

Case Study 3: fMRI Prediction

fMRI Prediction Task, Ridge, LASSO Review

Machine Learning for Big Data
CSE547/STAT548, University of Washington

*so far large/streaming N,
now big-p domain*

Emily Fox
January 28th, 2014

©Emily Fox 2014

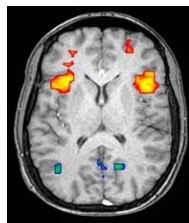
1

fMRI Prediction Task

- **Goal:** Predict word stimulus from fMRI image

Can we read your brain?

*scan after
↓ seeing word*



guess word

©Emily Fox 2014

2

fMRI



©Emily Fox 2014

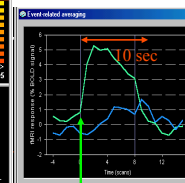
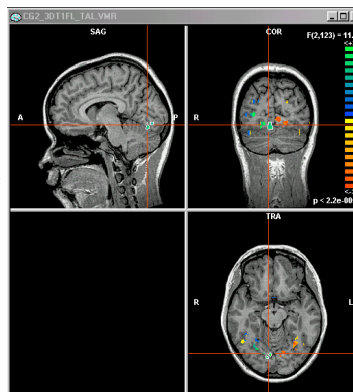
3

fMRI

high-res spatially
~1 mm resolution
pretty slow
~1 image per sec.

20,000 voxels/image
safe, non-invasive

measures Blood
Oxygen Level
Dependent (BOLD)
response

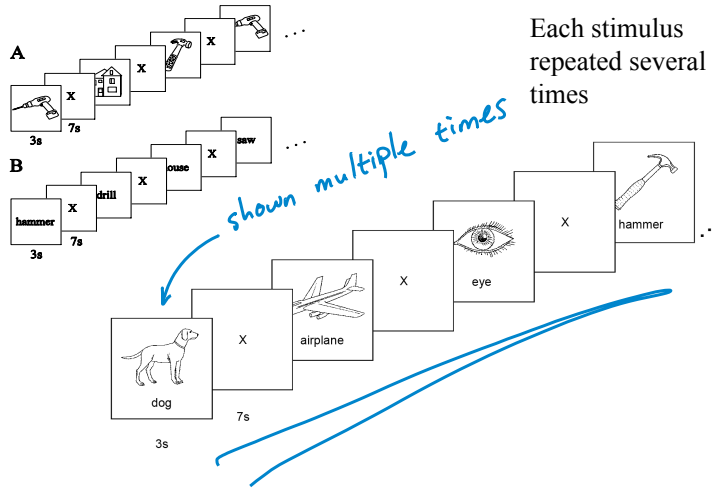


Typical fMRI
response to
impulse of
neural activity

©Emily Fox 2014

4

Typical Stimuli

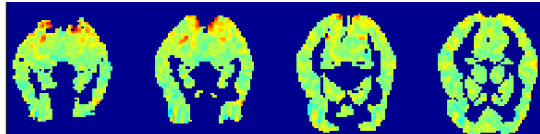


©Emily Fox 2014

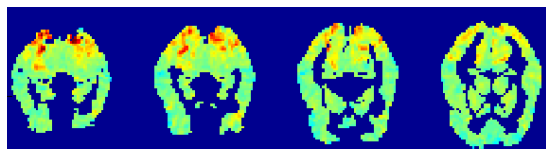
5

fMRI Activation

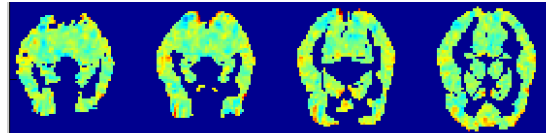
fMRI activation for "bottle":



Mean activation averaged over 60 different stimuli:



"bottle" minus mean activation:



is this enough?



bottle

fMRI activation

high

average

below average

©Emily Fox 2014

6

fMRI Prediction Task

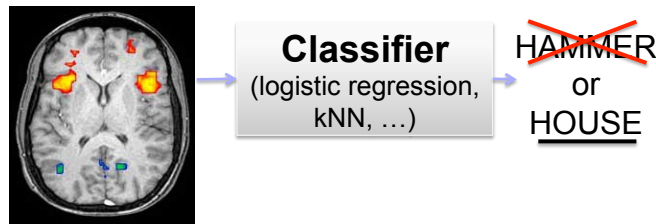
- **Goal:** Predict word stimulus from fMRI image

- **Challenges:**

- $p \gg N$ (feature dimension \gg sample size)
- Cost of fMRI recordings is high
- Only have a few training examples for each word

of voxels = # params

*many more
params than obs.
What can we do?*



©Emily Fox 2014

7

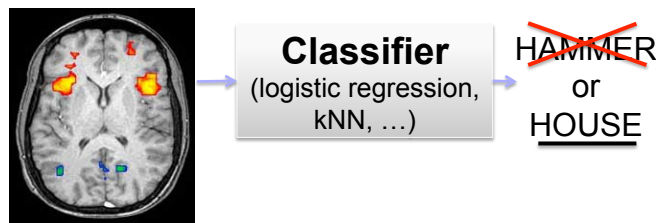
Zero-Shot Classification

- **Goal:** Classify words not in the training set

- **Challenges:**

- Cost of fMRI recordings is high
- Can't get recordings for every word in the vocabulary

Never showed "giraffe" in scanner



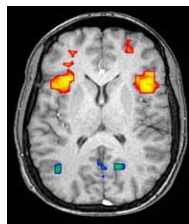
©Emily Fox 2014

8

Zero-Shot Classification

- **Goal:** Classify words not in the training set
- **Challenges:**
 - Cost of fMRI recordings is high
 - Can't get recordings for every word in the vocabulary
- We don't have many brain images, but we have a lot of info about the words and how they relate (co-occurrence, etc.)
- How do we utilize this "cheap" information?

many docs that contain "giraffe" also contain "neck" "animal" "zoo" ...



©Emily Fox 2014

9

Semantic Features

Google Trillion word corpus

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

CO-OCCURRENCE

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

©Emily Fox 2014

10

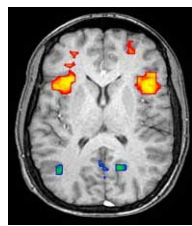
Zero-Shot Classification

- From training data, learn two mappings:

- S: input image \rightarrow semantic features
- L: semantic features \rightarrow word

- Can use "cheap" co-occurrence data to help learn L

Training: $\{ \text{image} \rightarrow \text{semantic feature VECs} \rightarrow \text{"dog"} \}$ N examples... N small



Features of word

Classifier
(logistic regression, kNN, ...)

~~HAMMER~~
or
HOUSE

Predict:



S

semantic feature VECs

"giraffe"

learned on training data

©Emily Fox 2014

11