UTHealth The University of Texas Health Science Center at Houston | School of Public Health

Large-scale Brain Network Modeling by Causal Dynamic Networks (CDN)

Xuefei Cao[1,2], Björn Sandstede[2], Xi (Rossi) Luo[1]

[1]Dept of Biostatistics and Data Science, Univ of Texas Health Science Center at Houston [2]Division of Applied Mathematics, Brown Univ

Analytics for Big Complex Data

Background

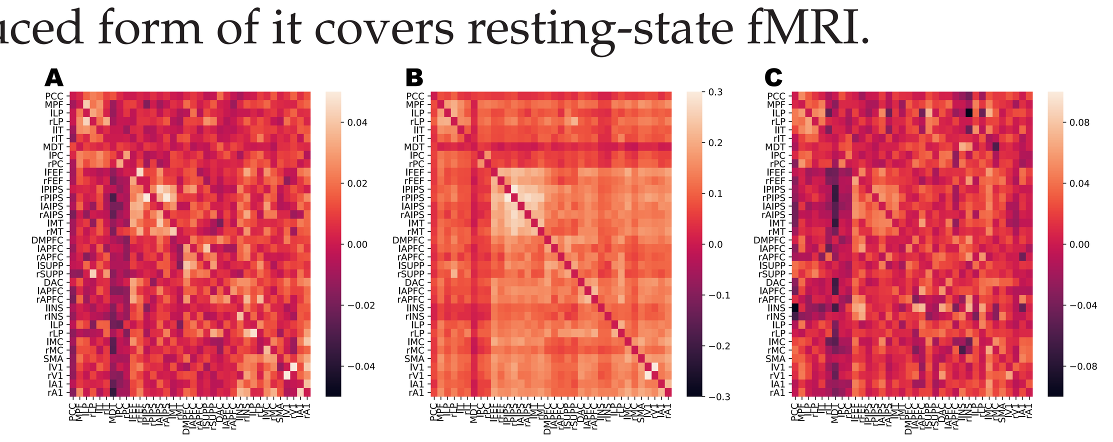
- Dynamic Causal Modeling (DCM) [1] infers causal activations and connections using a hypothesis-driven approach with limited scalability
- Major challenge for large-scale ODE network modeling is the prohibitive computational costs for model fitting and model selection
- Statistical machine learning and optimization tools were less developed before for this topic

Objectives

- Develop large-scale causal network models for task-related fMRI (and resting-state fMRI)
- Develop data-driven methods for searching all, exponentially many network models
- Validate and compare our methods
- Develop open-source, freely available software

Extension to Resting-state

Though CDN was developed for task fMRI, the reduced form of it covers resting-state fMRI.



