Deriving an Architecture from Brain Data

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Testing architectures with brain data

Task-based approach:
1. Find a task that looks different in two architectures
2. Find a way to derive neural predictions
3. Compare observed vs. predicted data

Borst, Van Rijn, Taatgen, Neuroimage, 2011
Architecture: We should be able to see it

John E. Laird, Christian Lebiere, Paul S. Rosenbloom

A mind is a functional entity that can think, and thus support intelligent behavior. Humans possess minds, as do many other animals. In natural systems such as these, minds are implemented through brains, one particular class of physical device. However, a key foundational hypothesis in artificial intelligence is that minds are computational entities of a special sort — that is, cognitive systems — that can be implemented through a diversity of physical devices (a concept lately reframed as substrate independence [Bostrom 2003]), whether natural brains, traditional general-purpose computers, or other sufficiently functional forms of hardware or wetware.
Laird, Lebiere, & Rosenbloom (2017)

THE STANDARD MODEL

FERMIONS (matter) | BOSONS (force carriers)
- Quarks | Leptons | Gauge bosons | Higgs boson

THE COMMON MODEL OF COGNITION (CMC)

Long-term Memory

Procedural Memory

Working Memory

Perception

Action
The CMC: Structural components

- Procedural Memory
- Working Memory
- Long-term Memory
- Perception
- Action
- Motor Planning + Execution
- Short-term Context Representation
- Feature-based representations + Metadata (Bayesian estimates)
- State-action pairs + Metadata (Rewards, RL)
- Attention-based Object recognition
Can we see the CMC in neural data?

> The CMC makes predictions about how components are connected
> This should be reflected in patterns of functional connectivity between regions
> It should be independent of the task
The Methods
What do we need?

> Need a method to:
  – Identify architecture components with brain structures
  – Derive neural predictions from the architecture
  – Compare between alternative architectures
What do we need?

> Need a method to:
  – **Identify architecture components with brain structures**
  – Derive neural predictions from the architecture
  – Compare between alternative architectures
Large-scale component identification
What do we need?

> Need a method to:
  – Identify architecture components with brain structures
  – Derive neural predictions from the architecture
  – Compare between alternative architectures
Creating a network model
Implementing the network model: Dynamic Causal Modeling

\[
\frac{dy}{dt} = Ay + \sum_i x_i B(i) y + Cx + \sum_j y_j D(j) y
\]

Traditional
GLM

Dynamic Causal
Modeling

\[y = \sum_i \beta_i x_i\]
Estimating the dynamic model

> Removing modulatory terms yields a linear model
  - \(\frac{dy}{dt} = Ay + \sum_i x_i B[i,..,1]y + Cx + \sum_j y_i D[j,..,1]y\)
  - \(\frac{dy}{dt} = Ay + Cx\)

> **A** and **C** estimated through Expectation/Maximization

> Variational Bayes (older but faster) instead of MCMC (newer but slower) to calculate PDFs
What do we need to test the CMC?

> Need a method to:
  – Identify architecture components with brain structures
  – Derive neural predictions from the architecture
  – Compare between alternative architectures
Alternatives 1 and 2: Hierarchical, recursive architecture

Hierarchical, Open
(Boly et al., 2011; Margulis et al., 2018)

Hierarchical, Closed
(Tononi et al., 2011)
Alternatives 3 and 4: Hub & Spoke brain architectures

Hub-and-Spoke, Basal Ganglia (Anderson, 2007)

Hub-and-Spoke, PFC (Cole et al., 2011, 2013)
Comparing architectures

> Many criteria exists
  – AIC, BIC, Log-likelihood...
> Here, **Bayesian approach**: Posterior probability that a model is **true**, given the **data**
  – Each architectures’ PDF is modeled as a **Dirichlet** distribution \( \sim \text{Dir}(\alpha) \)
  – Two metrics: **expected** and **exceedance** probabilities.
Comparing architectures

Calculate a distribution of probabilities $q$ that a model would fit participants’ data

Given $q$, calculate the probabilities that each model 1, 2... $k$ would best fit the data

Given $m$, estimate the probability that every model $k$ would fit each subject 1, 2, ... $n$
Comparing models

Expected probability $p = 0.74$

Exceedance probability $p = 0.96$

Dirichlet distribution Dir($\alpha = 14$)
The Data
The Human Connectome Project
The Human Connectome Project

