Probabilistic Models for Brain Data Analysis

Sanmi Koyejo
CS & Beckman, University of Illinois
Outline

- **Part 1:** Decoding brain activity using a large-scale probabilistic functional-anatomical atlas of human cognition
- **Part 2:** A Hierarchical Model for Time-Varying Functional Connectivity
Part 1: Decoding brain activity using a large-scale probabilistic functional-anatomical atlas of human cognition
Timothy Rubin @ Indiana => SurveyMonkey

Michael Jones @ Indiana

Chris Gorgolewski @ Stanford

Russ Poldrack @ Stanford

Tal Yarkoni @ UT Austin
Encoding

Pain

Source: Neurosynth
Decoding

Source: Neurosynth
Classifier loadings for 8 tasks (Poldrack et. al. 2009)

84% accuracy across subjects, 64% across tasks

Distinct connectivity patterns for 4 cognitive states (Shirer et. al. 2008)

85% LOOCV accuracy
Open ended decoding via meta-analysis

- Brainmap (Fox et. al. 1994)
  - brainmap.org

- Neurosynth (Yarkoni et. al. 2011)
  - neurosynth.org
Neurosynth (Yarkoni et al. 2011)

(a) Term-based search: "Pain" leads to related studies. Automated coordinate extraction results in a brain map with coordinates like X=23, Y=18, Z=45, and Study 1. Meta-analysis yields P(Pain|Activation).

(b) Forward inference: Pain leads to a brain map with red and yellow activations. Reverse inference questions Working Memory?, Emotion?, Pain?, ...?

(c) Classification: Working memory (P = 78%), Emotion (P = 64%), Pain (P = 87%) lead to "Pain".
Open ended Encoding & Decoding

Brain Image

Latent Representation

Cognitive Terms
Straightforward decoding of whole brain maps

Predicting risky choices from brain activity patterns

Sarah M. Helfinstein\textsuperscript{a,1}, Tom Schonberg\textsuperscript{a}, Eliza Congdon\textsuperscript{b,c}, Katherine H. Karlsgodt\textsuperscript{d,e}, Jeanette A. Mumford\textsuperscript{f}, Fred W. Sabb\textsuperscript{b,c,g}, Tyrone D. Cannon\textsuperscript{h,i}, Edythe D. London\textsuperscript{b,c,g,h}, Robert M. Bilder\textsuperscript{b,c,g,k}, and Russell A. Poldrack\textsuperscript{a,f,l}

Table 2. Pearson correlations between searchlight classification map and NeuroSynth term-based reverse inference activation maps

<table>
<thead>
<tr>
<th>Term</th>
<th>Correlation ($r$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>0.1451</td>
</tr>
<tr>
<td>Working</td>
<td>0.1159</td>
</tr>
<tr>
<td>Numerical</td>
<td>0.1157</td>
</tr>
<tr>
<td>Letter</td>
<td>0.1081</td>
</tr>
<tr>
<td>Attention</td>
<td>0.1062</td>
</tr>
<tr>
<td>Correct</td>
<td>0.1060</td>
</tr>
<tr>
<td>Cue</td>
<td>0.0995</td>
</tr>
<tr>
<td>Preparatory</td>
<td>0.0970</td>
</tr>
<tr>
<td>Load</td>
<td>0.0959</td>
</tr>
<tr>
<td>Hand</td>
<td>0.0924</td>
</tr>
</tbody>
</table>

The 10 most highly correlated terms are listed.
Decoding the Role of the Insula in Human Cognition: Functional Parcellation and Large-Scale Reverse Inference

Luke J. Chang¹,², Tal Yarkoni³, Mel Win Khaw⁴ and Alan G. Sanfey¹,⁵,⁶

Chang et. al. 2012
Terms are fine grained

Neurosynth database
(full text + coordinates for 5,809 papers)

Latent Dirichlet analysis

mental function
topic model

mental disorder
topic model

Chi-squared test

mental function
topic maps
(Figure 2)

mental disorder
topic maps
(Figure 3)

Text mining/
topic modeling

Topic Mapping

Poldrack et. al. (2012)
Topic 71 (115 docs):
narrative, discourse, comprehension, memory, discourse_processing

Topic 108 (128 docs):
empathy, pain, theory_of_mind, awareness, facial_expression

Topic 61 (441 docs):
memory, working_memory, maintenance, visual_working_memory, spatial_working_memory

Topic 93 (495 docs):
emotion, valence, arousal, attention, focus

Topic 20 (497 docs):
action, movement, goal, context, perception

Topic 86 (519 docs):
decision, decision_making, choice, fixation, uncertainty

Poldrack et. al. (2012)
Open Issues

• Current decoding approaches lack a formal model
• Same issue when combined with topic mapping
• Does not attempt to identify any latent structure that presumably makes such mappings useful for example, individual brain regions or functional brain networks that correspond to specific cognitive processes
Generalized Correspondence LDA (GC-LDA)
Generalized Correspondence-LDA