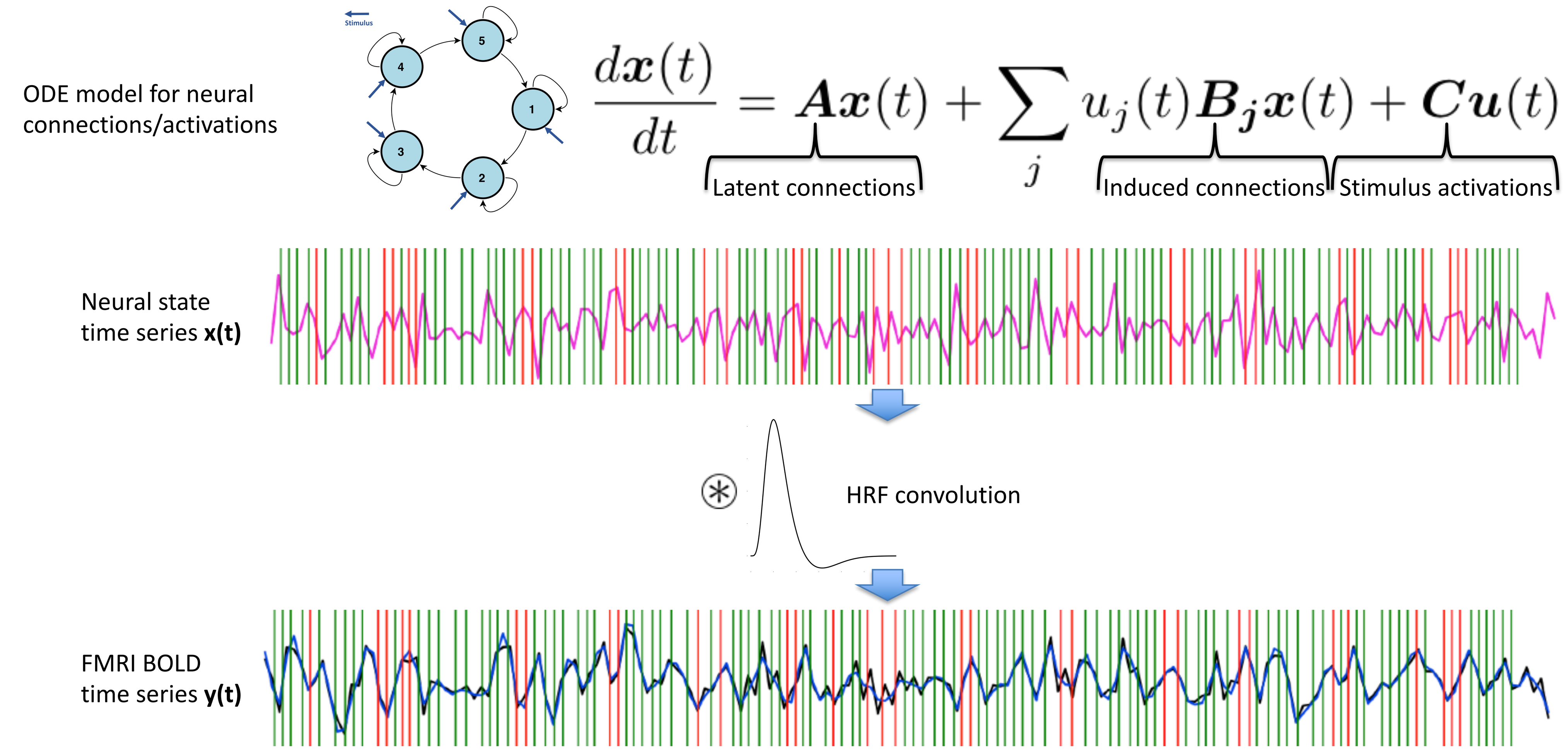
On an HCP dataset with 36 ROIs, CDN (A) yields similar connectivity patterns as resting-state DCM (C) [6], and both are different from correlations (B).

Conclusion

- Computationally efficient method for inferring large brain networks and task activations
- Higher accuracy than other competing methods
- Leads to better understanding of brain dynamics under task stimuli or during resting states

CDN: Model and Method

$$\frac{d\boldsymbol{x}(t)}{dt} = \underbrace{\boldsymbol{A}\boldsymbol{x}(t)}_{\text{Latent connections}} + \sum_j \underbrace{u_j(t)\boldsymbol{B_j}\boldsymbol{x}(t)}_{\text{Induced connections}} + \underbrace{\boldsymbol{C}\boldsymbol{u}(t)}_{\text{Stimulus activations}}$$



Two layer CDN [7] 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

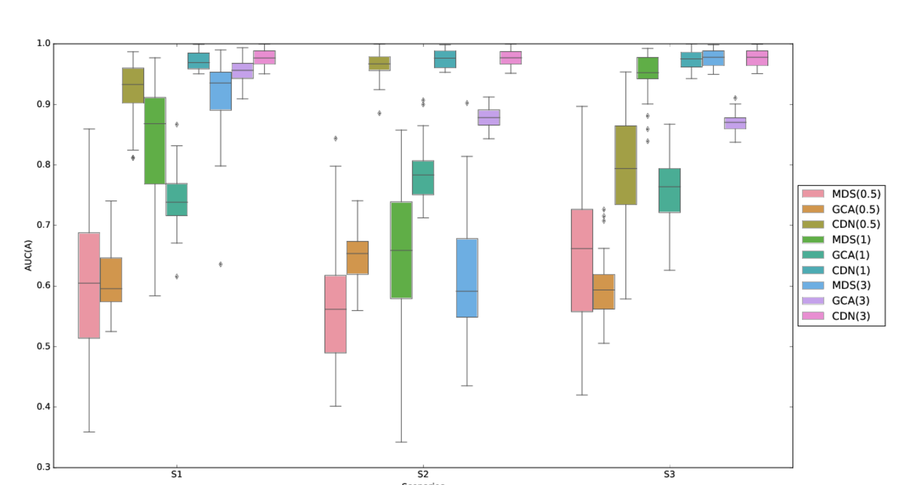
$$l(\boldsymbol{x}, \boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C}) = \sum_{t_i} \|\boldsymbol{y}(t_i) - h \circledast \boldsymbol{x}(t_i)\|^2 + \lambda \int \left\| \frac{d\boldsymbol{x}(t)}{dt} - (A\boldsymbol{x}(t) + \sum_j u_j(t)\boldsymbol{B_j}\boldsymbol{x}(t) + \boldsymbol{C}\boldsymbol{u}(t))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

