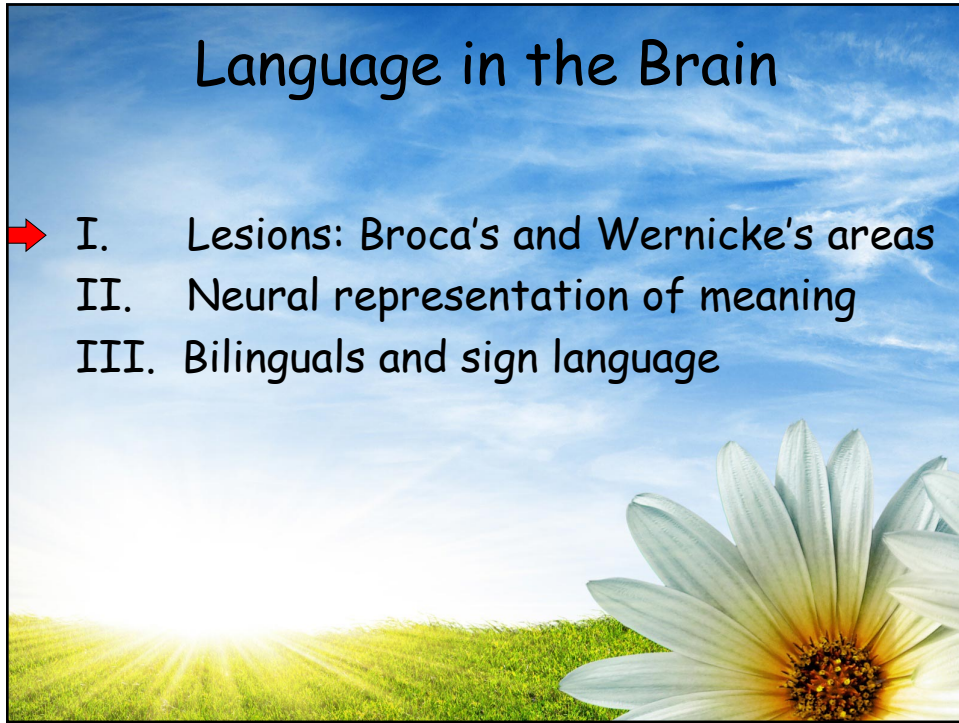


## Language in the Brain

- I. Lesions: Broca's and Wernicke's areas
- II. Neural representation of meaning
- III. Bilinguals and sign language

