Predicting Human Brain Activity Associated with the Meanings of Nouns

Tom M. Mitchell, Svetlana V. Shinkareva,Andrew Carlson,
Kai-Min Chang, Vicente L. Malave, Robert A. Mason,
Marcel Adam Just

Presented by Robert Forgues
November 19th, 2010

Outline

- Functional Magnetic Resonance Imaging
- The Model
  - Motivation
  - Construction
  - Approach
  - Results
  - Discussion

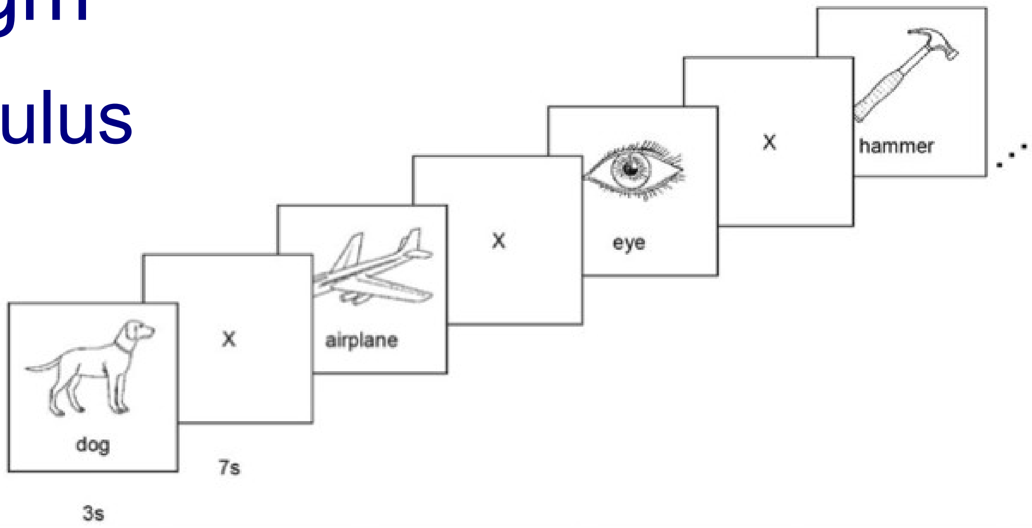
Functional Magnetic Resonance Imaging

Functional MRI (fMRI)

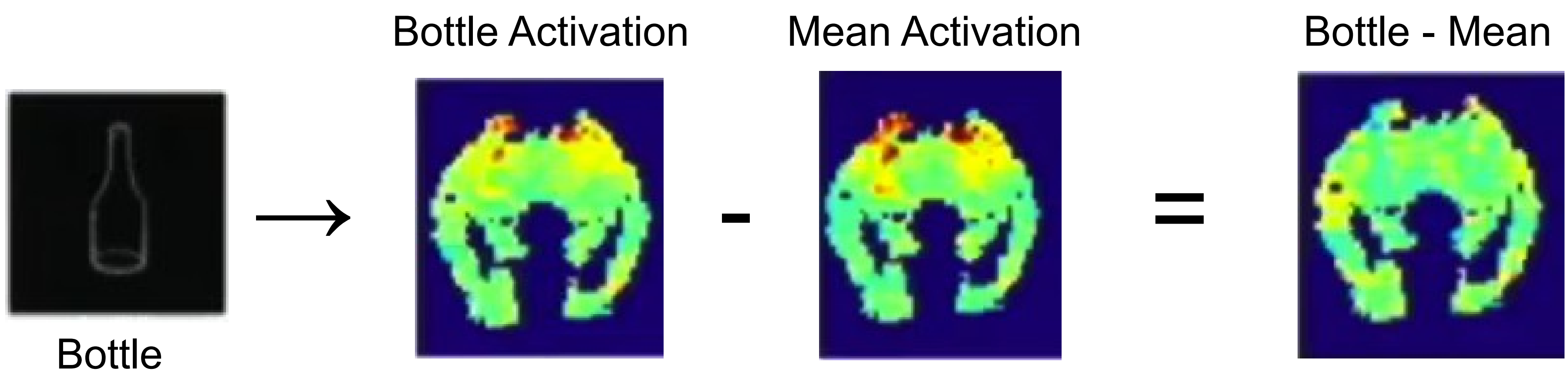
- Measures blood flow changes in the brain
- 3D images are generated by thinking about words
- Spatial resolution ~1mm
- Temporal resolution ~1 image/sec