> Contains high-quality neuroimaging data:
  – 1,200 Adult Participants (July 2018)
  – 7 Different Tasks
  – 4 Resting State Sessions
  – fMRI + MEG data (subset)
The Human Connectome Project

Contains high-quality neuroimaging data:

- **200 out of** 1,200 Adult Participants
- **6 out of** 7 Different Tasks
- 4 Resting State Sessions
- **fMRI** + MEG data

### Siemens Skyra, Multiband

<table>
<thead>
<tr>
<th>TR</th>
<th>720 ms</th>
<th>MB factor</th>
<th>8x</th>
<th>N Slices</th>
<th>72</th>
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</thead>
<tbody>
<tr>
<td>TE</td>
<td>33.1 ms</td>
<td>FOV</td>
<td>208 x 180 mm</td>
<td>Slice Gap</td>
<td>0mm</td>
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<tr>
<td>FA</td>
<td>52°</td>
<td>In-plane res</td>
<td>2 x 2 mm</td>
<td>Slice thick</td>
<td>2mm</td>
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### Tasks

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<td><strong>Hand, arm, foot, leg, voice</strong> responses</td>
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<td>Emotional</td>
<td>Hariri et al. (2002)</td>
<td><strong>Fearful faces</strong> vs. Neutral Shapes</td>
</tr>
<tr>
<td>Gambling</td>
<td>Delgado et al. (2000)</td>
<td>“<strong>Losing</strong>” blocks vs. “<strong>Winning</strong>” blocks of choices</td>
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<td>Language</td>
<td>Binder et al. (2011)</td>
<td><strong>Language blocks</strong> vs. Math blocks</td>
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<td>Working Memory</td>
<td>Dobryshevsky et al. (2006)</td>
<td><strong>2-back</strong> vs 0-back blocks</td>
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Analysis pipeline

GLM analysis, 1st level (canonical)

Subject-level quality Control

GLM analysis, 2nd Level

Group-level VOI coordinates

HCP Data
- Emotion
- Incentive
- Language
- Relational
- Social
- WM

GLM analysis, 1st level (for DCM)

Individual-level VOI coordinates

VOI data extraction (PCA)

DCM Model Estimation
- Common Model
- Hierarchical 1
- Hierarchical 2
- Hub & Spoke 1
- Hub & Spoke 2

Bayesian model comparison
Task-Specific Regions of Interest

Emotion ($N=187$)

Incentive ($N=199$)

Language/Math ($N=187$)

Relational ($N=185$)

Social ($N=188$)

Working Memory ($N=188$)
The Results
Canonical GLM analysis (Group-level)

- Emotion ($N=187$)
- Incentive ($N=199$)
- Language/Math ($N=187$)
- Relational ($N=185$)
- Social ($N=188$)
- Working Memory ($N=188$)
Bayesian model comparison

> Reminder
  – Estimating posterior probability $P(M \mid Y)$ of a model $M$ given data $Y$.

> Two measures
  – Expected probability
  – Exceedance probabilities

- Expected probability $p = 0.74$
- Exceedance probability $p = 0.96$
Results: Probability densities by task

- Emotion Processing
- Incentive Processing
- Language, Math
- Relational Reasoning
- Social Cognition
- Working Memory
Results: Expected Probability by Task

Emotion Processing

Incentive Processing

Language, Math

Relational Reasoning

Social Cognition

Working Memory
Results: Exceedance probability by task

- **Emotion Processing**: Common Model
- **Incentive Processing**: Common Model
- **Language, Math**: 0.753, 0.247
- **Relational Reasoning**: 0.950
- **Social Cognition**: 1.000
- **Working Memory**: 1.000
All tasks combined (repeated measures)

Expected Probability, All Tasks ($N=168$)

Exceedance Probability, All Tasks ($N=168$)
Is the CMC reasonable?

> Check connectivity parameters
  – Single model, all tasks
> All parameters are **positive**
  – Except self-connections
> All parameters are **likely**
> **Values** change by task
Same approach can be used to compare models within architectures.

Altmann, 2001

Lovett, 2005
Same approach can be used to compare models within architectures

Ketola, Jiang, & Stocco, *Comparing Models with Effective Connectivity.*
Thursday 7/25 @ CogSci, Paper session 18, 2:30-4pm
Thank you!

... Questions?
PSA: We are looking for a post-doc to work on this! Email stocco@uw.edu