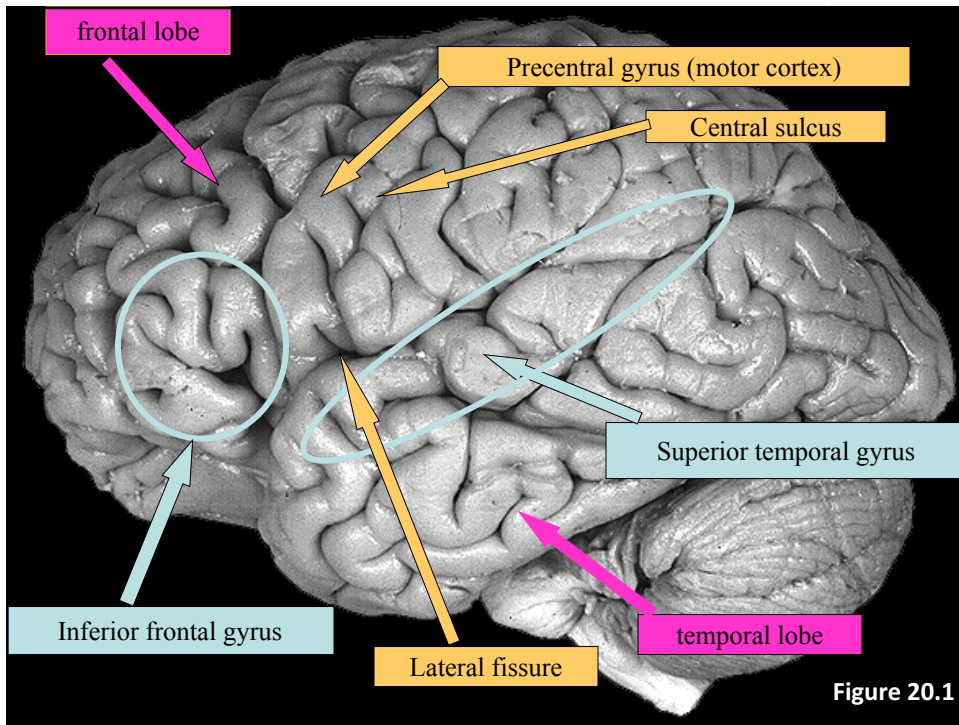


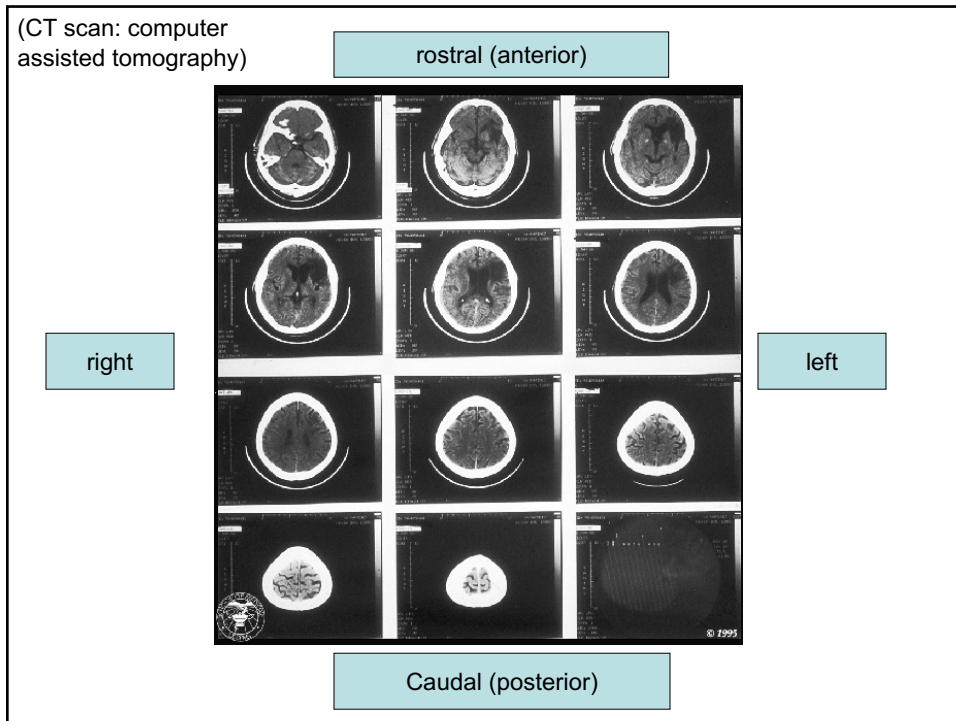
**Paul Broca**  
(1824-1880)



**Aphasia:**

“The collective deficits in language comprehension and production that accompany neurological damage”





