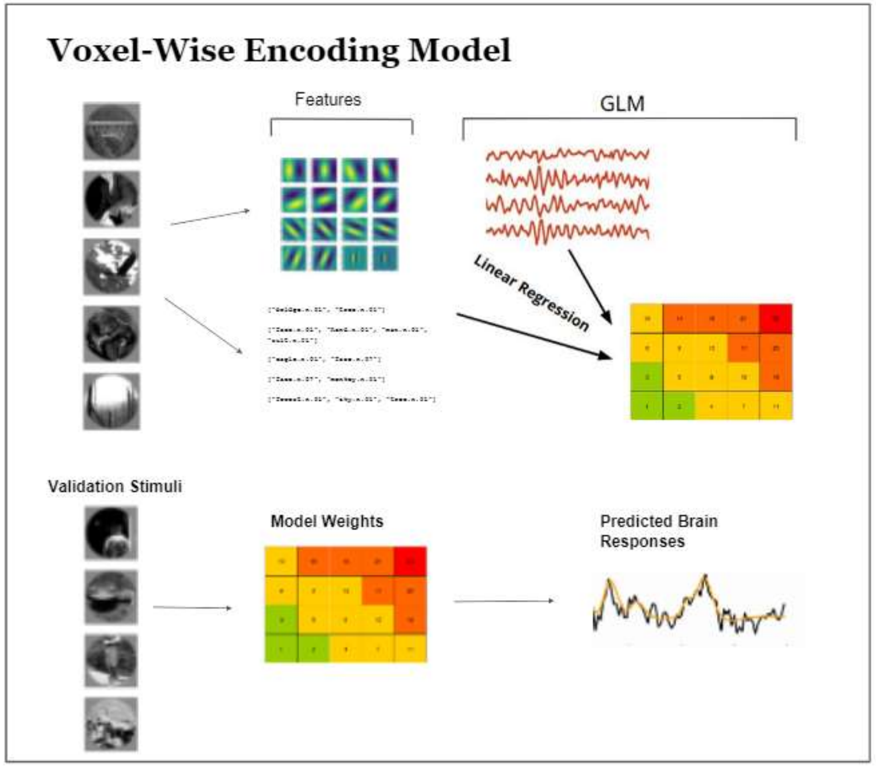

["forest.n.01", "sky.n.01", "tree.n.01"]

Background:
- Encoding models: estimate voxel 'tuning' to different features
- RSA: capture the 'representational geometry' of the brain

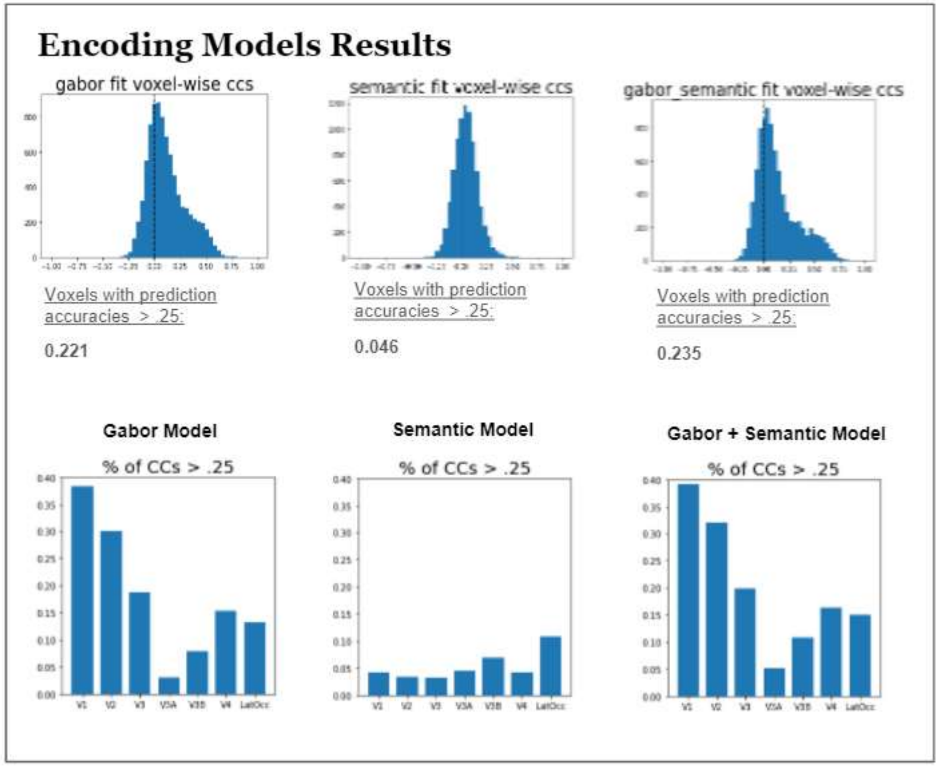
Our questions:
- Is there a fundamental relationship between these two methods?
- Do encoding model weights reflect the representational geometry of the brain?
- Could RSA be used to predict encoding model performance?