Getting fMRI Data

- Images shown to participant as white lines on dark background
- Participant thinks about properties of the item
- Event-related paradigm
  - 3 seconds of stimulus
  - 7 seconds of X



fMRI Example: Bottle



- Red areas denote high activation
- Mean activation is over 60 different stimuli
- The difference images are used during analysis

Motivation for the Model

How Does The Brain Represent Conceptual Knowledge?

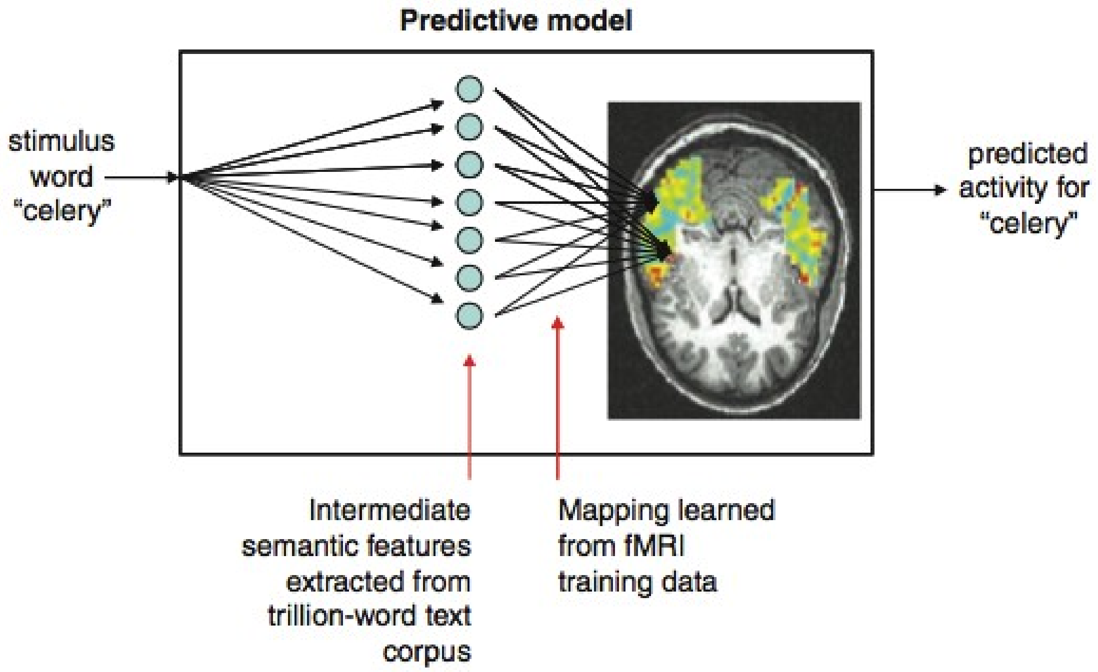
- Studied by many fields
  - Neuroscience
  - Linguistics
  - Computational Linguistics
  - Psychology
- Competing theories
- Can we predict it?