- A generalization of correspondence-LDA (Blei, Ng, & Jordan, 2003)
- Each latent topic is associated with both a spatial distribution and a set of word tokens
- Explicitly designed to produce region-like topics
- We apply a symmetric constraint to produce bilaterally distributed topics
Some useful properties

- Facilitates the learning of interpretable latent structures from a mass of superficial brain cognition mappings
- Provides the ability to decode bi-directionally
- Enables principled generation of novel exemplars or combinations of events that have never been seen before (e.g., what pattern of brain activity would a task combining painful stimulation and phonological awareness produce?).
Generative Model

- Each document is a collection of spatial activations and words
- Each “topic” is a combination of a linguistic topic and a spatial activation topic
- Model is trained using MCMC sampling
- Parameter estimation via maximum likelihood with bi-lateral constraints
Neurosynth database

- 11,362 total publications
- Avg. 35 peak activation tokens per document
- Avg. 46 word tokens after preprocessing
- Approximately 400k activation and 520k word tokens in total
- Learned model with 200 topics
Overlapping topics in Parietal cortex
Compositional nature of cognitive states related to emotion
Datadriven window into lateralization of function
(A) Text-to-image generation

1. "motor"
   - R: z=-18
   - L: z=4
   - R: z=32
   - L: z=60

2. "effort difficult demands"
   - R: z=-30
   - L: z=-4
   - R: z=26
   - L: z=50

3. "painful stimulation during a language task"
   - R: z=-2
   - L: z=22
   - R: z=44
   - L: z=66
(B) Discrete activation decoding

<table>
<thead>
<tr>
<th>Category</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>reading</td>
<td>0.02</td>
</tr>
<tr>
<td>mentalizing</td>
<td>0.02</td>
</tr>
<tr>
<td>pictures</td>
<td>0.02</td>
</tr>
<tr>
<td>mental</td>
<td>0.01</td>
</tr>
<tr>
<td>social</td>
<td>0.01</td>
</tr>
<tr>
<td>motion</td>
<td>0.01</td>
</tr>
<tr>
<td>face</td>
<td>0.01</td>
</tr>
<tr>
<td>auditory</td>
<td>0.01</td>
</tr>
<tr>
<td>gestures</td>
<td>0.01</td>
</tr>
<tr>
<td>visual</td>
<td>0.01</td>
</tr>
<tr>
<td>default</td>
<td>0.05</td>
</tr>
<tr>
<td>self</td>
<td>0.04</td>
</tr>
<tr>
<td>social</td>
<td>0.04</td>
</tr>
<tr>
<td>default_mode_network</td>
<td>0.03</td>
</tr>
<tr>
<td>moral</td>
<td>0.03</td>
</tr>
<tr>
<td>mental</td>
<td>0.03</td>
</tr>
<tr>
<td>emotional</td>
<td>0.03</td>
</tr>
<tr>
<td>intrinsic</td>
<td>0.03</td>
</tr>
<tr>
<td>pictures</td>
<td>0.02</td>
</tr>
<tr>
<td>reading</td>
<td>0.02</td>
</tr>
<tr>
<td>word</td>
<td>0.07</td>
</tr>
<tr>
<td>words</td>
<td>0.07</td>
</tr>
<tr>
<td>semantic</td>
<td>0.06</td>
</tr>
<tr>
<td>language</td>
<td>0.06</td>
</tr>
<tr>
<td>reading</td>
<td>0.05</td>
</tr>
<tr>
<td>speech</td>
<td>0.05</td>
</tr>
<tr>
<td>auditory</td>
<td>0.04</td>
</tr>
<tr>
<td>lexical</td>
<td>0.04</td>
</tr>
<tr>
<td>memory</td>
<td>0.04</td>
</tr>
<tr>
<td>sentences</td>
<td>0.03</td>
</tr>
</tbody>
</table>
Map Reconstruction

Original map

Reconstructed map

(A) Brainmap ICA maps
- thresh_zstat13: $R^2 = 0.86$
- thresh_zstat7: $R^2 = 0.83$

(B) NeuroVault maps
- 138: $R^2 = 0.57$
- 2686: $R^2 = 0.65$

$R = 0.90$ and $r = 0.91$

$R = 0.75$ and $r = 0.81$
Limitations

• Specificity of the extracted topics is limited (both spatially and semantically) by the quality of the metaanalytic data in the automatically extracted Neurosynth database.

• Output of the GCLDA model is necessarily data and context-dependent, and model is based on a simplifying one-to-one mapping between semantic representations and brain regions.