Dataset: Kay natural image dataset
- ~2000 naturalistic images
- fMRI responses to each image
- Number of subjects: 1

Fitting the encoding model:
- Created a set of low-level visual features for each stimulus by generating a range of different Gabor filters and applying them to each image.
- Hand-generated multiple semantic labels for each image, describing objects and scene features



- Applied a regularized linear regression to our stimulus features and the fMRI brain responses → a matrix of model weights.
- Generated three models:
  - Gabor features fit
  - Semantic features fit
  - Gabor and Semantic features fit
- Using these model weights to predicted brain responses to the validation stimuli set

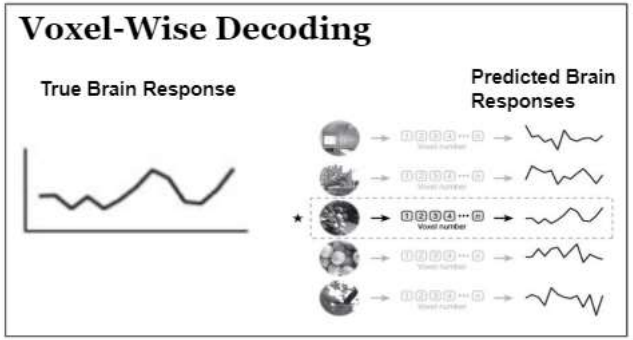


Upper row: Predicted accuracy distributions

- Gabor features predicted well in a decent number of voxels
- Semantic model performed comparatively worse
  - With a number of voxels that seem to be predicted above chance.

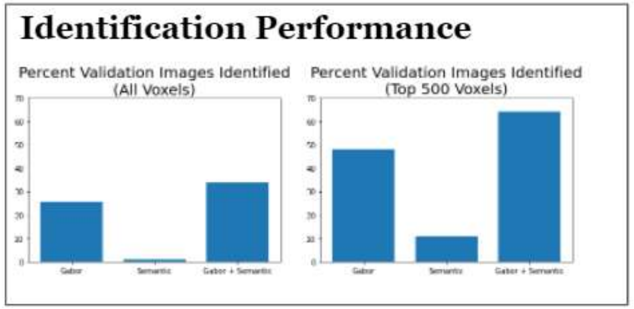
Lower row: Results on an ROI level

- Gabor model performed much better in early visual areas
- Semantic model performed much better in more anterior visual regions, in line with the well-accepted hierarchical structure of visual cortex.



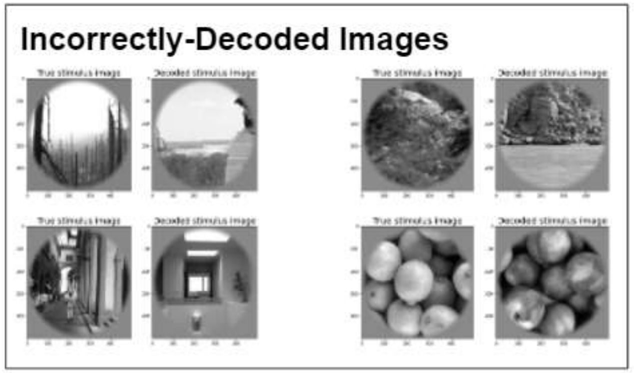
Background:

- Used the same models to perform stimulus identification
- Voxel responses to each validation image and our encoding model yielded *predicted* voxel responses to each image.
- By comparing each set of true responses to all of the predicted responses, we were able to infer which stimulus image most likely caused each volume of activity.