Only damage in the left hemisphere results in aphasia:

Paul Broca (1864)



**“Nous parlons avec l’hemisphere gauche!”**

## Carl Wernicke (1848-1904)



Carl Wernicke  
(1848-1904)

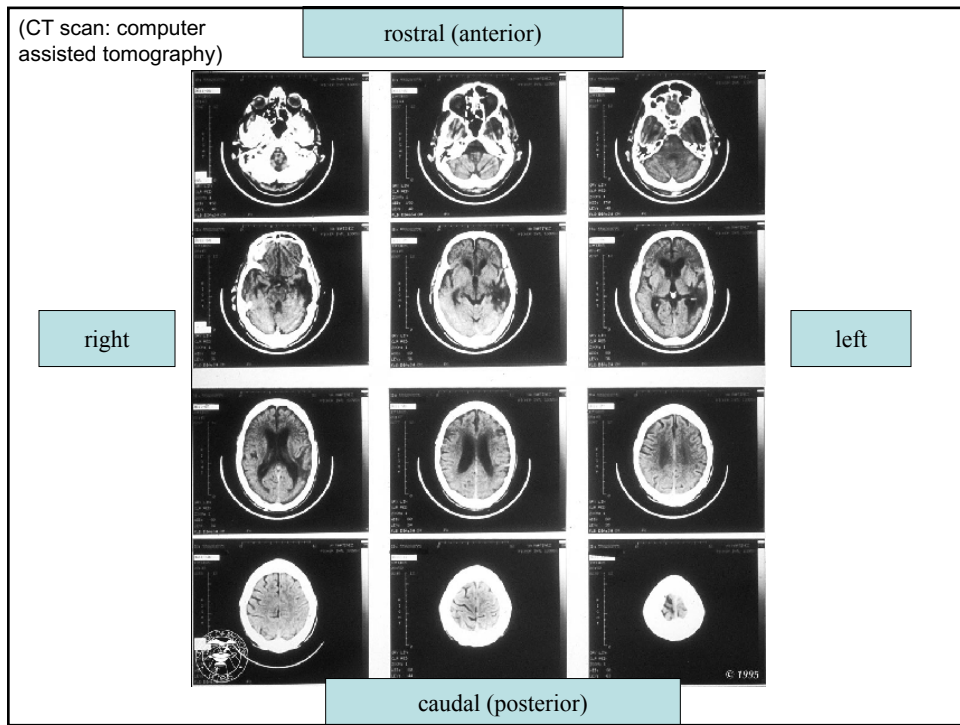
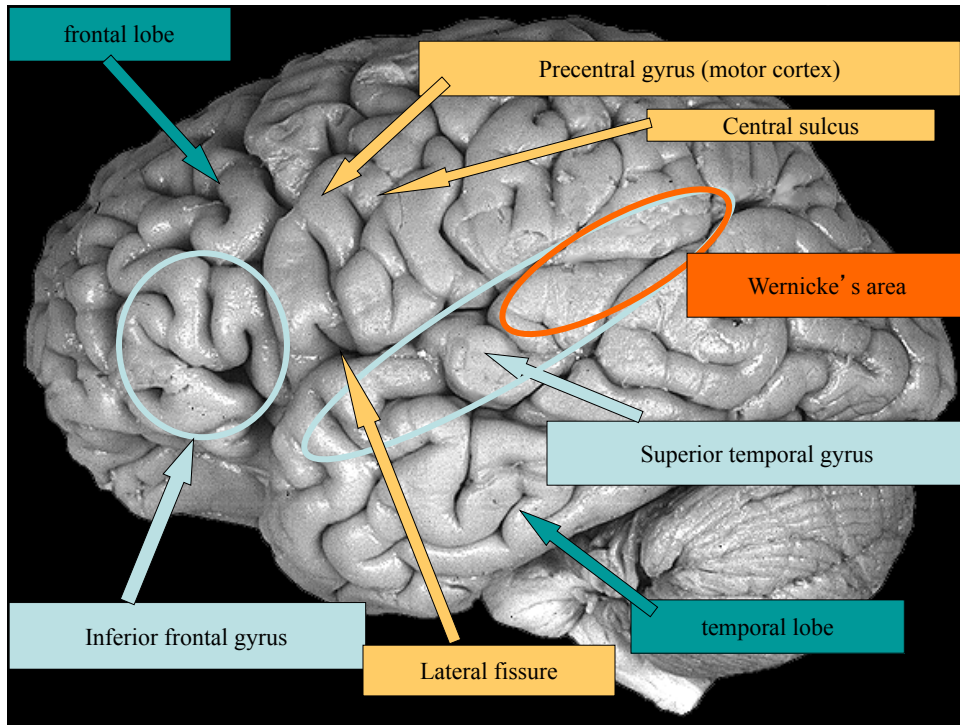


