Classifying resting and task state brain connectivity matrices using graph convolutional networks

Conference Paper · September 2017

6 authors, including:

Michael Craig
University of Cambridge

Ioannis Pappas
University of California, Berkeley

Lydia Vinals
Royal Holloway, University of London

David K Menon
University of Cambridge

Classifying resting and task state brain connectivity matrices using graph convolutional networks

Michael Craig (mmc7@cam.ac.uk)
Dept. of Clinical Neurosciences
Division of Anaesthesia
University of Cambridge, UK

Stefan Winzeck (sw742@cam.ac.uk)
Dept. of Medicine
Division of Anaesthesia
University of Cambridge, UK

David Menon (dkm13@cam.ac.uk)
Dept. of Clinical Neurosciences
Division of Anaesthesia
University of Cambridge, UK

Ioannis Pappas (ip322@cam.ac.uk)
Dept. of Clinical Neurosciences
Division of Anaesthesia
University of Cambridge, UK

Lydia Vinals (lv288@cam.ac.uk)
MRC Cognition and Brain Sciences Unit
Dept. of Theoretical and Applied Linguistics
University of Cambridge, UK

Emmanuel Stamatakis (eas46@cam.ac.uk)
Dept. of Clinical Neurosciences
Division of Anaesthesia
University of Cambridge, UK

Abstract:

The past few years has seen an increase in use of graph theoretical measures to study brain connectivity during task execution. One thread of research in this area has focused on using these measures to identify graph characteristics associated with various cognitive states. Our work expands on previous findings by applying graph convolutional networks (GCN) to distinguish between whole brain graphs during resting state or during task execution. GCNs use tools from spectral graph theory to generalize traditional convolutional neural networks (CNN) to be applied to high-dimensional data represented by graphs such as brain connectomes. We found that GCNs were able to distinguish between two cognitive states, resting state and an attentionally demanding stop signal task, with a high degree of accuracy (mean = 73.59%). This work suggests that GCNs are capable of identifying the underlying features important for discriminating between resting and task states.

Keywords: functional MRI, brain network; graph convolutional network; resting state; stop signal task

Introduction

Flexible cognition is mediated by alterations in large-scale functional brain network connectivity (**Park and Friston, 2013**). Alterations in connectivity have been characterized during a wide variety of behavioral tasks (**Vatansever et al., 2015**; **Telesford et al., 2016**), with contradicting evidence suggesting large-scale networks are stable across task conditions (**Cole et al., 2014**). Here we applied GCNs (**Defferrard et al., 2016**) to automatically classify whole brain connectivity graphs (**Ira Ktena et al., 2017**) as subject's rest or perform an attentionally demanding stop signal task. We hypothesized that the differences in whole brain connectivity weights between resting state and stop signal task would be sufficient for the GCN to automatically identify patterns associated with one state or the other, allowing it to make an accurate classification. We found that GCNs are capable of distinguishing brain graphs during rest or during task execution with a high degree of accuracy, suggesting connectivity is significantly altered between these states.

Methods

Participants and Paradigm Specifications

All participants (N = 21) were right handed and had no history of psychiatric or neurological disease. Participants performed a commonly used inhibitory control paradigm called the stop signal task (SST). In this task, participants responded to the direction of an arrow by pressing a button indicating if the arrow was pointing left or right. In a subset of trials, the arrow is followed quickly by an upward pointing arrow indicating that the participant should inhibit themselves from responding. Participants also underwent a resting state scan where they were instructed to lie still in the scanner with their eyes closed.

MRI Acquisition and Analysis

MRI data was obtained using a Siemens Trio 3T scanner at Addenbrooke's Hospital in Cambridge, UK. Functional scans were acquired using whole-brain echo planar imaging (EPI) for the resting-state and SST (TR = 2000ms; TE = 30ms; flip angle = 78°; FOV read = 192 mm; voxel size = 3.0 x 3.0 x 3.75mm; volumes = 160; slices per volume = 32). Data was preprocessed using standard methods including motion correction, slice timing correction, aCOMPCOR denoising, and highpass filtering. Functional brain graphs were constructed dynamically using a sliding window approach (30 TRs per window with a step size of 2 TRs) with the Lausanne parcellation (**Hagmann et al., 2008**) resulting in 118 regions of interest (ROI) after excluding 11 regions with spurious correlations. The use of dynamic connectivity, as opposed to averaging across an entire run, allowed us to extract 10 matrices per condition per subject, significantly augmenting the amount of data used as input in the GCN. We then constructed matching and non-matching pairs of matrices that were fed as an input to the neural network. Finally, we assigned a binary feature in each pair indicating similarity or dissimilarity of matrices.