Problem

- How to predict fMRI activation?
  - Statistics to the rescue
- Theory behind the model
  - The neural basis of the semantic representation of concrete nouns is related to the distributional properties of those words in a broadly based corpus of the language

The Model

Building a Predictive Model



Intermediate Semantic Features

- 25 semantic features defined by their co-occurrence with 25 verbs:
  - Sensory: *fear, hear, listen, see, smell, taste, touch*
  - Motor: *eat, lift, manipulate, move, push, rub, run, say*
  - Abstract: *approach, break, clean, drive, enter, fill, near, open, ride, wear*

Text Corpus

- Provided by Google
- Available from Linguistic Data Consortium
- A trillion-word corpus with (1-5)-grams
- Consists of public English web pages

fMRI Data Collection / Processing

- Test Subjects
  - 9 people (5 female, age 18 – 32, right-handed)
  - Each participant generated set of properties for each item prior to session
  - Tasked with thinking of properties of exemplar
  - Consistency across participants unenforced

fMRI Data Collection / Processing

- The Machine
  - Siemens Allegra 3.0T scanner
  - Gradient echo EPI pulse sequence
    - TR = 1000 ms, TE = 30 ms, 60° flip angle
  - Seventeen 5-mm oblique-axial slices imaged
    - 1mm gap between slices
  - 64 x 64 acquisition matrix
    - 3.125-mm x 3.125-mm x 5-mm voxels

fMRI Data Collection / Processing

- Stimuli
  - Line drawings of 60 concrete objects from 12 semantic categories
  - Presented 6 times each, randomly permuted for each presentation
  - 3s exposure, 7s rest period
  - 12 extra rest periods of 31s, scattered across session to provide baseline measure

fMRI Data Collection / Processing

Category	Exemplar 1	Exemplar 2	Exemplar 3	Exemplar 4	Exemplar 5
animals	bear	cat	cow	dog	horse
body parts	arm	eye	foot	hand	leg
buildings	apartment	barn	church	house	igloo
building parts	arch	chimney	closet	door	window
clothing	coat	dress	pants	shirt	skirt
furniture	bed	chair	desk	dresser	table
insects	ant	bee	beetle	butterfly	fly
kitchen utensils	bottle	cup	glass	knife	spoon
man made objects	bell	key	refrigerator	telephone	watch
tools	chisel	hammer	pliers	saw	screwdriver
vegetables	carrot	celery	corn	lettuce	tomato
vehicles	airplane	bicycle	car	train	truck

fMRI Data Collection / Processing

- Data Processing
  - Statistical Parametric Mapping software SPM2
  - Corrected for slice timing, motion, linear trend
  - Temporally filtered using a 190s cutoff
  - Normalized into MNI and resampled
  - A single fMRI mean image was created for each presentation of an item by taking mean of item

