Generating words from functional MRI data

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- a brief introduction to functional MRI
- a brief introduction to machine learning
- generating text from functional MRI data
a very brief introduction to fMRI

MRI - magnetic resonance imaging
  - a 3D grid of volume elements (voxels)
  - a given contrast highlights certain types of tissue
    - grey matter
    - white matter
    - blood vessels
    - ...

![Diagram of MRI scan](image-url)
a very brief introduction to fMRI

**functional MRI**
- neuronal activity consumes oxygen
- increased blood flow brings even more oxygen
a very brief introduction to fMRI

functional MRI

- neuronal activity consumes oxygen
- increased blood flow brings even more oxygen
- increase in oxygenated haemoglobin affects the MRI signal for a few seconds (BOLD contrast)
a very brief introduction to fMRI

**functional MRI**
- what is being detected where?
- spatial resolution is $O(1)\text{mm}$, typical $3\times3\times3\text{mm}$

[Menon,Kim 1999]
a very brief introduction to fMRI

functional MRI

- 10 second visual stimulus
- delayed/smeared response
- average of 54 trials

[Menon, Kim 1999]
a very brief introduction to fMRI

- 1 second flashing checkerboard
- 5 seconds between trials

[Grill-Spector/Wandell]
a very brief introduction to fMRI

- haemodynamic response to each trial cluster
- subtraction of one from two and two from three
a very brief introduction to fMRI

- with anatomical information, O(10K) voxels
- typical rate of acquisition is 1 3D image/sec, overall duration hundreds/thousands of images
- a few tens of tasks performances
traditional fMRI analysis

A typical experiment is designed to have the subject perform:
- a task of interest (e.g. read a word)
- a control task (e.g. read a nonsense word)

experimental conditions

---

**Task**

<table>
<thead>
<tr>
<th>0</th>
<th>50</th>
<th>100</th>
<th>150</th>
<th>200</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

control

**Reference time series**

**Time**
traditional fMRI analysis

The goal is to find voxels that match the reference

![Graph of task time series and voxel time series](image)

control | task | time | reference time series

control | task | time | voxel time series
traditional fMRI analysis

This is done univariately, for each voxel in the brain

- essentially a multiple regression on reference and other things
- yields an image with the matching score for each voxel
- that image is thresholded leaving statistically significant locations

statistical parametric map (GLM)
traditional fMRI analysis

This is done **univariately**, for each voxel in the brain

- essentially a multiple regression on reference and other things
- yields an image with the matching score for each voxel
- that image is thresholded leaving statistically significant locations

![statistical parametric map (GLM)](image)

a.k.a. BRAIN BLOBS
traditional fMRI analysis

“modern phrenology”?

- complex data are reduced to a set of locations
- locations reflect a contrast of interest
and all of this leads to...

if you can answer one question

“which brain areas are different across conditions?”

experiment design tends to focus on it

key words: “neural correlates of <X>”
and all of this leads to...

- there is information in fMRI data beyond this

- the questions one asks of data are often shaped by tools

- a community tends to favour certain tools...
what is machine learning?

- how to build computer systems that automatically improve with experience
what is machine learning?

- how to build computer systems that automatically improve with experience

- building models of data for
  - predicting numeric variables (regression)
  - predicting categoric variables (classification)
  - grouping data points (clustering)
  - ...

what is machine learning?

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  - ...

