Large-scale Causal Dynamic Network Modeling of Functional MRI

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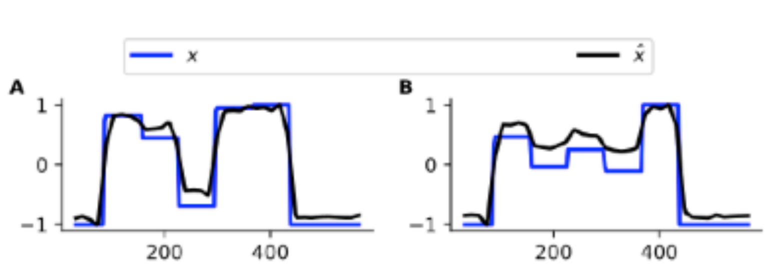
Background

- Inferring causal connections is an important goal for fMRI analysis
- Dynamic Causal Modeling (DCM) [1] achieves such using a hypothesis-driven approach with limited scalability
- Major challenge for large-scale ODE network modeling is the prohibitive computational costs for model fitting and model selection
- Yet powerful statistical machine learning and optimization tools were less developed before for this topic

Objectives

- Develop large-scale causal network models for task-related fMRI
- Develop data-driven methods for selecting network models
- Validate and compare our methods
- Develop open-source, freely available software implementations

Simulations: vs DCM



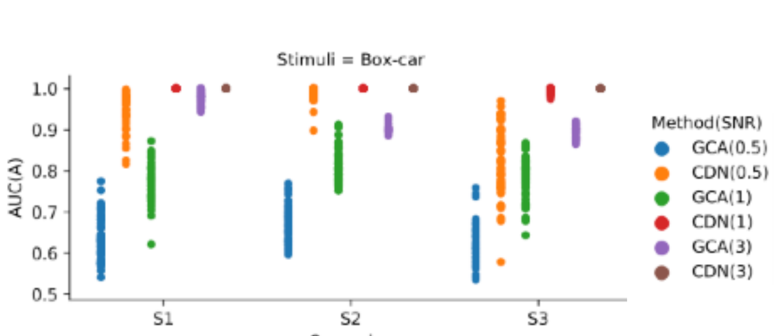
Method	AUC	Computation Time
CDN	0.69	18.95 seconds
DCM	0.54	24 hours and 15 minutes

Due to DCM's high computational cost, we simulate data from a five node network model adapted from [4].

Recovering neural states: our CDN recovers the neural state time series from fMRI BOLD, see for example the true $x(t)$ and estimated $\hat{x}(t)$ from two nodes (Fig A and B above).

Network recovery: our CDN estimate yields higher AUC than DCM while using only a small fraction of the computation time.

Simulations: vs Granger Causality



Across three different simulation scenarios, our CDN method yields higher accuracy (AUC) for network recovery than Granger Causality Analysis (GCA) (aka vector autoregressive models). The AUCs for both methods increase with increasing signal-to-noise ratios.

Conclusion

- Computationally efficient method for inferring large brain networks
- Provide higher accuracy than other competing methods
- Lead to better understanding of brain dynamics under task stimuli

References

[1] Friston KJ, Harrison L, Penny W. Dynamic Causal Modelling. Neuroimage. 2003 19(4):1273-302.
[2] Friedman J, Hastie T, Tibshirani R. The Elements of Statistical Learning. Springer; 2001.
[3] Power JD et al. Functional Network Organization of the Human Brain. Neuron. 2011 72(4):665-78.
[4] Smith SM et al. Network Modelling Methods for FMRI. Neuroimage. 2011 54(2):875-91.