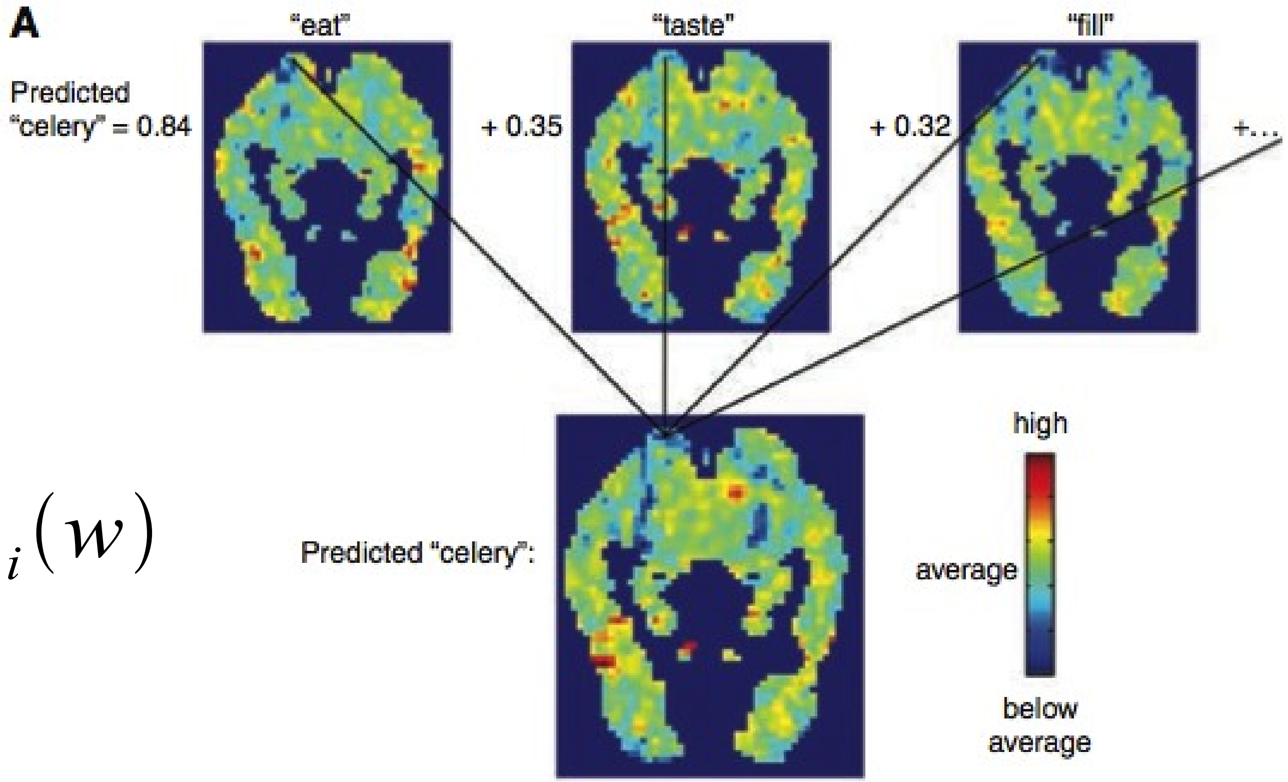
The Model: A Two-Step Approach

- Step 1: lookup stimulus word, generate normalized semantic feature vector

Semantic feature values: "**celery**"
0.8368, eat
0.3461, taste
0.3153, fill
0.2430, see
0.1145, clean
0.0600, open
0.0586, smell
0.0286, touch
...
...
0.0000, drive
0.0000, wear
0.0000, lift
0.0000, break
0.0000, ride

The Model: A Two-Step Approach

- Step 2: train the model so that it can predict neural activity



$$y_v = \sum_{i=1}^{n} c_{vi} f_i(w)$$

Training

- Alternative models trained based on different sets of of intermediate semantic features
- Trained and evaluated using cross validation
  - Trained repeatedly with 58 / 60 stimuli
  - Tested with 2 stimuli left out
  - On each iteration, model was given stimuli and corresponding fMRI, required to match
  - Performed 1770 times

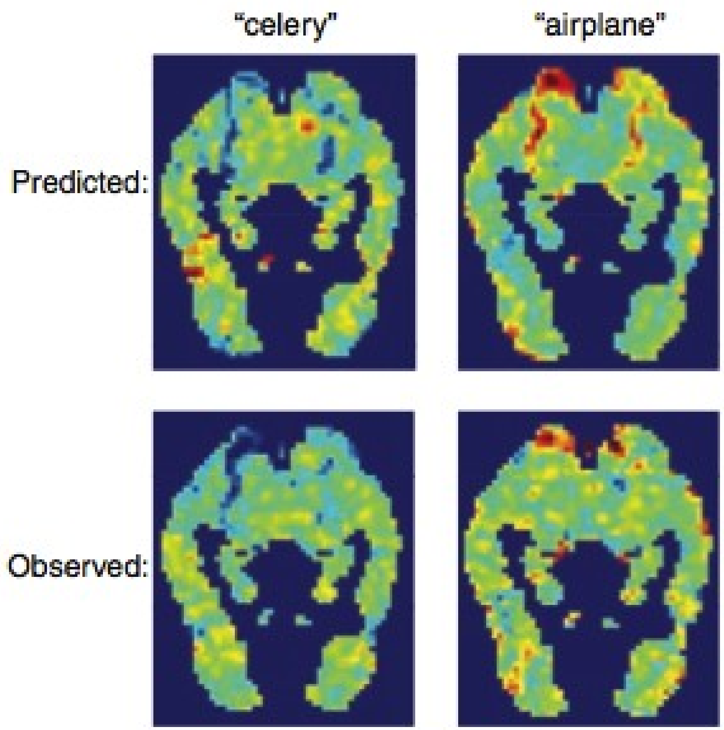
The Model: Theoretical Details

- Two key theoretical assumptions:
  (1) semantic features are reflected in statistics
  (2) some thoughts can be represented as a linear sum