- overlaps a lot with applied statistics...
Learning classifiers

given **training** data, learn to predict if Prof. X will play

<table>
<thead>
<tr>
<th>Day</th>
<th>Outlook</th>
<th>Temperature</th>
<th>Humidity</th>
<th>Wind</th>
<th>PlayTennis</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>Sunny</td>
<td>Hot</td>
<td>High</td>
<td>Weak</td>
<td>No</td>
</tr>
<tr>
<td>D2</td>
<td>Sunny</td>
<td>Hot</td>
<td>High</td>
<td>Strong</td>
<td>No</td>
</tr>
<tr>
<td>D3</td>
<td>Overcast</td>
<td>Hot</td>
<td>High</td>
<td>Weak</td>
<td>Yes</td>
</tr>
<tr>
<td>D4</td>
<td>Rain</td>
<td>Mild</td>
<td>High</td>
<td>Weak</td>
<td>Yes</td>
</tr>
<tr>
<td>D5</td>
<td>Rain</td>
<td>Cool</td>
<td>Normal</td>
<td>Weak</td>
<td>Yes</td>
</tr>
<tr>
<td>D6</td>
<td>Rain</td>
<td>Cool</td>
<td>Normal</td>
<td>Strong</td>
<td>No</td>
</tr>
<tr>
<td>D7</td>
<td>Overcast</td>
<td>Cool</td>
<td>Normal</td>
<td>Strong</td>
<td>Yes</td>
</tr>
<tr>
<td>D8</td>
<td>Sunny</td>
<td>Mild</td>
<td>High</td>
<td>Weak</td>
<td>No</td>
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<tr>
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<td>Sunny</td>
<td>Cool</td>
<td>Normal</td>
<td>Weak</td>
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</tr>
<tr>
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<td>Mild</td>
<td>Normal</td>
<td>Weak</td>
<td>Yes</td>
</tr>
<tr>
<td>D11</td>
<td>Sunny</td>
<td>Mild</td>
<td>Normal</td>
<td>Strong</td>
<td>Yes</td>
</tr>
<tr>
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<td>Overcast</td>
<td>Mild</td>
<td>High</td>
<td>Strong</td>
<td>Yes</td>
</tr>
<tr>
<td>D13</td>
<td>Overcast</td>
<td>Hot</td>
<td>Normal</td>
<td>Weak</td>
<td>Yes</td>
</tr>
<tr>
<td>D14</td>
<td>Rain</td>
<td>Mild</td>
<td>High</td>
<td>Strong</td>
<td>No</td>
</tr>
</tbody>
</table>
learning classifiers

- there are many types of classifier
- all of them are functions from data to label
- in this case, a decision tree
testing classifiers

given test data, predict whether Prof. X will play

test: Rain, Hot, Normal, Weak
more on classifiers

- **generalization**: success on new data, not used to train
- **examples**: cases a classifier learns from or is tested on
- **features**: the attributes that make up an example
more on classifiers

- **generalization**: success on new data, not used to train
- **examples**: cases a classifier learns from or is tested on
- **features**: the attributes that make up an example

- many different kinds (inductive biases)
- ML basic ideas:
  - learning applies to anything that can be extracted from data
  - the test of what is learned is generalization
what is machine learning?

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May 5, 2012
what is machine learning?

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  - predicting numeric variables (regression)
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  - grouping data points (clustering)
  - ...

- overlaps with applied statistics
why use it at all?

to tell a story about data
once upon a time there was a sample...
... and then came a beautiful model...

fit model by estimating parameters

![Graph showing reaction time vs age with fitted line and equation RT = 503.7 - 0.530age]

[adapted from slides by Russ Poldrack]
very suggestive, but...

Is RT really related to age?

RT = 503.7 + age*−0.530

[adapted from slides by Russ Poldrack]
is RT related to age?

Model:
$$RT = \beta_0 + \beta_1 \times \text{age} + \varepsilon$$

parameters in the population

[adapted from slides by Russ Poldrack]
is RT related to age?

Model:
\[ RT = \beta_0 + \beta_1 \times \text{age} + \varepsilon \]

parameters in the population

parameters estimated from the sample

\[ \beta_{\text{est}} = (X'X)^{-1}X'y \]

[adapted from slides by Russ Poldrack]
is RT related to age?

Model:
\[ RT = \beta_0 + \beta_1 \cdot \text{age} + \varepsilon \]

parameters in the population

parameters estimated
from the sample

\[ \beta_{\text{est}} = (X'X)^{-1}X'y \]

Hypothesis:
Is \( \beta_1 \) different from 0?

[adapted from slides by Russ Poldrack]
is RT related to age?

Null hypothesis: \( \beta_1 = 0 \)

Alternative: \( \beta_1 \neq 0 \)

RT = 503.7 + age*–0.530

[adapted from slides by Russ Poldrak]
is RT related to age?

Null hypothesis: \( \beta_1 = 0 \)
Alternative: \( \beta_1 \neq 0 \)

How likely is the parameter estimate (\( \beta_1 = -0.53 \)) if the null hypothesis is true?