• Interpreting scores: lack of consistent reporting standard for decoding between researchers.
Summary

• Open-ended encoding & decoding are important for understanding the relationship between brain function and cognitive processes
• Proposed the GC-LDA model for learning a joint latent representation
• Extensive empirical validation of proposed model, applications include:
  o encoding & decoding (both fine grained and broad)
  o exploratory analysis
  o contextual predictions
  o summary & reconstruction
• Estimated topics maps are available in Neurovault
Part 2: A Hierarchical Model for Time-Varying Functional Connectivity
Michael Riis Andersen @ Technical University of Denmark

Russ Poldrack @ Stanford
Time Varying Connectivity
Motivating Questions

• How are the regions of the brain functionally connected?
• How do these connections change over time?
• ...

• How are the changing connections related to behavior, disease, etc.? 

Shine et. al. (2016)
Estimating Time-Varying Functional Connectivity

- Non-parametric
  - Kernel / Sliding Window
  - Change points
    - e.g. Cribben et. al. (2012)
- Parametric
  - DCC
    - Lindquist et. al. (2014)
  - Latent variable model
    - e.g. Vidaurre et. al. (2017)
Calhoun et. al. (2015)
Open Issues

- Latent states may not be discrete
- Window size significantly affects results
- Separate window estimation can only use information within window
Model Hypotheses

• Subnetworks combined dynamically over time

\[
\Sigma_t = \beta^{-1}I + \sum_{k=1}^{K} \alpha_{k,t} S_k,
\]

• Subnetworks should be “simple”

\[
S_k = v_k v_k^T, \quad p(v_{k,i}) = (1 - p_k) \delta(v_{k,i}) + p_k \mathcal{N}(v_{k,i} | 0, \tau_k)
\]
Model Hypotheses

- Dynamics are continuous, sparse, and smoothly varying over time

\[ a \sim \mathcal{GP}(\mu_k, C_k) \]

\[ \alpha = \max(0,a) \]

\[ a_{k,t} \sim \mathcal{GP}(\mu_k, C_k), \quad \alpha_{k,t} = \max(0, a_{k,t}) \]
Proposed Models

(a) Subject specific mixing weights
(b) Shared mixing weights across subjects
Simulated time-varying Connectivity (SimTB toolbox)
Factor Model Visualization
Evaluation

- HCP data, Gordon 333 atlas, Motor task
  - Right/left hand tapping, right/left foot tapping, tongue wagging, rest
- Task block + motion regressed out, model the residual
- Evaluate using cross-validation for predicting task on held-out subjects
- Compared to sliding window
Right Hand Tapping

Left Hand Tapping
Task: Right Hand Tapping

Covariance matrix for $S_2$
Task: Left Hand Tapping

Covariance matrix for $S_{23}$

L R L R L R
Summary (Part 2)

- Improved model for time varying connectivity that captures scientific intuition, e.g., spatial sparsity and temporal smoothness
- Empirical validation of proposed model on HCP, better classification of task states
- Work in Progress:
  - Improving computational scalability
  - Predictive evaluation for resting state data
  - Incorporating spatial structure (particularly for high resolution)
Overall Summary

• Model-based approach provides a straightforward mechanism for synthesizing, evaluating and comparing scientific hypotheses
• Shown applications to decoding and time varying connectivity
• Multiple open-source tools for (almost) math-free inference e.g. STAN, infer.NET, …
Research interests: developing methods for understanding the brain

- Closed-world Interpretable Encoding and Decoding
- Open-Ended Encoding & Decoding (This Talk)
- Improved estimators for time varying connectivity (This Talk)
- Investigating relationships between connectivity and behavior / disease

- Also, Research on Probabilistic & Statistical Machine Learning
Interpretable Models for Decoding

HCP relational reasoning -> Penn Matrix task (Wu et. al, 2015)
Sparse CCA for Imaging & Behavior

HCP 2-back and Relational Reasoning (Khanna et. al. 2016)
Relationship between Connectivity and Behavior

Shine et al. (2016)
Thank You!!!

Questions?

contact: sanmi@illinois.edu
References-I

• Poldrack, R. A., Halchenko, Y. O., & Hanson, S. J. (2009). Decoding the large-scale structure of brain function by classifying mental states across individuals. Psychological Science, 20(11), 1364-1372.
References-II

References-III


References – Prior Work

Replication of Poldrack et al. (2012)

A  Topic 71 (115 docs):
  narrative, discourse, comprehension, memory, discourse_processing

Topic 61 (441 docs):
  memory, working_memory, maintenance, visual_working_memory, spatial_working_memory

B  Topic 33 (479 docs):
  sentences, language, comprehension, sentence, processing

  Topic 22 (485 docs):
  memory, working, verbal, term, load, maintenance, performance