Predicting multiple-demand patterns of frontal and parietal activity in fMRI imaging using Deep Learning

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1 Introduction

My research in this PhD will focus on using deep learning methods to predict salient patterns of activity between different regions of the human cerebral cortex in response to various cognitive challenges. These distinguishable patterns in brain activity, commonly referred to as multiple-demand (MD) patterns [2] are associated with a diverse range of cognitive tasks: rapid reorganisation of cognitive operations to support changes in mental focus, and in the assembly and selective organising of content for complex operations. Using functional magnetic resonance imaging (fMRI), we can associate specific cognitive tasks with brain activity. This research will center around deep learning methods for using 2D and 3D fMRI data to predict MD patterns in response to specific cognitive exercises and, in particular, dynamic models which are able to take previously observed patterns and stimuli into account. New deep learning methods could greatly improve statistical analysis of fMRI data by contributing to high dimensional image analysis problems in machine learning and equipping medical professionals with the tools to improve lives.

2 Motivation

In the last decade, the field of deep learning has seen unprecedented growth. Flexible and powerful new methods allow for the application of prediction, classification and representation learning tasks in entirely new areas of research [5]. More recently, we have seen successful utilisation of deep learning methods in the field of neuroscience and neuroimaging [7, 8]. 3D brain maps produced by fMRI have been used in deep generative models to create latent representations and classify neurological illnesses [1]. Automatic feature learning models such as CNNs have also been used to pre-process fetal fMRI data [6]. As medical fields increasingly employ the use of data-driven techniques, the development of new deep learning methods to solve problems unique to neuroscience will inevitably bring lasting changes to both deep learning and neuroscience. Coupled with relative availability of data, we can see that an integration between the two fields is gaining traction quickly and that there is room to make an impact with new research. Furthermore, state-of-the-art deep learning architectures take inspiration from the field of biology, so deepening our understanding of the underlying neuronal processes of the human brain could lead to unforeseen rapid developments in machine learning.

MD systems in human brains have been described as ”task control networks” [3]. Its functions involve responding to complex and multi-component cognitive challenges where goals are achieved by assembling and solving individual sub-tasks. These systems demonstrate a capability for structured problem-solving and appear to perform a central role in the organising, storing, and controlling of components in integrated mental processes. Therefore, in marrying the two areas, deep learning and neuroscience, we can move closer to an understanding of what could be considered intelligence.

3 Objectives

After reviewing current literature on deep learning for fMRI, MD patterns and recent advances in deep neural architectures for representation learning, I have identified three research questions which will serve as my objectives and be the focus of my research:

1. **Prediction of high-dimensional MD patterns from fMRI**
   High-dimensional fMRI is known to capture MD patterns, however, predicting these patterns directly from the task-dependent stimuli (e.g. images) and explicit goals is so far an unsolved (and largely unexplored) task. While deep learning and neural networks have been shown to perform very well in basic perceptual tasks (e.g. standard object classification) on single images, it is not yet clear how to apply them in this complex setting with multiple and interrelated inputs. This is mainly due to the fact that current neural networks are not well-suited to directly take into account and reason about multiple inputs with complex relationships. A core aim of my research is therefore to design a new neural network architecture which supports such structured inputs, and use it to predict MD patterns in the form of high-dimensional (fMRI) images. I will base this research on recent advances in variational inference [13, 14], feature learning in fMRI [11] and in particular graph-based neural networks which are capable of modelling and providing predictive models for this kind of high-dimensional and relational data. To train and evaluate the models, I will, in collaboration with the Psychology department, design suitable image-based experiments using state-of-the-art neuroimaging techniques. If successful, this will allow better understanding of frontal and parietal lobe functionality, as well as provide a high-quality fMRI dataset which can support new MD research.

2. **Temporal prediction of MD patterns**
   Brain states (and fMRI images) are inherently temporal as brain activity is coupled between any one state and the states prior to it. However, the models developed in objective 1 do not depend on previous states. Thus a more sophisticated model which utilises information from previous fMRI states, could potentially provide more accurate predictions and insight into the dynamics of the MD patterns. In order to address this question, I will modify an existing recurrent neural network model, such as a Long-Short-Term-Memory network (LSTM) for fMRI and structured inputs as in [12], to predict the next fMRI state based on the previous state. This will furthermore be combined with insight from objective 1 to also allow predictions from current experimental stimuli and goals to provide a predictive model integrating all the available information. The developed model will be evaluated in a similar way to objective 1 (same dataset), and will if successful produce a probabilistic deep learning method which is able to predict conditionally from high-dimensional fMRI data as well as structured inputs. If this evaluation is successful we can gain an understanding of the kinds of temporal dependencies between MD patterns and in particular frontal and parietal lobe mechanisms for cognitive problem solving.

3. **Abstraction: Structured outputs and latent representations**
   Machine learning tasks have benefited from symbolic or abstracted representations of data. Modelling fMRI and brain networks in such a way could reduce the dimensionality of the output predictions and improve model accuracy (on the level where human interpretation is viable). Computational graphs have been successfully used to model the brain as a network [15], and deep representation learning models have been able to create latent manifolds from high-dimensional

data [16]. My research would aim to develop a model of functional connectivity of MD patterns from fMRI data in abstract rather than image form by using representation-learning techniques, and predict structure (e.g. graph-based) MD patterns from experimental stimuli using this latent embedding. We expect both the latent representation of the patterns and the structured predictions to provide valuable insight into the nature of MD patterns due to their easy interpretability by e.g. practitioners in the neuroscience domain.

3.1 Timeline

In outlining the goals above I expect to spend approximately a year of the 3.5-year PhD on each. I expect each goal to involve research, designing experiments, design and implementing machine learning models, and evaluating and disseminating results. I estimate the final 6 months of the PhD to be spent writing my overall thesis.

4 Significance

Deep learning has seen rapid advancements in depth and scope of application. Solving problems using deep learning has achieved human-level ability by using sophisticated and specialised neural architectures [9, 10]. The challenges posed by fMRI data - and in particular MD patterns - for deep learning demands innovative new techniques. Such techniques include neural networks which can model complex stimuli and the relations between them, specific prior distributions for predicting high dimensional voxel outputs, and extended recurrent models for handling complex temporal fMRI images to extract patterns. The objectives outline above will contribute to solving the aforementioned challenges and will contribute with new models and insight in theoretical machine learning and its application to high-dimensional and non-trivial imaging problems.

Aside from the core contribution to computing science/machine learning, the research will furthermore contribute to understanding the mental programs of MD patterns, which are believed to play a major role in intelligent behaviour. It would indicate that heterogeneous and modular architectures similar to the brain's circuitry are necessary to solve the diverse challenges that confront an agent which exhibits intelligent behaviour [4], and the findings could inform future design of intelligent software and AI.

5 Collaborations

The project will be supervised by Dr Bjørn Jensen who has expertise in machine learning and perceptual modelling, but the project will also rely on the main supervisor's existing collaboration with Professor Frank Pollick (Psychology) to provide expertise and resources regarding the neuroimaging aspect of the project. The project will as a result of the collaboration benefit from the specialised neuroimaging equipment and experimental procedure expertise from Psychology..

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