Software: install python pkg using **pip install cdn-fmri**

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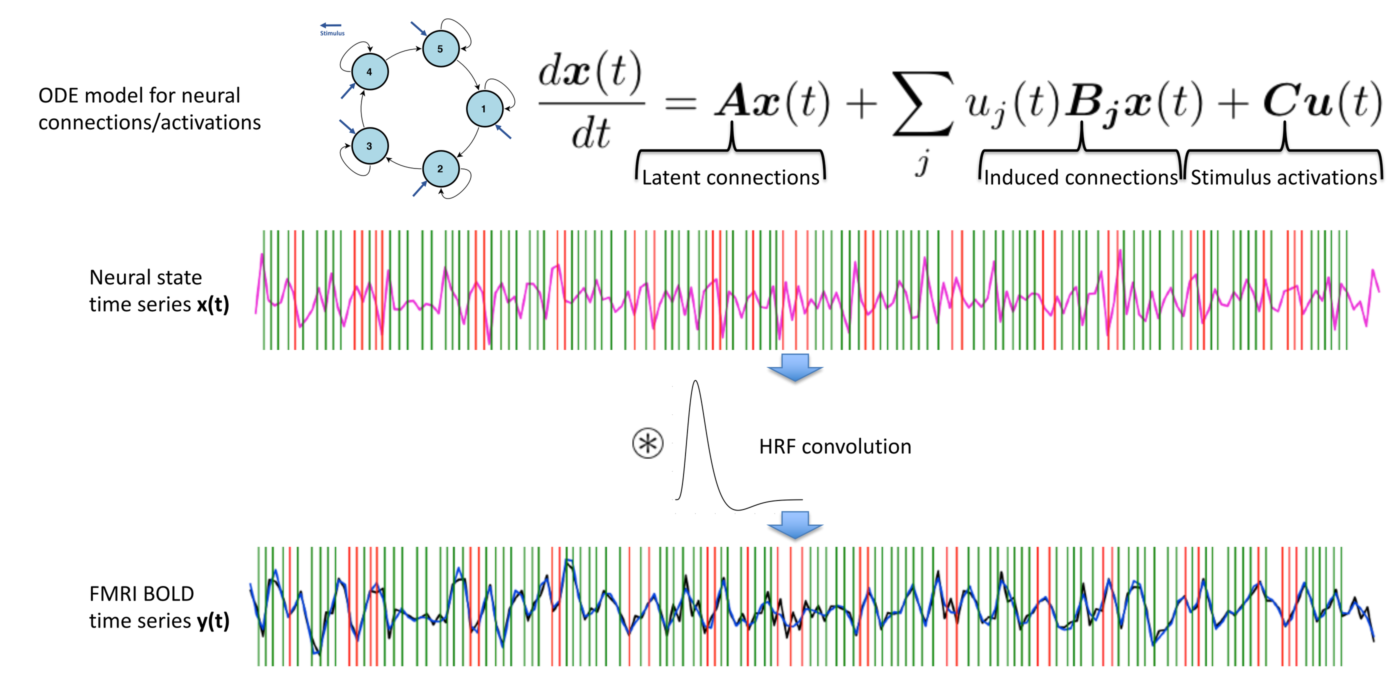
Model and Method



Two layer model: the first layer is the classical DCM neural model for causal connections and stimulus activations; the second layer relates neural states to fMRI bold time series via HRF convolutions.

Method: find $(\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C})$ that minimizes the following criterion

$$l(\boldsymbol{x}, \boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C}) = \sum_{t_i} \|\boldsymbol{y}(t_i) - h \circledast \boldsymbol{x}(t_i))\|^2$$

$$+\lambda \int \left\| \frac{d\boldsymbol{x}(t)}{dt} - (A\boldsymbol{x}(t) + \sum_j u_j(t)\boldsymbol{B_j}\boldsymbol{x}(t) + \boldsymbol{C}\boldsymbol{u}(t)) \right\|^2 dt + \text{pen}(\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C})$$

where $\boldsymbol{y}(t_i)$ are multivaraite time series from multiple brain regions sampled at discrete time points t_i, $\boldsymbol{u}(t)$ is a vector stimulus input (shown as vertical lines of different colors), and pen is a Lasso [2] penalty function for encouraging parsimonious estimates.

Algorithm: l is conditional convex and we optimize via block coordinate descent.

Inference and p-values: we use block bootstrap to obtain p-values for $(\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C})$ estimates.

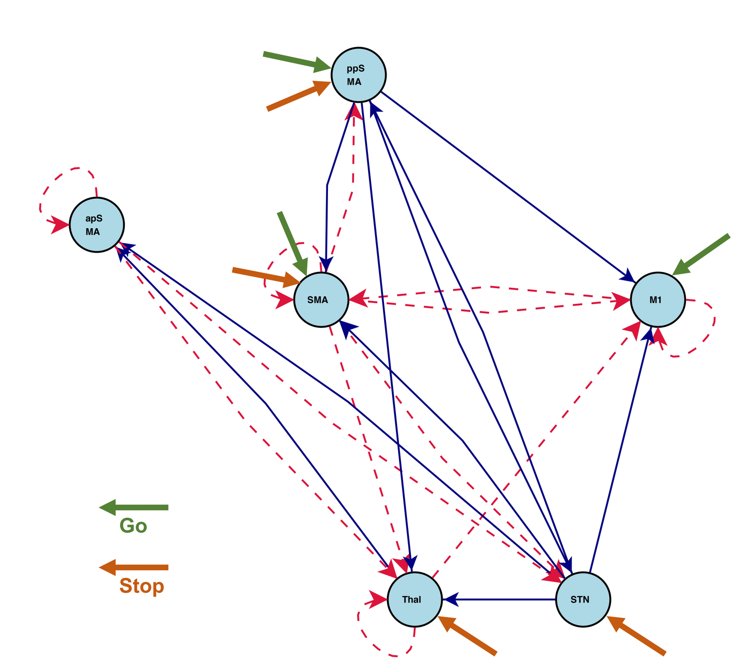
Experiment 1: Stop Signal Task

Data: public OpenfMRI.org dataset ds000030

Task: stop/go, event related

6 ROI model: M1, STN, Thalamus (Thal), SMA, anterior-preSMA (apSMA), and posterior-preSMA (ppSMA)

Result: figure shows significant latent connections and activations (p-values < 0.01). This leads to better understanding of brain dynamics, such as the different roles of the anterior and posterior parts of preSMA.



Experiment 2: Motor Movement

Data: Human Connectome Project

Task: motor, block design

264 ROI model: ROI atlas from [3]

Result: figure shows sparse and directional connections for a 264 node network. The estimated network can be used in other graph analysis tools. Our method can also recover connections and activations under different movement stimuli (not shown here due to space).