Identification performance:

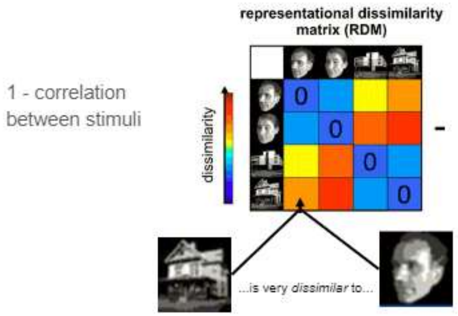
- Bar plots: % correctly identified images
- Gabor and semantic features model had the best performance: 64%
    - Suggesting this model has a robust ability to infer stimulus identity from brain activity.



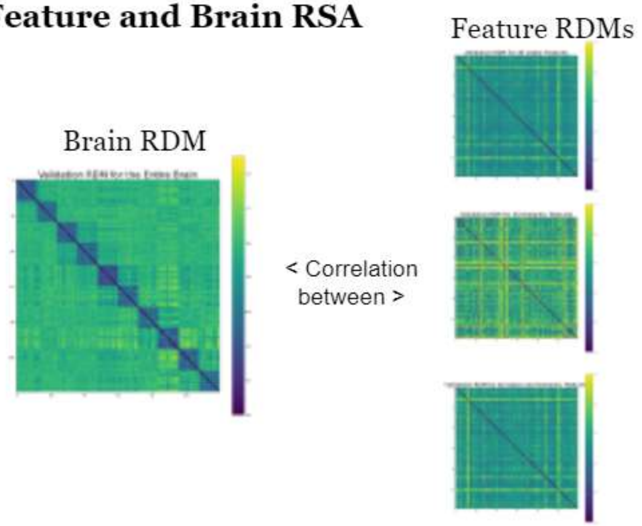
Examples of incorrectly-decoded images:

- revealing that images that are incorrectly identified tend to have high visual similarity to the true stimulus images.