- The training data determines which locations are modulated by which aspects of word meanings (all voxels are considered)
  - 500,000 parameters, for each 25 verbs, there were 20,000 voxels that coefficients were learned on

Results

Celery and Airplane



Predicted and observed fMRI images for celery and airplane after training on 58 other words

A Closer Look

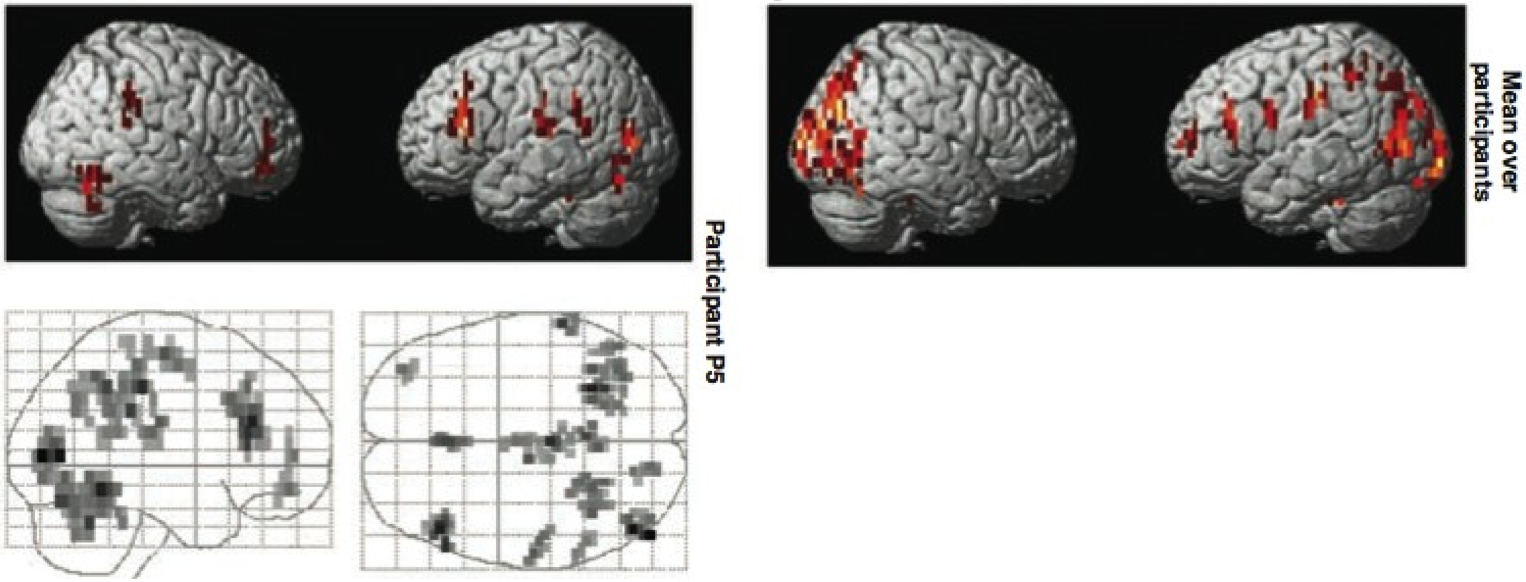
- The model trained on 58 / 60 words and has 1770 test pairs in leave-2-out
- How well can it predict fMRI images for the other two words?
  - Chance is 0.50
  - Accuracy above 0.61 is significant ($p < 0.05$)
  - The accuracy for subjects P1 through P9 was

    0.83, 0.76, 0.78, 0.72, 0.78, 0.85, 0.73, 0.68, 0.82

    Mean accuracy over the 9 subjects was **0.77**

Accuracy

- The model is differentially accurate in different parts of the brain



Rendering of the correlation between predicted and actual voxel activations for words outside the training set. Clusters contain at least 10 contiguous voxels.