“I called my mother on the television and did not understand the door. It was not too breakfast, but they came from far to near. My mother is not too old for me to be young.”



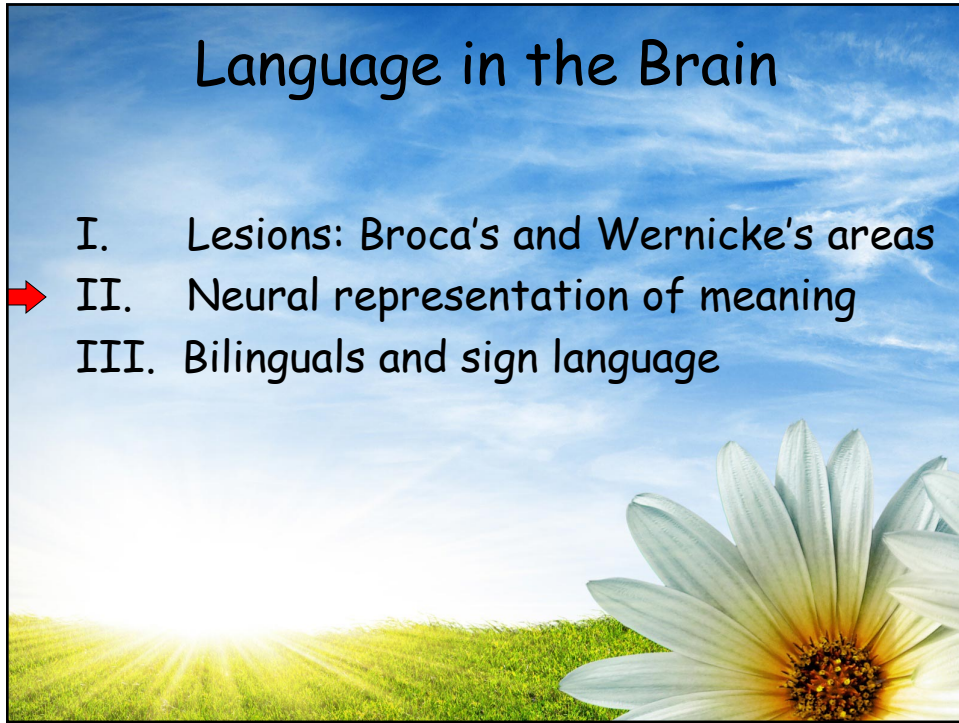
Wernicke's aphasia

Fluent speech, but nonsensical; loss of ability to understand language



# Language in the Brain

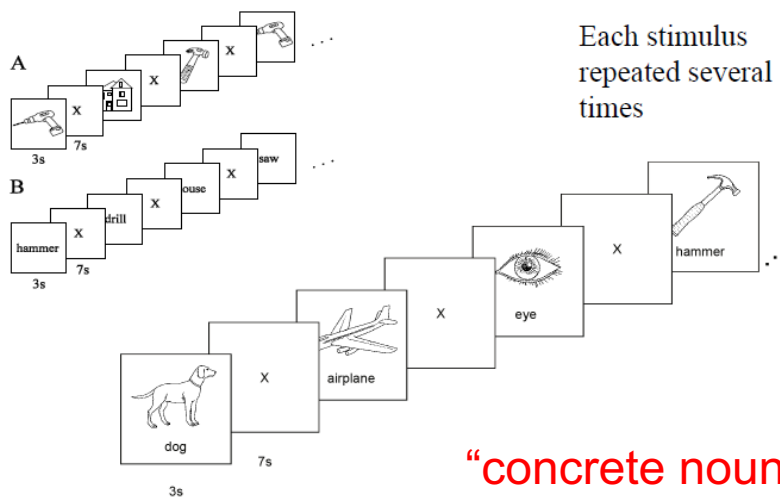
- I. Lesions: Broca's and Wernicke's areas
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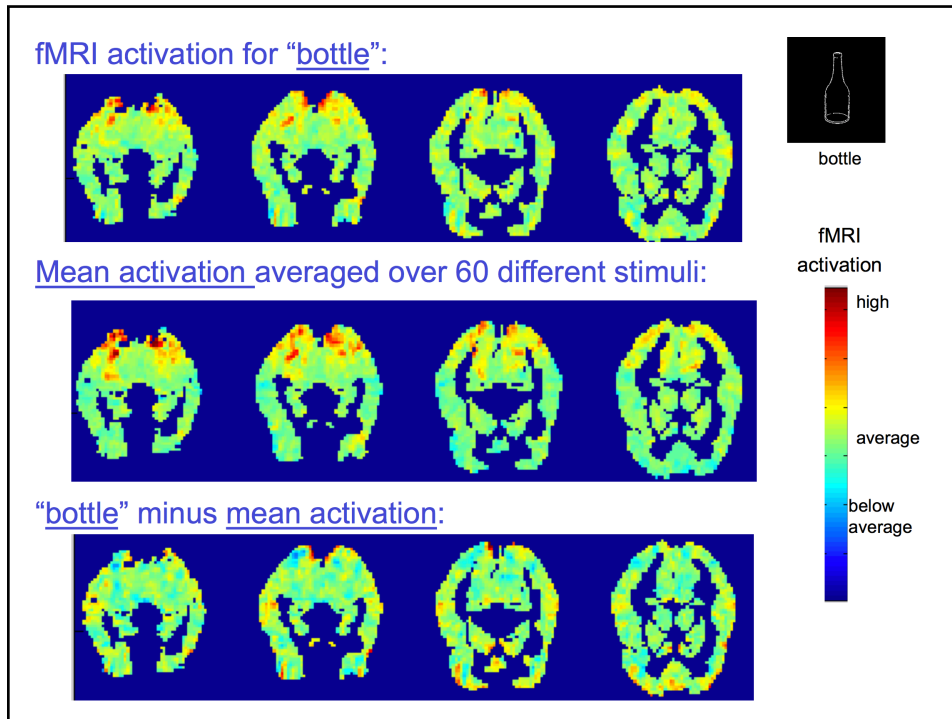


## fMRI experiment

Tom Mitchell et al

### Typical stimuli





## Neuroscience Research Questions

- Can we observe differences in neural activity as people think about different concepts?
- Is the neural activity that represents concepts localized or distributed?
- Are neural representations similar across people?
- Can we discover underlying principles of neural representations? (e.g., are representations built up from more primitive components?)

## Classifiers

- A **classifier** accepts a description of an object and predicts what class it belongs to
- Supervised learning** works from **labeled training examples**:

apple pear apple apple pear pear      What's this?

and then **tests** on new examples:

- Approach:
  - Describe each example by values for a **set of features**  
 <color, size, shape, has-stem, has-leaf, texture,...>  
 <red, small, round, yes, yes, smooth,...>
  - Training examples must be different from testing examples

## Lab 4: ANNs as classifiers

**Neural Pattern Recognition (nprtool)**

Welcome to the Neural Pattern Recognition app.  
Solve a pattern-recognition problem with a two-layer feed-forward network.

**Introduction**

In pattern recognition problems, you want a neural network to classify inputs into a set of target categories.

For example, recognize the vineyard that a particular bottle of wine came from, based on chemical analysis *(wine)*, identify or classify a tumor as benign or malignant, based on uniformity of cell size, clump thickness, mitosis *(cancer\_dataset)*.

The Neural Pattern Recognition app will help you select data, create and train a network, and evaluate its performance using cross-entropy and confusion matrices.

**Neural Network**

A two-layer feed-forward network, with sigmoid hidden and softmax output neurons *(softmax)*, can classify vectors arbitrarily well, given enough neurons in its hidden layer.

The network will be trained with scaled conjugate gradient backpropagation *(trainscgl)*.

5	7	2	3	4	3	6	7	8	8
3	1	3	5	5	9	7	2	4	6
3	8	8	2	3	8	5	9	9	5
5	8	8	3	0	5	1	5	5	5
8	1	9	5	4	9	9	5	3	2
2	3	9	5	2	4	5	2	5	7
6	3	5	5	7	7	3	3	9	3
7	5	7	6	0	4	4	9	8	3
9	2	9	5	2	3	9	8	2	5
2	3	9	9	9	9	6	8	9	5

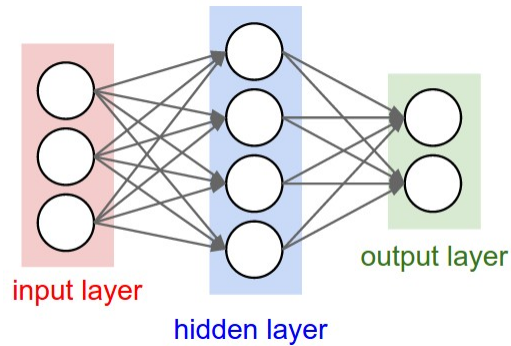
input layer      hidden layer      output layer

Pixel light levels

Which digit is it?