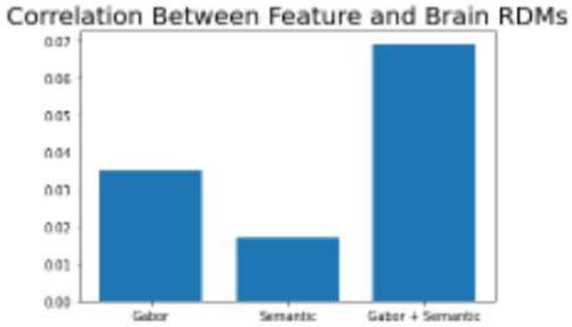
RSA Theory



Feature and Brain RSA



RSA Results

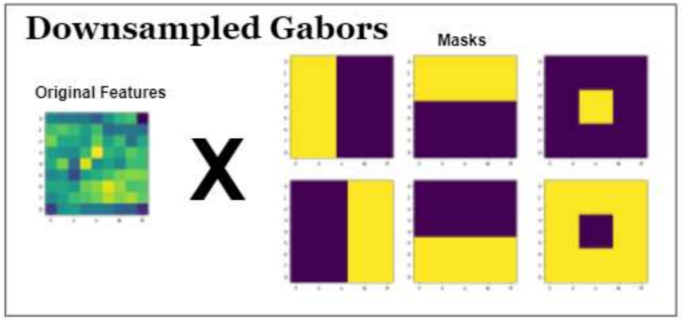


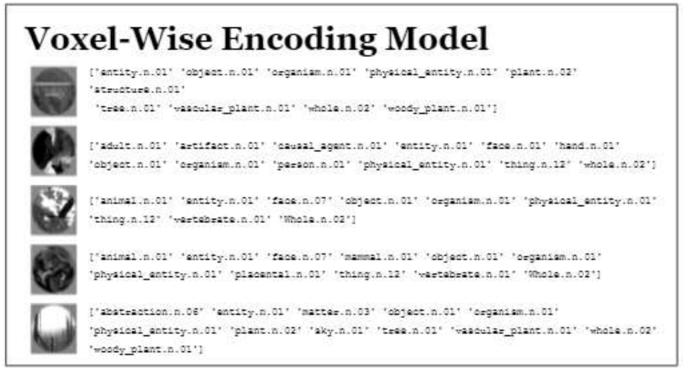
In addition to our encoding models, we also applied RSA to our data:

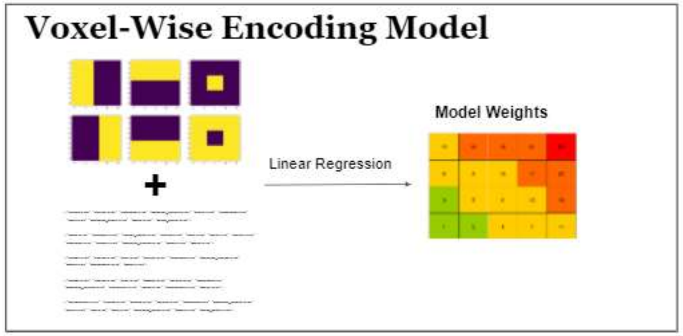
- An RDM was generated based on the measured brain data and for each sets of features
- Computed the correlation between each of the feature RDMs and the RDM of the brain
- Determined the extent to which each set of features effectively captured the information represented in the brain.

RSA Results:

- Bar plots represent the correlation metric
- All of the feature RDMs capture some non-zero degree of the representational geometry of the brain
- Between relative decoding performance and relative feature-brain RDM correlations suggest a potential relationship between these two metrics.







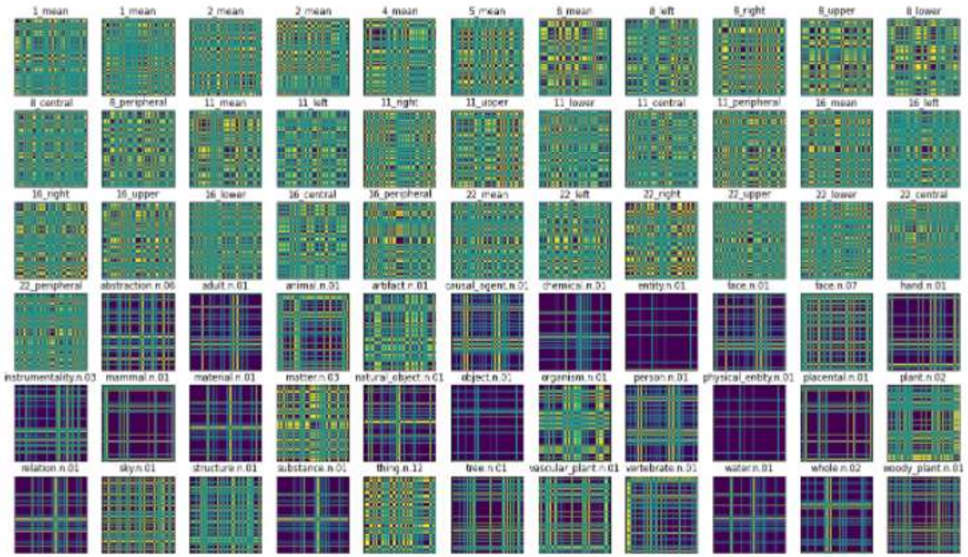
To address whether the weights of our model reflect the extent to which a specific stimulus feature is represented in the brain:

- Generated simplified versions of each of our sets of features
- Averaged our Gabor features in different regions of the visual field

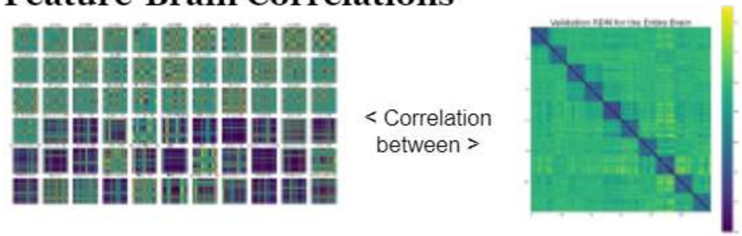
- Used our semantic labels and the wordnet hierarchy to extract 32 different high-level semantic features which were each present in at least 10% of the training images

- Fitted a unique encoding model for each of these two new sets of features, as well as a third model using both sets.