Can We Extrapolate Beyond Training Data?

- Predicting in a new semantic category
  - Retrain, but drop all examples belonging to the same semantic category as the two held-out words
  - Mean = 0.70
- Predicting when the two held-out words are in the same category
  - Harder to differentiate between words
  - Mean = 0.62

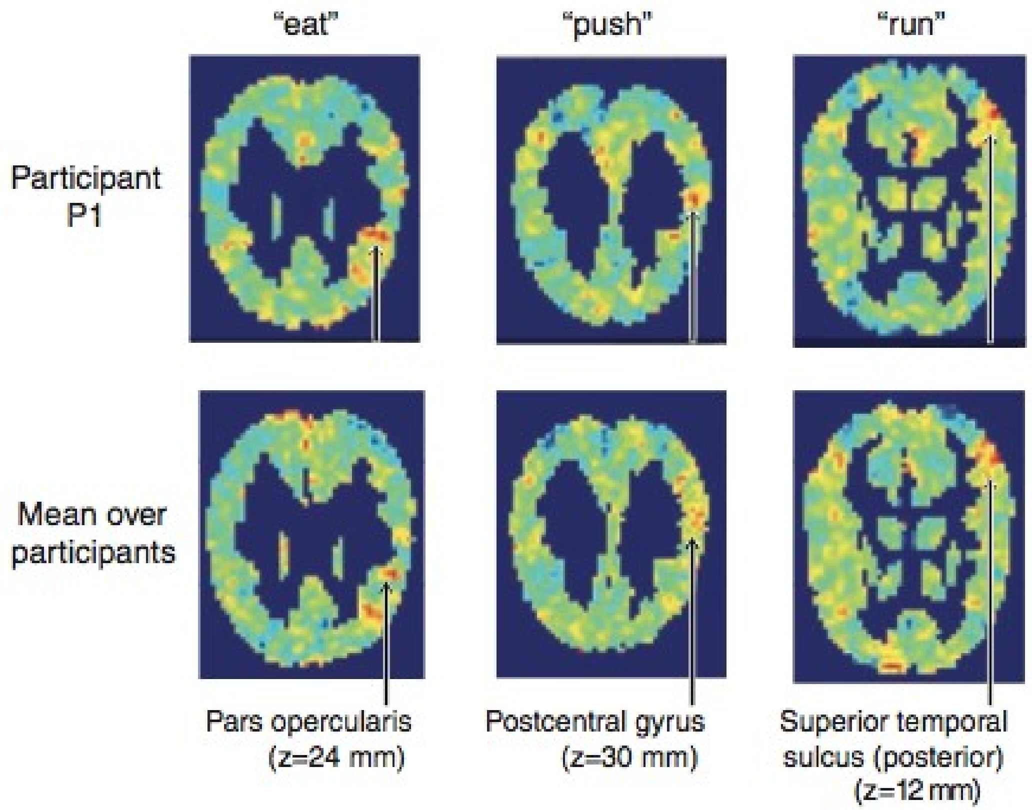
Testing Even Greater Diversity

- The model was given 1000 high frequency words
- Tested with leave-one-out, using 59 / 60 nouns
- Given the fMRI for the hold out, and 1001 candidate words, can it predict the image?
  - Mean over 9 participants = 0.72