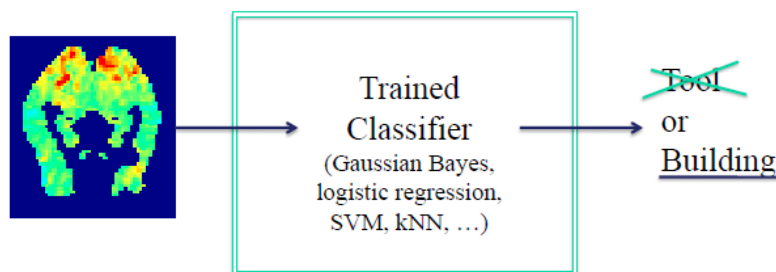
## Neural Network Classifier as



- Model of how the brain perceives
- Tool for applications like face recog, navigation
- **Tool for seeing what information is in an experimentally measured neural signal**

### Q1: Can one classify mental state from fMRI images?

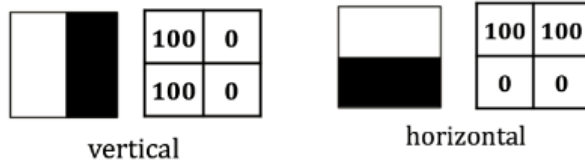
Given 84 nouns, present word, and capture fMRI data  
 Training example is fMRI output and presented word  
 Train on 83 and then test on 1 (repeat 84 times)



(classifier as virtual sensor of mental state)

## Remember Lab 5: template matching for face recognition

Consider a very simple example where we have two known image patterns corresponding to a vertical or horizontal edge, as shown below:

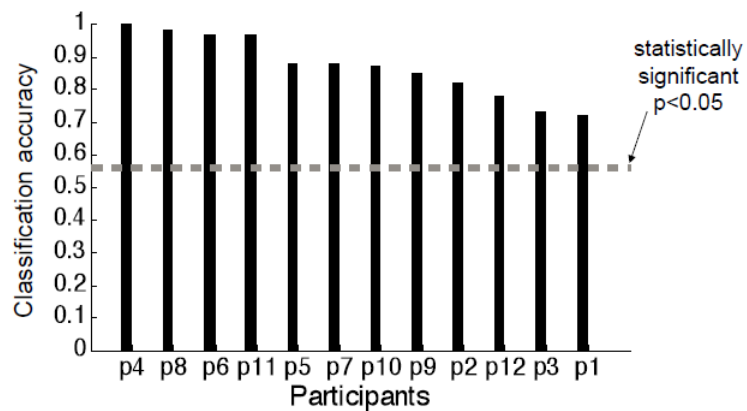


Suppose we are given a "mystery" image and want to determine whether it has a vertical or horizontal edge pattern:



### Classification task: is person viewing a "tool" or "building"?

I.e. Compare current fMRI activation pattern to average "tool" pattern and average "building" pattern—choose whichever "template" it is closer to.

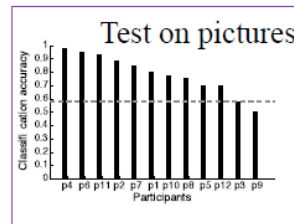
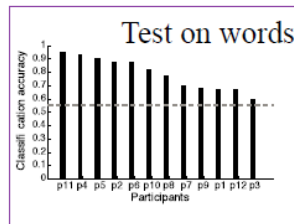


But is it learning just the *appearance* of the stimulus (the letter sequence) or its *meaning*?

## Question 2: Is our classifier capturing neural activity encoding stimulus meaning or appearance?

Can we train on word stimuli, then decode picture stimuli?

**YES:** We can train classifiers when presenting English words, then decode category of picture stimuli, or Portuguese words

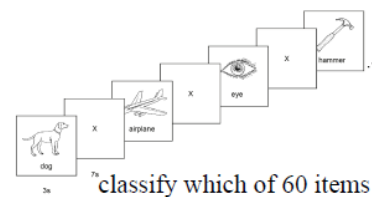
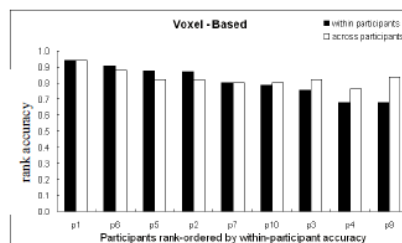


Therefore, the learned neural activation patterns must capture how the brain represents the meaning of input stimulus

## Question 3: Are representations similar across people?

Can we train classifier on data from a collection of people, then decode stimuli for a new person?

**YES:** We can train on one group of people, and classify fMRI images of new person

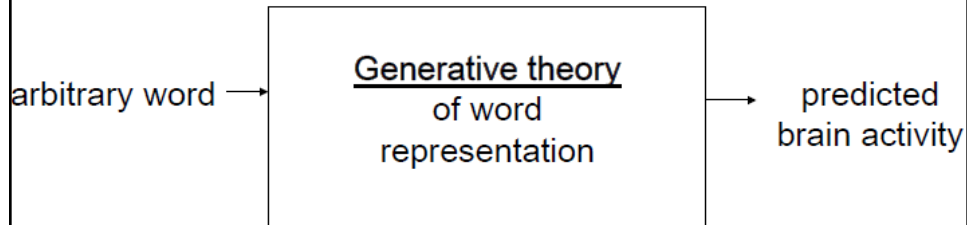


Therefore, seek a theory of neural representations common to all of us (and of how we vary)

## Question 4: Can we discover underlying principles of neural representations?

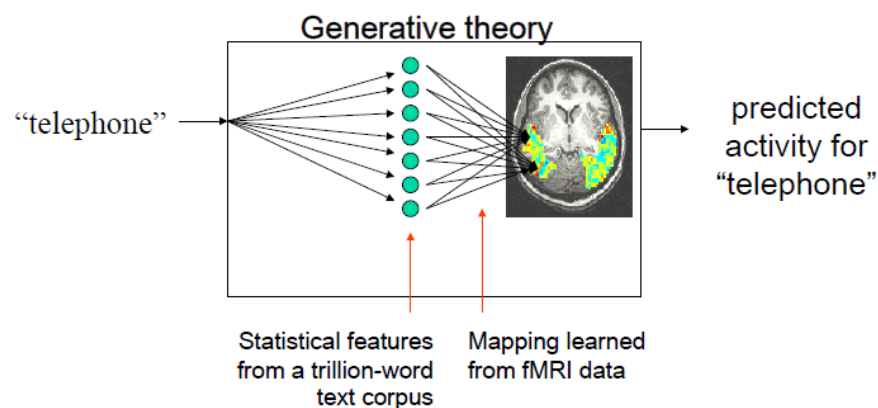
I.e. can activation patterns for novel words be **predicted** as **combinations** of known feature-related activity patterns?

