Identificação e Validação de Biomarcadores em Imagem Médica - Análise de redes e métricas de Conectividade

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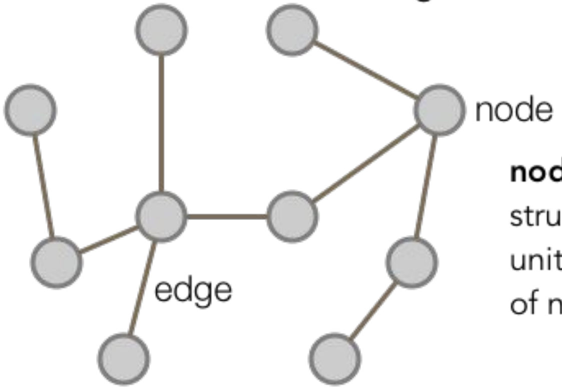
Questions

- Statistical reliability of the estimated functional connections
- Feasibility of tracking network metrics in real-time
- Limitations in the biological interpretation of artificial intelligence models

Statistical reliability of the estimated functional connections

Networks can be modeled as graph of nodes connected by edges



nodes. Represent basic units - structural, functional, processing units (e.g. neuron or population of neurons)

edges. Represent the interactions between units or nodes (structural or functional connection between units)

Statistical reliability of the estimated functional connections

- *it may generally lead to conflicting results depending on the connectivity measure and statistical testing approach used*
    - *Spurious connectivity*

(Haufe, et al., Neuroimage 2013)

Statistical reliability of the estimated functional connections

- *This study found* ***systematic differences in group-mean connectivity*** *acquired during task and rest acquisitions and* ***preserved individual differences in connectivity due to intrinsic differences in an individual's brain activity and structural brain architecture****.*

- *We also show that* ***longer scan times are needed to acquire data on single subjects*** *for information on connections between specific ROIs****. Longer scans may be facilitated by acquisition during task paradigms, which will <u>systematically affect functional </u>connectivity but may preserve individual differences in connectivity on top of task*** *modulations.*

(Shah et al., Brain and Behavior, 2016)

Statistical reliability of the estimated functional connections

(Shah et al., Brain and Behavior, 2016)

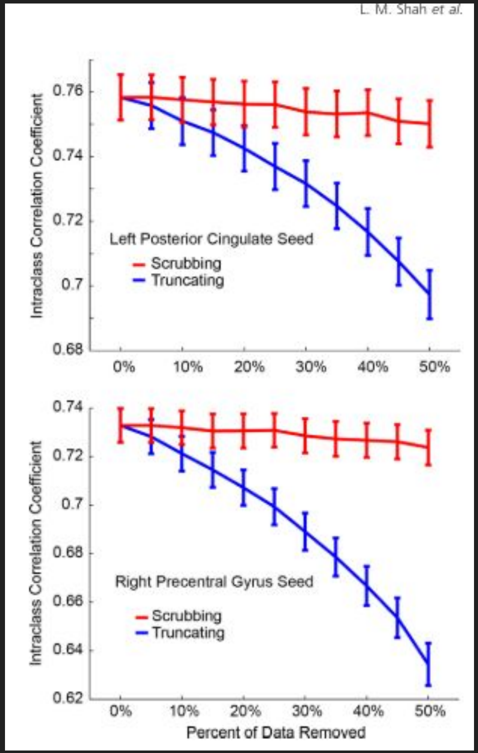


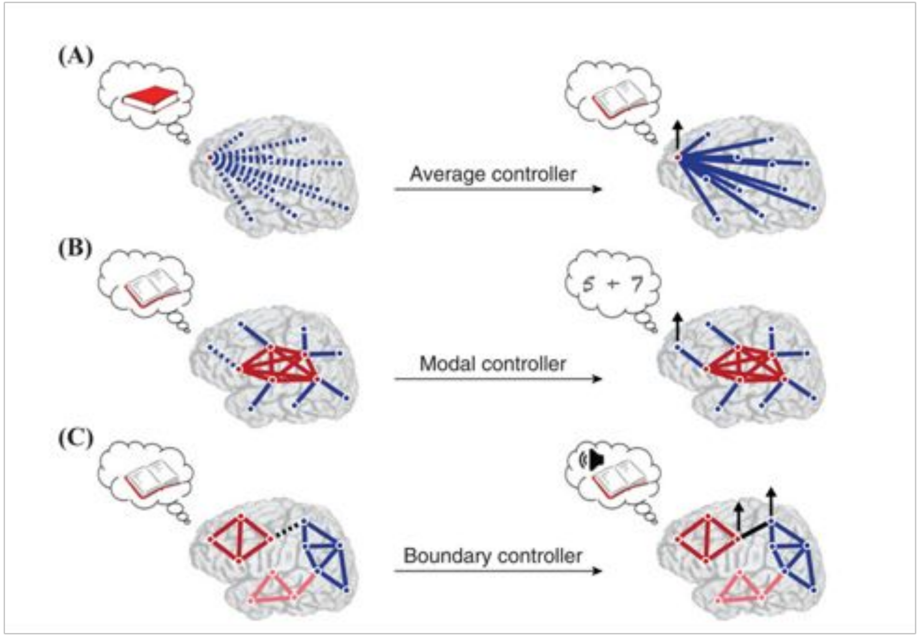
Figure 6. Effect of two strategies of data removal on reliability is shown. Intraclass correlation coefficient is shown for functional connectivity measurements from two seeds (left posterior cingulate, above; right precentral gyrus, below) to 264 ROIs after sequentially removing up to half of the volumes in the time series. Red curves (scrubbing) represent removal of randomly selected points in the time series. Blue curves (truncating) represent inclusion of timepoints from the beginning of the scan. Reliability is only minimally affected for scrubbing, even with removal of half of the data points. However, truncating the time series with removal of time points from the end of the time series shows much larger effects on reliability of functional connectivity measurements.