[adapted from slides by Russ Poldrack]
is RT related to age?

Null hypothesis: $\beta_1 = 0$
Alternative: $\beta_1 \neq 0$

How likely is the parameter estimate ($\beta_1 = -0.53$) if the null hypothesis is true?

We need a statistic with a known distribution to determine this!

[adapted from slides by Russ Poldrack]
Is RT related to age?

The CLT tells us

\[ \hat{\beta}_1 \sim N(\beta_1, Var(\hat{\beta}_1)) \]

but we don’t know

\[ Var(\hat{\beta}_1) \]

[adapted from slides by Russ Poldrack]
is RT related to age?

the CLT tells us

\[ \hat{\beta}_1 \sim N(\beta_1, \text{Var}(\hat{\beta}_1)) \]

but we don’t know

\[ \text{Var}(\hat{\beta}_1) \]

we do know

\[ t = \frac{\hat{\beta}_1}{\sqrt{\text{Var}(\hat{\beta}_1)}} \sim T_{N-p} \]

[adapted from slides by Russ Poldrack]
is RT related to age?

\[ t(10) = -4.76 \]

How likely is this value in this \( t \) distribution?

\[ p < .001 \]
what can we conclude?

- in this sample
  - $p < 0.001$ - there is a relationship between age and RT
  - $R^2$ - age accounts for 69% of variance in RT

- very unlikely if no relationship in the population

- the test does not tell us how well we can predict RT from age in the population
what happens with a new sample?

draw a new sample from the same population

compute the R2 using parameters estimated in the original sample

[adapted from slides by Russ Poldrak]
what happens with a new sample?

repeat this 100 times…
using model parameters estimated from the original sample

average $R^2 = 0.578$

a measure of how good the model learned from a single sample is

[adapted from slides by Russ Poldrack]
the learning perspective

When we estimate parameters from a sample, we are **learning** about the population from **training** data.
the learning perspective

When we estimate parameters from a sample, we are **learning** about the population from **training** data.

How well can we measure the prediction ability of our learned model? Use a new sample as **test** data.
test data and cross-validation

If you can’t collect more split your sample in two...

entire dataset

estimate parameters from training data

test accuracy on untrained data

[adapted from slides by Russ Poldrack]
test data and cross-validation

If you can’t collect more split your sample in two...

k-fold cross-validation:
- split into k folds
- train on k-1, test on the left out
- average prediction measure on all k folds
- several variants: all possible splits, leave-one-out

[adapted from slides by Russ Poldrack]
leave-one-out cross-validation

regression lines on each training set

original sample
$R^2 = 0.694$

leave-one-out on original
$R^2 = 0.586$

mean over 100 new samples
$R^2 = 0.591$

[adapted from slides by Russ Poldrack]
As model complexity goes up, we can always fit the training data better.

What does this do to our predictive ability?
model complexity

polynomials of higher degree fit the training data better...

[adapted from slides by Russ Poldrack]
model complexity

polynomials of higher degree fit the training data better...

... but they do worse on test data: overfitting

[adapted from slides by Russ Poldrack]
model complexity

if the relationship in the population were more complicated

[adapted from slides by Russ Poldrack]
model complexity

if the relationship in the population were more complicated we could use CV to determine adequate model complexity

(this would need to be done with nested CV, CV inside the training set)
what is machine learning, redux

- generalization: make predictions about a new individual

- a model that generalizes captures the relationship between the individual and what we want to predict

- cross-validation is a good way of
  - measuring generalization
  - doing model selection (there are others)
what is machine learning, redux

- generalization: make predictions about a new individual
  - a model that generalizes captures the relationship between the individual and what we want to predict

- cross-validation is a good way of
  - measuring generalization
  - doing model selection (there are others)

- “all models are wrong but some are useful”
  George Box
what does this have to do with fMRI?