RSA on New Feature RDMs



Feature-Brain Correlations

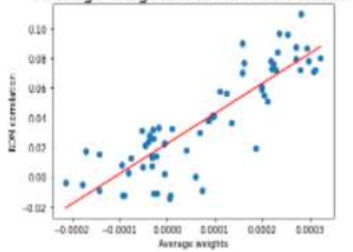


RSA and Model Weights Comparison

Correlation: **0.8599**

Suggests strong relationship between:

- Encoding model weights
- Information represented in the cortex (representational geometry)



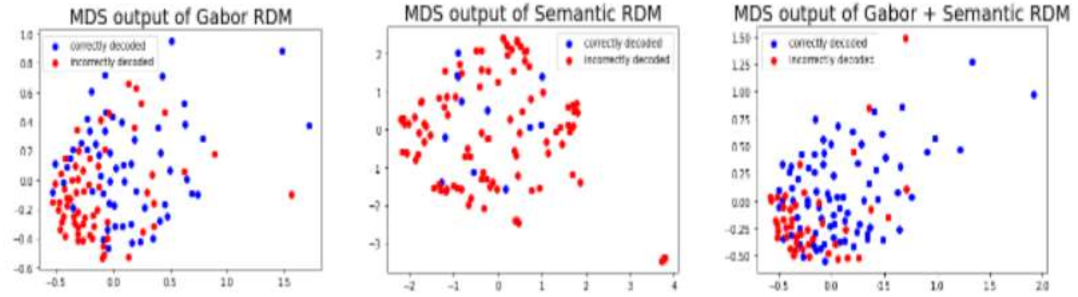
- Generated RDMs for each of these 66 new Gabor and semantic features.

- Computed the correlations between each feature RDM and the RDM for the entire brain.
- Resulted in a quantitative metric of the extent to which each new feature was represented in the brain.
- Correlation of .86 between these RSA-derived metrics and the average encoding model weights for these features
- Suggests encoding model weights indeed seem to be a clear reflection of the representational geometry of the brain.

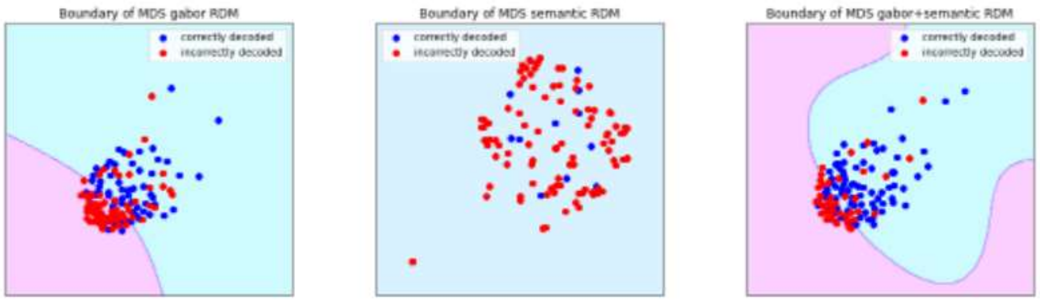
One final question…

- **Can we quantitatively predict decoding performance using RSA?**

Multidimensional Scaling



Multidimensional Scaling (Boundary with SVM)




```
CV mean accuracy: 0.68
F1: ~0.68
```

```
CV mean accuracy:  0.89
F1: ~0.47
```

```
CV mean accuracy:0.75
F1: ~0.71
```

To determine whether we could actually predict decoding model performance using RSA

- We applied multidimensional scaling to the RDMs for our features, revealing the clusters and dissimilarities between the stimuli.