Graph Convolutional Network

Graph convolution networks generalize traditional convolutional architectures to signals lying in a graph structure (**Defferrard et al., 2016**). We assumed a common graph structure for all matrices obtained by calculating the Euclidean distance between ROIs. The pooling operation requires meaningful neighborhoods on graphs, where similar vertices are clustered together. We used the Defferrard et al., algorithm to augment and coarsen the graph as seen in *Table 1*. We then constructed a siamese neural network that consisted of two identical models sharing the same weights, each one taking a single matrix from the rest-SST pairs. The layers included the following: We used a graph convolution filter of size F = 32 with a K = 20 localized filter using Chebyshev polynomials to reduce the complexity of calculating the eigenvalue spectrum. Graph convolution was followed by a ReLU layer and a max pooling layer with p = 2. We applied this methodology for levels 1, 2, and 3 using the respective coarsened graphs. After the coarsest resolution was executed, we fed the output of the network into a fully connected layer that output a binary feature for each matrix. We used the contrastive loss function in order to account for similarities between the features of the two models. We trained the network for 30 epochs using 112,896 pairs out of which, at each epoch, 45,158 were randomly selected for validation. We used an Adam optimizer with a batch size of 30, learning rate 0.001, and l_2 regularization. The remaining pairs were used for testing the network. Performance was evaluated by calculating classification accuracy between condition matching (rest + rest; SST + SST) and non-matching (rest + SST) pairs of graphs.

Table 1: Graph layers after coarsening

Layers	Nodes	Edges
0	120 nodes (2 added)	6903
1	60 nodes (1 added)	1711
2	32 nodes (0 added)	435
3	15 nodes (0 added)	105

Results

Accuracy on the validation set increased after 30 epochs (mean = 90.93%) while loss was decreased (*Fig. 1*). Model testing accuracy peaked at 80% (mean of 73.59%) on the test data set. This means the model was capable of accurately classifying whether a particular pair of graphs were matching or non-matching with a high accuracy.

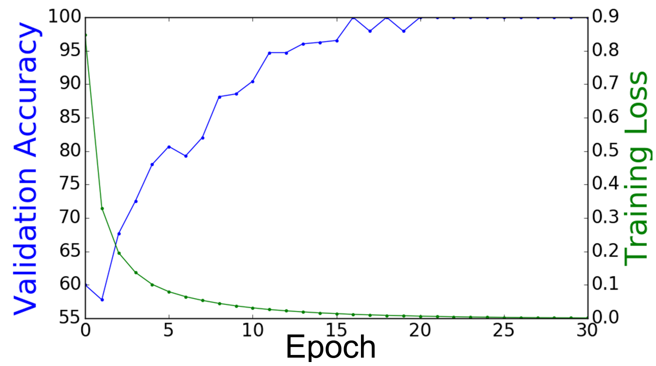

Fig. 1: Training loss and validation accuracy for 30 epochs

Discussion

Our results show that GCNs are capable of accurately classifying brain connectivity graphs during resting state and an attentionally demanding task. This suggests that whole brain connectivity weights from each condition contain sufficient information for the model to identify characteristic patterns to differentiate between cognitive states. This stands in contrast to previous work showing that large-scale brain networks are stable across conditions (**Cole et al., 2014**). Previous work has shown that GCNs are better at classifying healthy versus clinical populations than other machine learning approaches (**Ira Ktena et al., 2017**; **Parisot et al., 2017**). Future work could restrict the input of the graph by specifying specific rows and columns corresponding to different large scale brain networks. This would allow for the identification of specific brain networks that differentially predict behavioral state, suggesting alterations in their connectivity weights drive that cognitive process.

References

Cole, M.W., Bassett, D.S., Power, J.D., Braver, T.S., Petersen, S.E. (2014) *Intrinsic and task-evoked network architectures of the human brain*. Neuron. 83: 238-51

Defferrard, M., Bresson, X., Vandergheynst, P. (2016) *Convolutional Neural Networks on Graphs with Fast Localized Spectral Filtering.* Neural Information Processing Systems, 2016

Ira Ktena, S., Parisot, S., Ferrante, E., Rajchl, M., Lee, M., Glocker, B., Rueckert. (2017). *Distance Metric Learning using Graph Convolutional Networks: Application to Functional Brain Networks.* arXiv: 1703.02161v1

Parisot, S., Ira Ktena, S., Ferrante, E., Lee, M., Guerrerro Moreno, R., Glocker, B., Rueckert, D. (2017). *Spectral Graph Convolutions for Population-based Disease Prediction*. arXiv: 1703.03020v1

Park, H.J. & Friston, K. (2013) *Structural and functional brain networks: from connections to cognition.* Science 342*,* 1238411.

Telesford, Q.K., Lynall, M.E., Vettel, J., Miller, M.B., Grafton, S.T., Bassett, D.S. (2016) *Detection of functional brain network reconfiguration during task-driven cognitive states.* NeuroImage 15;142:198-210.

Vatansever, D., Menon, D.K., Manktelow, A.E., Sahakian, B.J., Stamatakis, E.A. (2015). *Default mode dynamics for global functional integration.* J. Neurosci. **35**, 15254-15262