Is the neural code for language “compositional”?



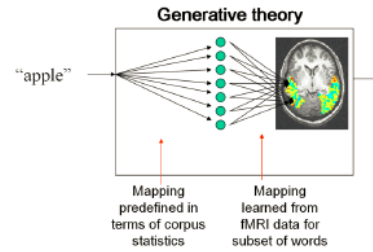
## Idea: Predict neural activity from corpus statistics of stimulus word

[Mitchell et al., *Science*, 2008]



I.e. define a limited number of “**semantic features**” to characterize each word by its **set of feature weights**—coordinates in **semantic feature space**!

## Which corpus statistics?



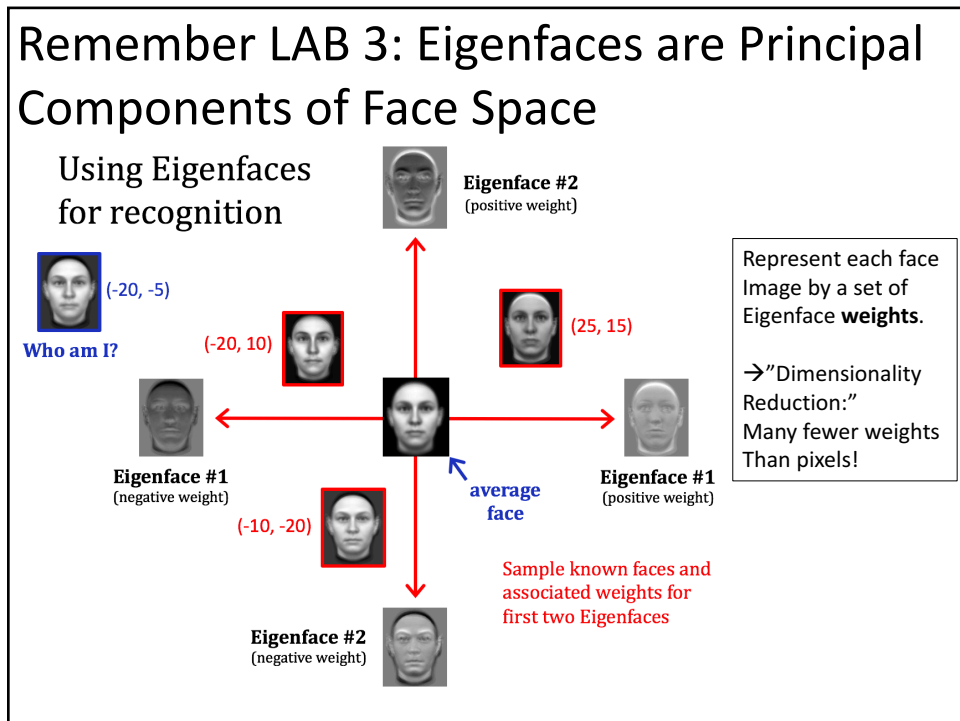
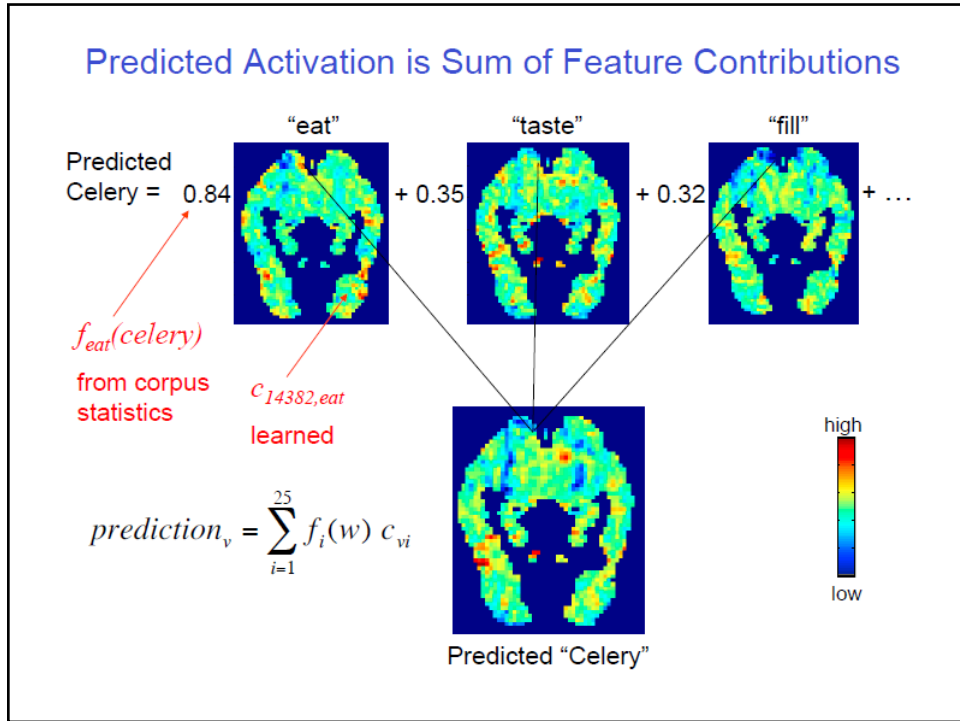
- Feature  $i$  = co-occurrence frequency of stimulus noun with verb  $i$
- The model uses 25 verbs:
  - Sensory: *see, hear, listen, taste, touch, smell, fear,*
  - Motor: *rub, lift, manipulate, run, push, move, say, eat,*
  - Abstract: *fill, open, ride, approach, near, enter, drive, wear, break, clean*