In this talk:

- prediction is classification
- generalization is within subject (population of trials)
- how to draw conclusions with statistical significance
- what has it been used for?
two different questions

GLM

stimulus → fMRI activation
(single voxel)
fMRI analysis with a classifier

[Kamitani&Tong, 2005]

subjects see gratings in one of 8 orientations
fMRI analysis with a classifier

subjects see gratings in one of 8 orientations

voxels in visual cortex respond similarly to different orientations

Kamitani & Tong, 2005
fMRI analysis with a classifier

Subjects see gratings in one of 8 orientations.

Yet, voxels can be combined to predict the orientation of the grating being seen.
two different questions

GLM

stimulus → fMRI activation
(single voxel)

Classifier

stimulus ← fMRI activation
(multiple voxels)
We can predict!


- what is the orientation of a stimulus visual grating?
- is the subject seeing a sentence or a picture?
- which of several categories of words or pictures is a subject seeing?
- is the subject reading an ambiguous sentence?
- same or different sentence?
- what is the subject perceiving?
- is the subject concealing information?
- “do you know this terrorist, sir?”
- “is there still a fire for me in his brain?”
classifiers on fMRI, mind-reading, etc

We can predict!


- what is the orientation of a stimulus visual grating?
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two different questions revisited

GLM

stimulus → fMRI activation (single voxel)

Classifier

stimulus ← fMRI activation (multiple voxels)
two different questions revisited

GLM

stimulus \rightarrow fMRI activation
(single voxel)

Classifier

stimulus \rightarrow fMRI activation
(multiple voxels)

stimulus \rightarrow mind \rightarrow brain \rightarrow fMRI activation
(multiple voxels)
two different questions revisited

**GLM**

stimulus → fMRI activation
(single voxel)

**Classifier**

stimulus ← fMRI activation
(multiple voxels)

stimulus → mind → brain → fMRI activation
(not an endorsement of dualism)
(multiple voxels)
the main point

how is the meaning of something assembled in the mind...

- kitchen
- slice
- sharp
- has handle
- stab
- used with cutting board
- knife

... and how does that manifest in the (fMRI) brain?
- a brief introduction to functional MRI
- a brief introduction to machine learning
- generating text from functional MRI data
BREAK
12 categories experiment

Task:

- stimulus: word + drawing
- subject visualizes object, thinks of properties, using it, etc
- 3 seconds per trial

[Mitchell et al, 2008]

Table
12 categories experiment

Task:
- stimulus: word + drawing
- subject visualizes object, thinks of properties, using it, etc
- 3 seconds per trial

Dataset:
- 12 categories, 5 exemplars of each
- 6 epochs with all 60 exemplars
- 360 examples (average image at trial peak)
- even/odd epoch cross-validation (and leave-one-out inside)
12 categories experiment

[Mitchell et al, 2008]

### 60 exemplars

<table>
<thead>
<tr>
<th>Categories</th>
<th>Exemplars</th>
</tr>
</thead>
<tbody>
<tr>
<td>BODY PARTS</td>
<td>leg, arm, eye, foot, hand</td>
</tr>
<tr>
<td>FURNITURE</td>
<td>chair, table, bed, desk, dresser</td>
</tr>
<tr>
<td>VEHICLES</td>
<td>car, airplane, train, truck, bicycle</td>
</tr>
<tr>
<td>ANIMALS</td>
<td>horse, dog, bear, cow, cat</td>
</tr>
<tr>
<td>KITCHEN UTENSILS</td>
<td>glass, knife, bottle, cup, spoon</td>
</tr>
<tr>
<td>TOOLS</td>
<td>chisel, hammer, screwdriver, pliers, saw</td>
</tr>
<tr>
<td>BUILDINGS</td>
<td>apartment, barn, house, church, igloo</td>
</tr>
<tr>
<td>PART OF A BUILDING</td>
<td>window, door, chimney, closet, arch</td>
</tr>
<tr>
<td>CLOTHING</td>
<td>coat, dress, shirt, skirt, pants</td>
</tr>
<tr>
<td>INSECTS</td>
<td>fly, ant, bee, butterfly, beetle</td>
</tr>
<tr>
<td>VEGETABLES</td>
<td>lettuce, tomato, carrot, corn, celery</td>
</tr>
<tr>
<td>MAN MADE OBJECTS</td>
<td>refrigerator, key, telephone, watch, bell</td>
</tr>
</tbody>
</table>
where are we?

stimulus ➔ mind ➔ brain ➔ fMRI data

(task)
what do we want?

stimulus \rightarrow \text{mind} \rightarrow \text{brain} \rightarrow \text{fMRI data}

(task)

what is present in the mind as the task is performed?
image decomposition

(a,b,c) is the representation of example “Building”

in a basis of 3 (eigen)images
(a,b,c) is the representation of example “Building” in a basis of 3 (eigen)images.