- The results for our poorly-performing semantic feature set show no clear distinction between correctly- and incorrectly-decoded images,

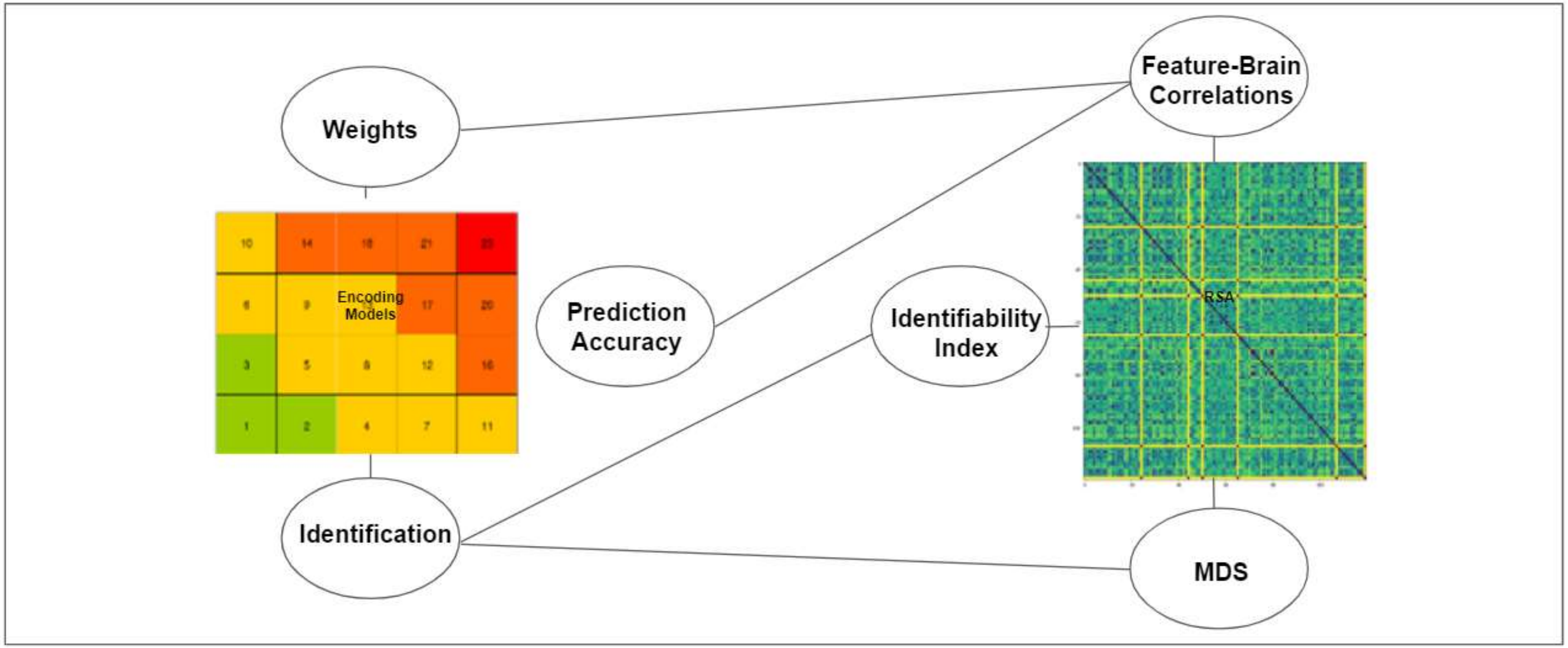
- Looking at the results for our Gabor features, we see a relatively striking difference between images based on decoding results.

- If we add in our semantic features as well, we see an even clearer difference.

We fit a support vector classifier to the RDM results

- A relatively good fit for the two sets containing Gabor features
- Suggesting that feature RDMs could be used to predict decoding performance for individual stimuli.

Conclusions



Both encoding models and RSA can not only be used to perform a number of different interesting analyses, but analyses can be directly and quantitatively related between these two approaches, suggesting that voxel-wise encoding models and RSA are in many ways investigating the same underlying information about the brain.