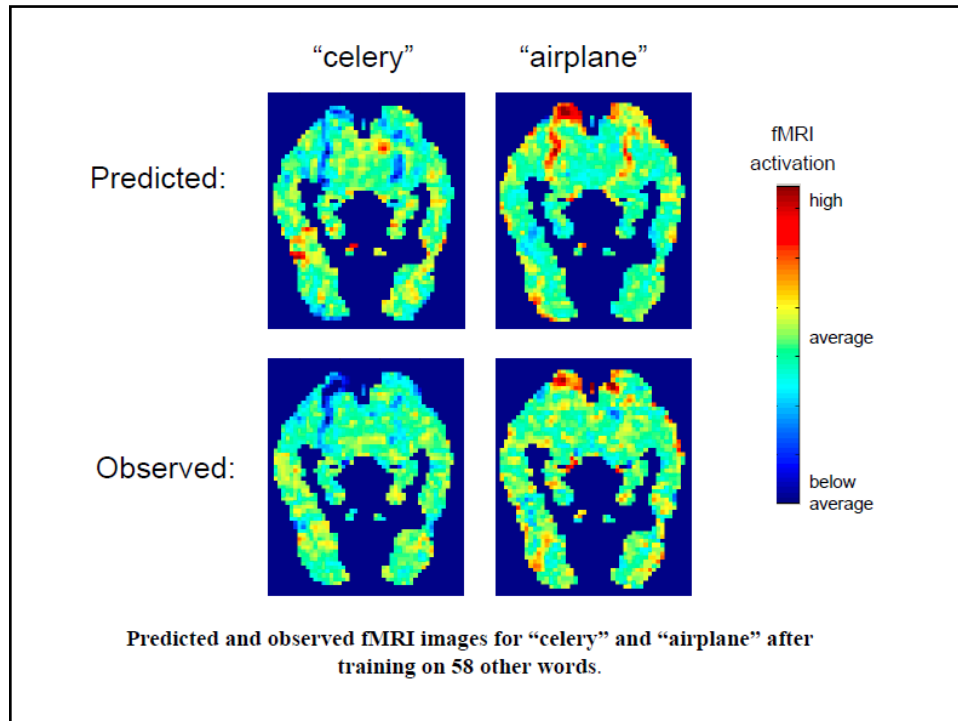
### Semantic feature values: “celery”

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

### Semantic feature values: “airplane”

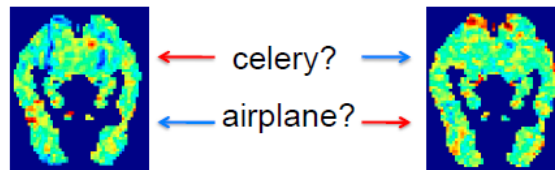
0.8673, ride  
 0.2891, see  
 0.2851, say  
 0.1689, near  
 0.1228, open  
 0.0883, hear  
 0.0771, run  
 0.0749, lift  
 ...  
 ...  
 0.0049, smell  
 0.0010, wear  
 0.0000, taste  
 0.0000, rub  
 0.0000, manipulate





## Evaluating the Computational Model

- Train it using 58 of the 60 word stimuli
- Apply it to predict fMRI images for other 2 words
- Test: show it the observed images for the 2 held-out, and make it predict which is which