(a,b,c) can also be seen as feature values in a low-dimensional feature representation.
dataset decomposition

\[
\begin{align*}
(a_1, b_1, c_1) &= \ldots \\
(a_n, b_n, c_n)
\end{align*}
\]

examples 1 to n \hspace{1cm} 3 basis images

why express a dataset in terms of a basis of images?

- capture spatial patterns of activity over many voxels
- coordinates give a succinct representation of the data
dataset decomposition

\[
\begin{align*}
(a_1, b_1, c_1) &= \ldots \\
(a_n, b_n, c_n) &= \text{3 basis images}
\end{align*}
\]

examples 1 to n

\[
X = Z \times W
\]

n examples

m voxels

l-dimensional representation of data

m voxels

\{l\} basis images
what do we want?

stimulus ➔ mind ➔ brain ➔ fMRI data

(task)

what is present in the mind as the task is performed?
where can it come from?

stimulus \(\rightarrow\) mind \(\rightarrow\) brain \(\rightarrow\) fMRI data

(task)

what is present in the mind as the task is performed?

features!

- known or constrained from behavioural experiments
- modelled mathematically or computationally
- hypothesized
- learnt elsewhere
how do we know they are there?

1. stimulus (task) → mind → brain → fMRI data
   ▪ model → predicted fMRI data

- Kay et al. 2008
- Mitchell et al. 2008
how do we know they are there?

2

stimulus mind brain fMRI data
(task)

predicted stimulus or task

- Thirion et al. 2006
- Miyawaki et al. 2008
- Naselaris et al. 2009
- van Gerven et al. 2010
- Pereira et al. 2011
- Nishimoto et al. 2011
learning features from text

- **from text alone** [Landauer+Dumais 97, Griffiths et al 07]
  - LSA, topic models

- **verbs + co-occurrence with them** [Mitchell et al 08]
feature extraction

- 25 verbs reflecting sensory/motor/function aspects
  - sensory: see, hear, listen, taste, touch, smell, fear, ...
  - motor: rub, lift, run, push, move, say, eat, ...
  - abstract: fill, open, ride, approach, drive, enter, ...
feature extraction

- 25 verbs reflecting sensory/motor/function aspects
  - sensory: see, hear, listen, taste, touch, smell, fear, ...
  - motor: rub, lift, run, push, move, say, eat, ...
  - abstract: fill, open, ride, approach, drive, enter, ...

- 25 features
  - co-occurrence of a stimulus noun with each of 25 verbs
  - co-occurrence is normalized
feature extraction

- example: “airplane”
  - 0.87, ride
  - 0.29, see
  - 0.17, near
  - 0.08, run
  - ...
learning features from text

- from text alone [Landauer+Dumais 97, Griffiths et al 07]
  - LSA, topic models

- verbs + co-occurrence with them [Mitchell et al 08]

- text + people [Pereira et al. 2011, in press]
  - use word norms to choose concrete concepts
  - collect wikipedia articles for those concepts
  - build topic model from articles
Seeking Life’s Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today’s organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn’t be enough.

Although the numbers don’t match precisely, those predictions are not all that far apart,” especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. “It may be a way of organizing any newly sequenced genome,” explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

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intuition:
- each word is drawn from one topic
- topics are present in different proportions
topic models

- used to model a document corpus
- documents are bags-of-words: words and counts
topic models

- used to model a document corpus
- documents are bags-of-words: words and counts
- model:
  - per document: the probability of each topic
  - per topic: a probability distribution over words

[Blei et al 2003]
## Topic Models

A topic can be summarized by its high-probability words:

<table>
<thead>
<tr>
<th><strong>“molbio”</strong></th>
<th><strong>“evolution”</strong></th>
<th><strong>“disease”</strong></th>
<th><strong>“computing”</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>human</td>
<td>evolution</td>
<td>disease</td>
<td>computer</td>
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<tr>
<td>genome</td>
<td>evolutionary</td>
<td>host</td>
<td>models</td>
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<tr>
<td>dna</td>
<td>species</td>
<td>bacteria</td>
<td>information</td>
</tr>
<tr>
<td>genetic</td>
<td>organisms</td>
<td>diseases</td>
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<td>life</td>
<td>resistance</td>
<td>computers</td>
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<td>sequence</td>
<td>origin</td>
<td>bacterial</td>
<td>system</td>
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<td>biology</td>
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<td>network</td>
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<td>groups</td>
<td>strains</td>
<td>systems</td>
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<td>sequencing</td>
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<td>control</td>
<td>model</td>
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<td>infectious</td>
<td>parallel</td>
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<tr>
<td>information</td>
<td>diversity</td>
<td>malaria</td>
<td>methods</td>
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<td>genetics</td>
<td>group</td>
<td>parasite</td>
<td>networks</td>
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<td>two</td>
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<tr>
<td>sequences</td>
<td>common</td>
<td>tuberculosis</td>
<td>simulations</td>
</tr>
</tbody>
</table>
topic models

[Blei et al 2003]

- used to model a document corpus
- documents are bags-of-words: words and counts

model:
- per document: the probability of each topic
- per topic: a probability distribution over words
topic models and semantic features

- if a document corresponds to a concept...
  - topics ↔ semantic features
  - topic probabilities ↔ semantic feature values

[Pereira et al. 2011, in press]
if a document corresponds to a concept…
- topics
- topic probabilities

the “Wee-kipedia”
- corpus of 3500 Wikipedia hand-picked articles
- articles about concrete/imageable concepts
- vocabulary of about 50K words

[Perreira et al. 2011, in press]
our topic model(s)

http://en.wikipedia.org/wiki/Liver
The liver is a vital organ present in vertebrates and some other animals; it has a wide range of functions, a few of which are detoxification, protein synthesis, and production of biochemicals necessary for digestion. The liver is necessary for survival; a human can only survive up to 24 hours without liver function. (…) Mammal and bird livers are commonly eaten as food by humans. Liver can be baked, boiled, broiled, fried or eaten raw, but is perhaps most commonly made into spreads.
The liver is a vital organ present in vertebrates and some other animals; it has a wide range of functions, a few of which are detoxification, protein synthesis, and production of biochemicals necessary for digestion. The liver is necessary for survival; a human can only survive up to 24 hours without liver function. (…)

Mammal and bird livers are commonly eaten as food by humans. Liver can be baked, boiled, broiled, fried or eaten raw, but is perhaps most commonly made into spreads.
from concept to topic

Liver → topic #14 (0.68)

blood milk cause health increase heart body disease patient diabetes fat risk stroke food death obesity cell weight result lead reduce level liver study diet tissue human brain medical develop type treatment people insulin fetus time artery factor loss age effect infarction symptom occur rate physical glucose test myocardial exercise leave week child produce
from concept to topic

Liver → topic #14 (0.68)

→ topic #4 (0.27)

blood milk cause health increase heart body disease patient diabetes fat risk stroke food death obesity cell weight result lead reduce level liver study diet tissue human brain medical develop type treatment people insulin fetus time artery factor loss age effect infarction symptom occur rate physical glucose test myocardial exercise leave week child produce

muscle bone frog nerve body branch join limb human tissue form anatomy ligament lateral structure leg function skin cell anterior iris lower organ medial surface birch head foot spinal cord posterior movement skull contain knee lung artery gland position cactus animal region hip lip tendon upper attach vein refer locate
from concept to topic

Liver → topic #14 (0.68)

→ topic #4 (0.27)

