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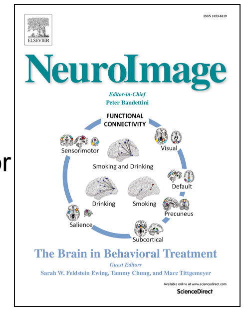

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Generalized Recurrent Neural Network accommodating Dynamic Causal Modelling for functional MRI analysis

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Abstract

Dynamic Causal Modelling (DCM) is an advanced biophysical model which explicitly describes the entire process from experimental stimuli to functional magnetic resonance imaging (fMRI) signals via neural activity and cerebral hemodynamics. To conduct a DCM study, one needs to represent the experimental stimuli as a compact vector-valued function of time, which is hard in complex tasks such as book reading and natural movie watching. Deep learning provides the state-of-the-art signal representation solution, encoding complex signals into compact dense vectors while preserving the essence of the original signals. There is growing interest in using Recurrent Neural Networks (RNNs), a major family of deep learning techniques, in fMRI modeling. However, the generic RNNs used in existing studies work as black boxes, making the interpretation of results in a neuroscience context difficult and obscure.

In this paper, we propose a new biophysically interpretable RNN built on DCM, DCM-RNN. We generalize the vanilla RNN and show that DCM can be cast faithfully as a special form of the generalized RNN. DCM-RNN uses back propagation for parameter estimation. We believe DCM-RNN is a promising tool for neuroscience. It can fit seamlessly into classical DCM studies. We demonstrate face validity of DCM-RNN in two principal applications of DCM: causal brain architecture hypotheses testing and effective connectivity estimation. We also demonstrate construct validity of DCM-RNN in an attention-visual experiment. Moreover, DCM-RNN enables end-to-end training of DCM and representation learning deep neural networks, extending DCM studies to complex tasks.

Keywords: Recurrent Neural Network, Dynamic Causal Modeling, functional magnetic resonance imaging, causal architecture, effective connectivity

1 Introduction

Dynamic Causal Modelling (DCM) (Friston et al., 2003) is a nonlinear generative model, the only one that models explicitly the entire process from stimulus to functional magnetic resonance imaging (fMRI) blood oxygen level dependent (BOLD) signal via neural activity and cerebral hemodynamics. It is thus considered by many to be the most biologically plausible as well as the most technically advanced fMRI modeling method (Smith, 2012)(Smith et al., 2013). A causal brain architecture, defined in terms of effective connectivity, describes how neural activity in distributed brain regions influence each other - and how input stimuli perturb neuronal dynamics. DCM is classically used to test hypotheses of causal brain architectures and estimate associated brain effective connectivity. Various approaches have been proposed for DCM parameter inference, such as Expectation Maximization (EM) Gauss-Newton search (Friston, 2002), variational Bayes (Friston et al.,