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.

Simulations



Method	AUC	Frobenius Loss	Computation Time
CDN	0.77	1.29	18.95 seconds
DCM	0.56	1.42	>24 hours
MDS	0.77	1.57	580 seconds

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

Setup: data were simulated from CDN (top figure) or DCM (bottom table).

Evaluation metrics: AUC for identifying nonzero/zero connections; the Frob loss for estimating connection strengths.

Network recovery accuracy: CDN yields the highest AUC and lowest MSE (by the Frobenius norm loss), vs DCM and MDS [5].

Computational speed: CDN improves the computation speed by 30 – 4000 folds.

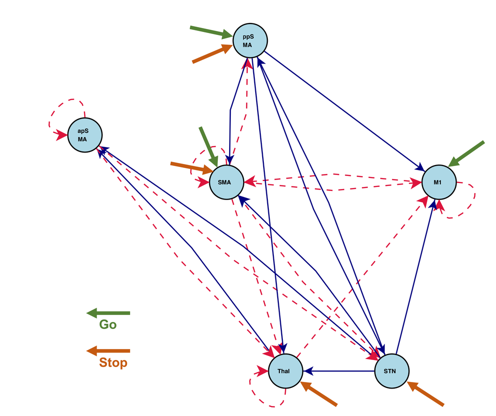
Robustness: CDN tends to have smaller variations in AUCs across different simulation scenarios and SNRs (numbers in brackets).

Stop Signal Task

Data: OpenfMRI.org dataset ds000030

Task: stop/go, event

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



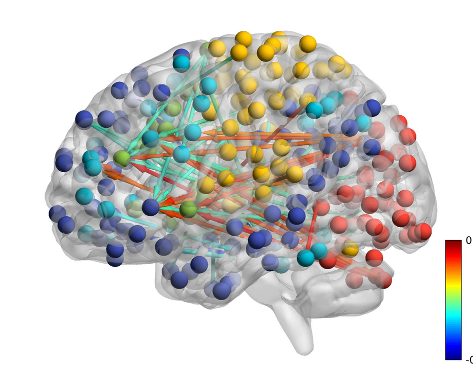
Result: figure shows significant latent connections and activations (p-values < 0.01). The results are consistent with prior evidence. However, the enlarged network leads to better understanding of brain dynamics, such as the different roles of the anterior and posterior parts of preSMA.

Motor Movement Task

Data: Human Connectome Project

Task: motor, block

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 also recovers connections and activations under different movement stimuli (not shown here).

References

[1] Friston KJ, Harrison L, Penny W. Dynamic Causal Modelling. Neuroimage. 2003 19(4):1273-1302.

[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):665-678.

[4] Smith SM et al. Network Modelling Methods for FMRI. Neuroimage. 2011 54(2):875-891.

[5] Ryali S et al. Multivariate dynamical systems models for estimating causal interactions in fMRI. Neuroimage. 2011 54:807-823.

[6] Razi A et al. Large-scale DCMs for resting state fMRI. Network Neuroscience. 2017 1(3):222-241.

[7] Cao X, Sandstede B, Luo X. A Functional Data Method for Causal Dynamic Network Modeling of Task-Related fMRI. Frontiers in neuroscience. 2019 13.

Software publicly available via: pip install cdn-fmri

Funding: NIH R01EB022911