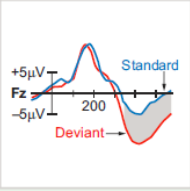

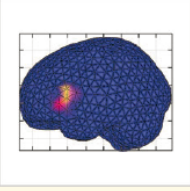

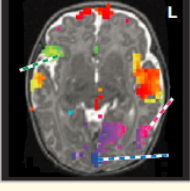


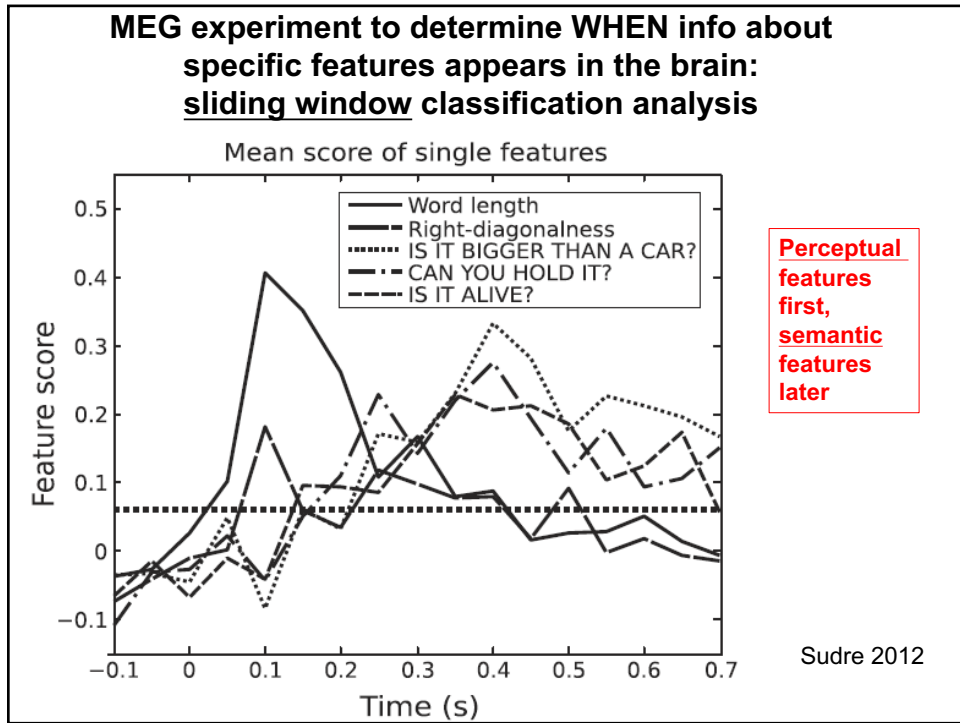
1770 test pairs in leave-2-out:

- Random guessing  $\rightarrow$  0.50 accuracy
- Accuracy above 0.61 is significant ( $p < 0.05$ )

**Mean accuracy over 9 subjects: 0.79**

**Neuroscience techniques used with infants**

Inexpensive		<p><b>EEG/ERP: Electrical potential changes</b></p> <ul style="list-style-type: none"> <li>• Excellent temporal resolution</li> <li>• Studies cover the life span</li> <li>• Sensitive to movement</li> <li>• Noiseless</li> </ul>	
Expensive		<p><b>MEG: Magnetic field changes</b></p> <ul style="list-style-type: none"> <li>• <b>Excellent temporal</b> and spatial resolution</li> <li>• Studies on adults and young children</li> <li>• Head tracking for movement calibration</li> <li>• Noiseless</li> </ul>	
Expensive		<p><b>fMRI: Hemodynamic changes</b></p> <ul style="list-style-type: none"> <li>• Excellent spatial resolution</li> <li>• Studies on adults and a few on infants</li> <li>• Extremely sensitive to movement</li> <li>• Noise protectors needed</li> </ul>	



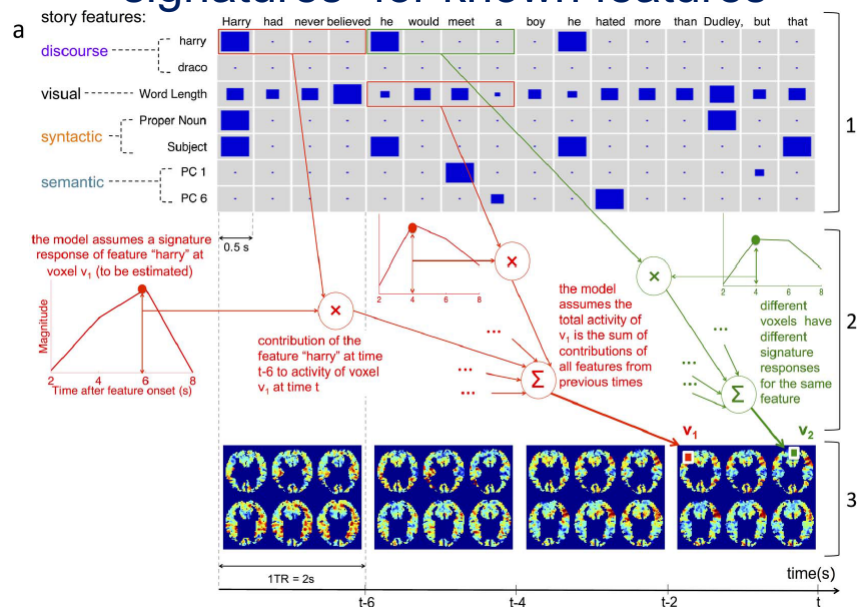


# Simultaneously Uncovering the Patterns of Brain Regions Involved in Different Story Reading Subprocesses

## Abstract

Story understanding involves many perceptual and cognitive subprocesses, from perceiving individual words, to parsing sentences, to understanding the relationships among the story characters. We present an integrated computational model of reading that incorporates these and additional subprocesses, simultaneously discovering their fMRI signatures. Our model predicts the fMRI activity associated with reading arbitrary text passages, well enough to distinguish which of two story segments is being read with 74% accuracy. This approach is the first to simultaneously track diverse reading subprocesses during complex story processing and predict the detailed neural representation of diverse story features, ranging from visual word properties to the mention of different story characters and different actions they perform. We construct brain representation maps that replicate many results from a wide range of classical studies that focus each on one aspect of language processing and offer new insights on which type of information is processed by different areas involved in language processing. Additionally, this approach is promising for studying individual differences: it can be used to create single subject maps that may potentially be used to measure reading comprehension and diagnose reading disorders.

## Predict fMRI activation by adding up "signatures" for known features



## Lab 8: General Linear Model!