→ topic #47 (0.03)
from topic to concept

topic

#14 (0.68)
from topic to concept

**topic #14 (0.68)**

- Diabetes_mellitus (0.993)
- Stroke (0.991)
- Myocardial_infarction (0.990)
- Fetus (0.914)
- Overweight (0.888)
- Amniotic_fluid (0.879)
- Obesity (0.869)
- Blood_vessel (0.843)
- Hunger (0.833)
- Umbilical_cord (0.782)
- Heart (0.756)
- Starvation (0.677)
- Liver (0.676)
- Autopsy (0.641)
- Gold_standard_(test) (0.636)
- Milk (0.627)
- Health (0.618)
- Blood_bank (0.614)
- Malnutrition (0.584)
- Adipose_tissue (0.559)
- Dietary_fiber (0.540)
- Blood_type (0.496)
- Death (0.495)
- Portal_venous_system (0.481)
- Diet_food (0.462)
- Hyperthermia (0.428)
- Fetus_(biology) (0.422)
- Udder (0.412)
- Blood (0.408)
- Death_rattle (0.397)

**topic #4 (0.27)**

- Human_leg (0.990)
- Spinal_cord (0.978)
- Knee (0.974)
- Elbow (0.944)
- Arm (0.943)
- Hip (0.931)
- Human_abdomen (0.925)
- Shoulder (0.923)
- Ankle (0.904)
- Neck (0.862)
- Wrist (0.849)
- Bone (0.771)
- Thigh (0.761)
- Hand (0.750)
- Chest (0.684)
- Abdomen (0.671)
- Hip_bone (0.665)
- Neural_pathway (0.621)
- Torso (0.607)
- Lung (0.600)
- Toe (0.569)
- Sclera (0.565)
- Lip (0.563)
- Throat (0.560)
- Limb_(anatomy) (0.549)
- Nerve (0.545)
- Mouth (0.541)
- Skull (0.501)
- Leaf (0.490)
- Thorn_(botany) (0.487)
from topic to concept

**topic #14 (0.68)**

Diabetes_mellitus (0.993) Stroke (0.991) Myocardial_infarction (0.990) Fetus (0.914) Overweight (0.888) Amniotic_fluid (0.879) Obesity (0.869) Blood_vessel (0.843) Hunger (0.833) Umbilical_cord (0.782) Heart (0.756) Starvation (0.677) Liver (0.676) Autopsy (0.641) Gold_standard_(test) (0.636) Milk (0.627) Health (0.618) Blood_bank (0.614) Malnutrition (0.584) Adipose_tissue (0.559) Dietary_fiber (0.540) Blood_type (0.496) Death (0.495) Portal_venous_system (0.481) Diet_food (0.462) Hyperthermia (0.428) Fetus_(biology) (0.422) Udder (0.412) Blood (0.408) Death_rattle (0.397)

**topic #4 (0.27)**

Human_leg (0.990) Spinal_cord (0.978) Knee (0.974) Elbow (0.944) Arm (0.943) Hip (0.931) Human_abdomen (0.925) Shoulder (0.923) Ankle (0.904) Neck (0.882) Wrist (0.849) Bone (0.771) Thigh (0.761) Hand (0.750) Chest (0.684) Abdomen (0.671) Hip_bone (0.665) Neural_pathway (0.621) Torso (0.607) Lung (0.600) Toe (0.569) Sclera (0.565) Lip (0.563) Throat (0.560) Limb_(anatomy) (0.549) Nerve (0.545) Mouth (0.541) Skull (0.501) Leaf (0.490) Thorn_(botany) (0.487)

**topic #47 (0.03)**

Breakfast (0.992) Curry (0.980) French_toast (0.957) Pickling (0.947) Mustard_(condiment) (0.943) Pickled_cucumber (0.933) Coconut_milk (0.924) Supper (0.920) Soup (0.905) Fruit_preserves (0.902) Salad (0.884) Sauce (0.869) Pudding (0.864) Sichuan_pepper (0.858) Brunch (0.826) Capsicum (0.817) Butter (0.814) Carrot_cake (0.802) Side_dish (0.795) Sponge_cake (0.787) Lemon (0.787) Condiment (0.782) List_of_cuisines (0.765) Lime_(fruit) (0.765) Sausage (0.763) Peel_(fruit) (0.757) Black_pudding (0.756) Orange_juice (0.752) Macaroni (0.746) Macaroni_and_cheese (0.744)
topic model

Table

Hammer

Bear

...  