Feasibility of tracking network metrics in real-time

- Type of measure
- Frequency sampling
- Iterative/recursive approaches?
- How to interact with the network in real time

Feasibility of tracking network metrics in real-time

How to define a target?



Bassett, D. S., & Khambhati, A. N. (2017). A network engineering perspective on probing and perturbing cognition with neurofeedback. Annals of the New York Academy of Sciences, 1396, 126–143. https://doi.org/10.1111/nyas.13338

Limitations in the biological interpretation of artificial intelligence models

- *By choosing an **appropriate DNN architecture with substantial homology with neural representations**, **brain- decoded DNN features could be rendered into movies, sounds, text, or other forms of sensory/mental representations.***

- *The **externalization of mental contents** by this approach might prove useful in communicating our internal world via **brain–machine/computer interfaces**.*

Shen et al., Plos Comp. Bio 2019

Limitations in the biological interpretation of artificial intelligence models

- *The renaissance of deep neural networks in neuroscience has been accompanied by skepticism regarding the extent to which* ***DNNs could be relevant to the brain.***
- *Most obviously,* ***current DNNs are at best loosely analogous to actual neural circuits,*** *and so at present d****o not provide circuit-level models of neural computation****. These limitations alone render them inappropriate for many purposes.*
- *Moreover, if the details of neural circuitry place strong constraints on neural representations and behavior, DNNs could be limited in their ability to predict even relatively coarse-scale phenomena like neural firing rates and behavior.*

Kell and McDermott, Current Opinion in Neurobiology 2019

Limitations in the biological interpretation of artificial intelligence models

- *As it currently stands,* ***deep learning is also clearly not an account of biological learning****. Most obviously, biological organisms* ***do not require the millions of labeled examples*** *needed to train contemporary deep networks. Moreover, whatever learning algorithms are employed by the brain may* ***not have much similarity to the standard backpropagation algorithm***

Kell and McDermott, Current Opinion in Neurobiology 2019

Limitations in the biological interpretation of artificial intelligence models

- *Whether the brain uses **an algorithm like backpropagation for learning is controversial.** Several biologically plausible implementations of backpropagation or closely related forms of supervised learning have been suggested*
- ***Reinforcement Learning and unsupervised learning of neural network parameters are rapid current progress***

Kriegeskorte and Douglas, Nature Neuroscience 2018

Limitations in the biological interpretation of artificial intelligence models

- *the **reward prediction error theory of dopamine** has explained a wealth of empirical phenomena, providing a unifying framework for understanding the **representation of reward and value in the brain***
- *Here we propose an account of dopamine-based **reinforcement learning inspired by recent artificial intelligence research on distributional reinforcement learning***

Dabney et al., Nature 2019,

Limitations in the biological interpretation of artificial intelligence models

Review

Reinforcement Learning, Fast and Slow

Matthew Botvinick,[1,2,*] Sam Ritter,[1,3] Jane X. Wang,[1] Zeb Kurth-Nelson,[1,2] Charles Blundell,[1] and Demis Hassabis[1,2]

Although these techniques were developed in an AI context, we propose that they may have rich implications for psychology and neuroscience. A key insight, arising from these AI methods, concerns the fundamental connection between fast RL and slower, more incremental forms of learning

Neurofeedback, AI learning lessons

*When an efficient cognitive strategy is unavailable, desired brain activation can be r**einforced by providing contingent feedback and/or rewards,** rather than by the cognitive strategy itself. Therefore, **reinforcement learning**—or more specifically, neural operant conditioning—may well explain the training mechanism of DecNef and FCNef.*

However, to develop a clinically useful neurofeedback paradigm, it is necessary to compare the effect of various instruction, feedback, and reward conditions in future studies

Yamada et al., International Journal of Neuropsychopharmacology 2017