Evaluating The Model Beyond Qualitative Measures

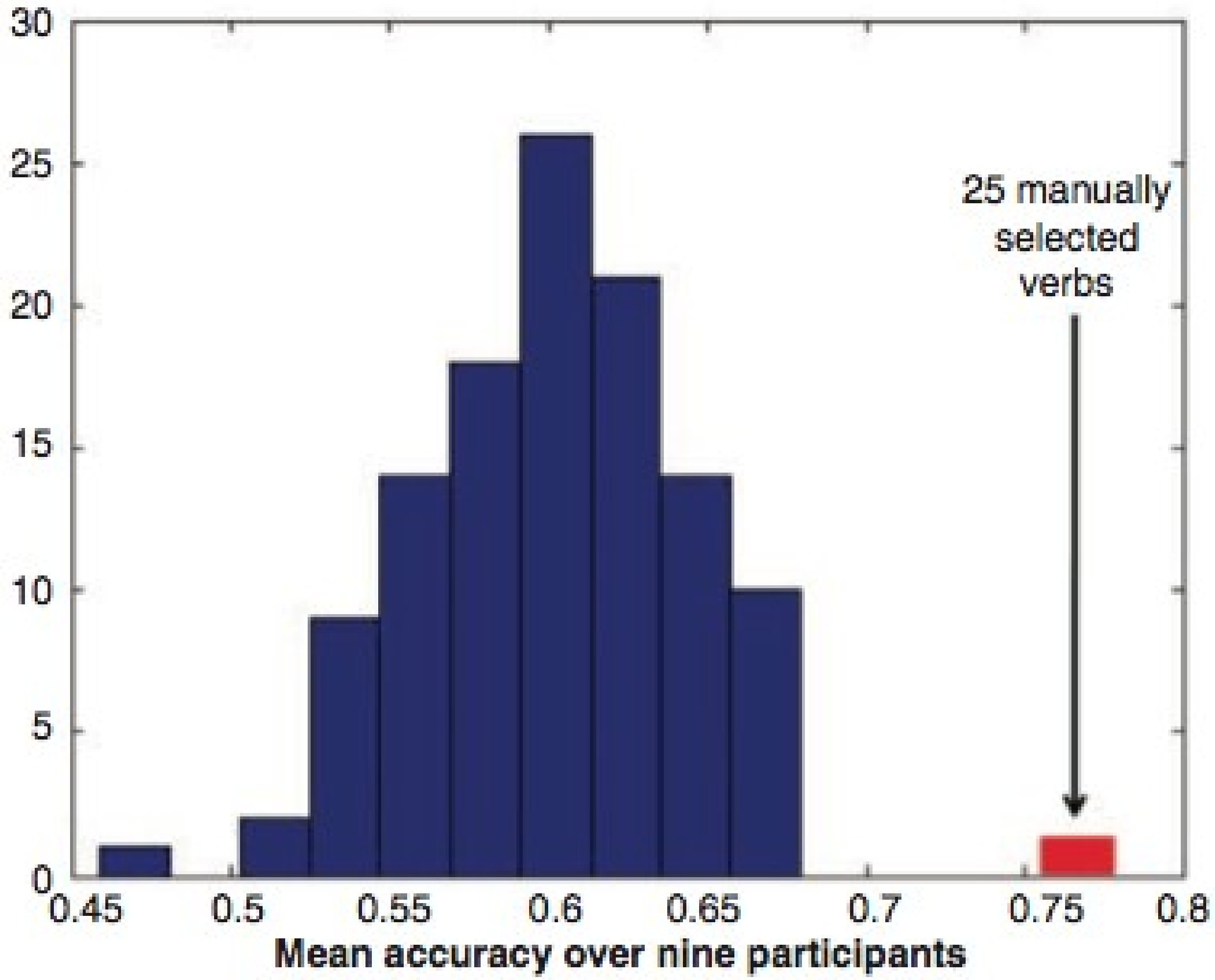
- Examining the learned basis set of fMRI images for the 25 verbs
  - The learned signatures cause the model to predict neural activity representing a noun in brain areas that perceive actions described by a verb to the degree that the noun co-occurs with said verb
  - Example: noun *n* will exhibit neural activity in the *gustatory cortex* to the degree it co-occurs with *eat*

Surprising Result



The model generated all of these images from the 20,000 coefficients learned from the verbs. It was not given any information with respect to physical location voxels. This emerged from training.

How About Other Semantic Features?



Discussion

- There is a direct and predictive relationship between statistics of word co-occurrence in text and neural activation associated with word meanings
- Neural representations of concrete nouns are in part grounded in sensory-motor features, but involve other regions as well

Questions?