wiki  =  Z  and  word distribution  

40K words  

K-topics  

40K words  

K-topic representation of each article
**topic model**

Table

Hammer

Bear

... 40K words

wiki = Z and word distribution

{ K topics

40K words

K-topic representation of each

vegetables
animals
insects
body parts
tools
clothing
kitchen
obj. (other)
furniture
buildings
build. parts
vehicles

10 20 30 40
Topics
topic model

Table
Hammer
Bear
...

wiki = Z and word distribution

K topics

40K words

K-topic representation of each

plant fruit seed grow leaf flower tree sugar produce species

iron blade steel handle head cut hair metal tool nail

material wood paint build wall structure construction design size window
topic model and fMRI model

\[
\begin{align*}
\text{Table Hammer Bear ...} & \quad \text{wiki} = Z \quad \text{and} \quad \text{word distribution} \quad \{K \text{ topics}\} \\
\text{Table Hammer Bear ...} & \quad \text{fMRI} = Z \quad \times \quad \text{basis} \quad \{K \text{ basis images}\}
\end{align*}
\]

40K words

K-topic representation of each article

40K words

m voxels

m voxels
predicting text

- Wikipedia articles
- Train $m$ voxels
- Known Z
- Learn
- Basis images $m$ voxels
- Predict test
- Predicted Z
- "Article" about the images
predicting text

- original article is a “bag of words”
- a topic is a distribution over words
- article comes from a mixture of topics
predicting text

Building = a + b + c... basis image #1 basis image #2
predicting text

\[ \text{Building} = a + \text{basis image #1} + \text{basis image #2} + \cdots \]

\[
\begin{array}{c}
\text{city material build} \\
\text{wood street town wall} \\
\text{window home store}
\end{array}
= a
\begin{array}{c}
\text{city house street} \\
\text{build town home} \\
\text{state store bus road}
\end{array}
+ b
\begin{array}{c}
\text{material wood build} \\
\text{wall design window paint} \\
\text{size structure construction}
\end{array}
\]

online model browser:
http://minerva.csbmb.princeton.edu/wikipedia
classification via word probability

**Test**
- apartment
- screwdriver

**Train**
- concept 1
- concept 58

**Predicted topic probabilities**
- image basis

**Wikipedia topic model**
classification via word probability

**test**
- apartment
- screwdriver

**train**
- concept 1
- ... concept 58

predicted topic probabilities

house
building
door
...

predicted word distributions

tool
screw
torque
...

prob("apartment")
apartment

prob("screwdriver")
screwdriver

prob("apartment")
apartment

prob("screwdriver")
screwdriver

A screwdriver is a tool for driving screws ...
the screwdriver is made up of a head or tip ...

"apartment" wikipedia article

An apartment or flat is a self-contained housing unit that occupies only part of a building ...

"screwdriver" wikipedia article
classification via word probability

Apartment

An apartment is a self-contained housing unit that occupies only part of a building. Apartments may be owned (by an "owner occupier") or rented (by "tenants"). In the US, some apartment-dwellers own their own apartments, either as co-ops, in which the residents own shares of a corporation that owns the building or development; or in condominiums, whose residents own their apartments and share ownership of the public spaces. Most apartments are in buildings designed for the purpose, but large older houses are sometimes divided into apartments. "Apartment" connotes a division in a building. In some of the United States, the word is owned by the building typically used for a residential purpose by apartment landlords, each tenant pays a loss of income from

Hammer

A hammer is a tool meant to deliver an impact to an object. The most common uses are for driving nails, fitting parts, and breaking up objects. Hammers are often designed for a specific purpose, and vary widely in their shape and structure. Usual features are a handle and a head, with most of the weight in the head. The basic design is hand-operated, but there are also many mechanically operated models for heavier uses. The hammer is a basic tool of many professions, and can also be used as a weapon. By analogy, the name "hammer" has also been used for devices that are designed to deliver blows, e.g., in the caplock.

probability ratio assigned to each word in brain-derived distributions

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classification via word probability

results averaged over several topic models to prevent bias
representation similarity

results from best subject
conclusions

- we can learn features directly from text
- learned features capture semantic knowledge
- further work
  - finer grained topic models/basic features
  - new experiment involving reading
Thank you!