Decoding Neuroimaging Data with Graph Convolutional Neural Networks

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Introduction

The relationship of brain activity and the external world is extremely complicated and poorly understood. It is of interest to **"decode"** a subject's **external condition** from **fMRI data**.

We here apply the **Graph Convolutional Neural Network (GCNN) model to predict the experimental condition of a subject during a gambling task (gain/loss domain) from their fMRI data.**

Objectives:

- Build a model to predict Gain/Loss condition in Cups Task experiment from fMRI data.
- Compare performance of Graph CNN with existing methods.
- Compare effects of different graph structures on Graph CNN performance.

Graph CNN

- Neuroimaging data, such as from fMRI, can be interpreted as a multi-dimensional signal on a graph.
- The GCNN model generalizes the Fourier transform to extend the usual CNN to general undirected graphs with nonnegative edge weights
- The edge weights represent a measure of proximity between the nodes of the graph when the convolutional filter is applied.

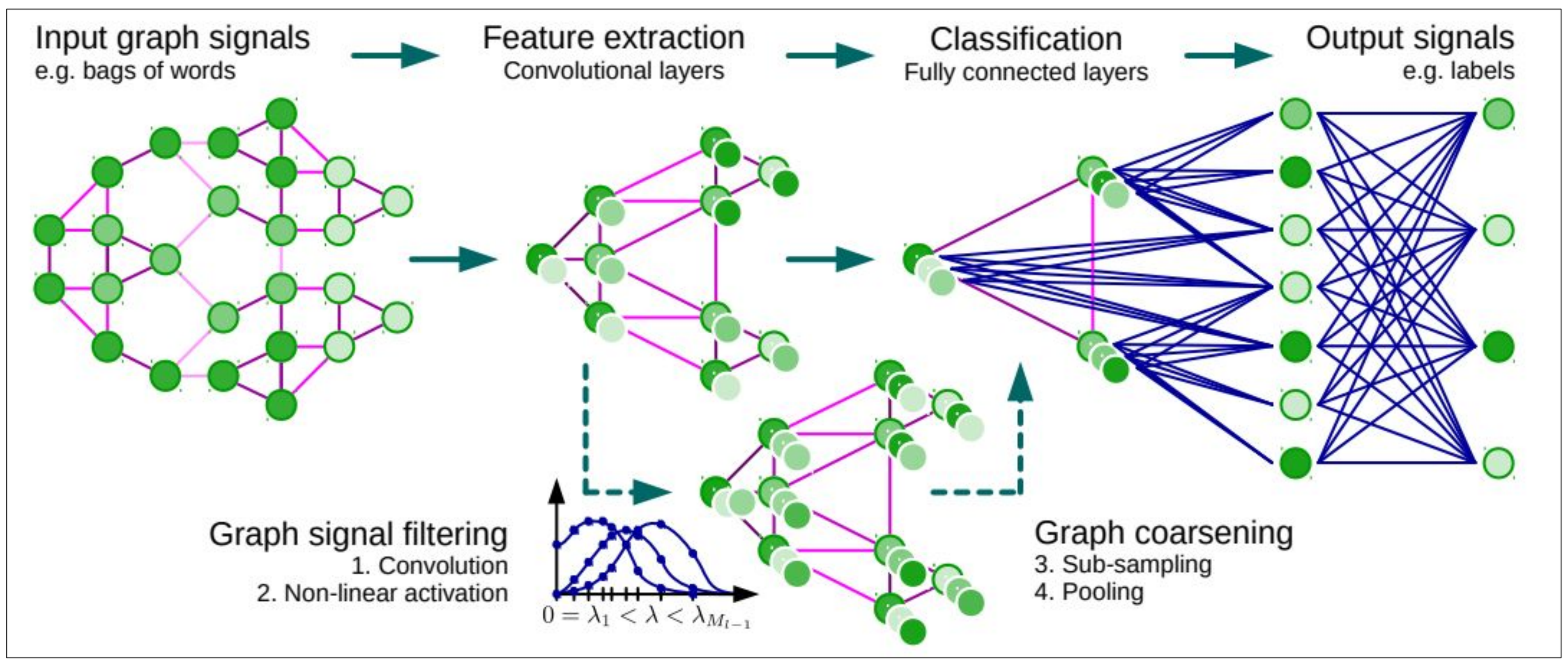


Figure 1: Architecture of Graph Convolutional Neural Network and the four ingredients of a (graph) convolutional layer. [Defferrard et. al, 2016]

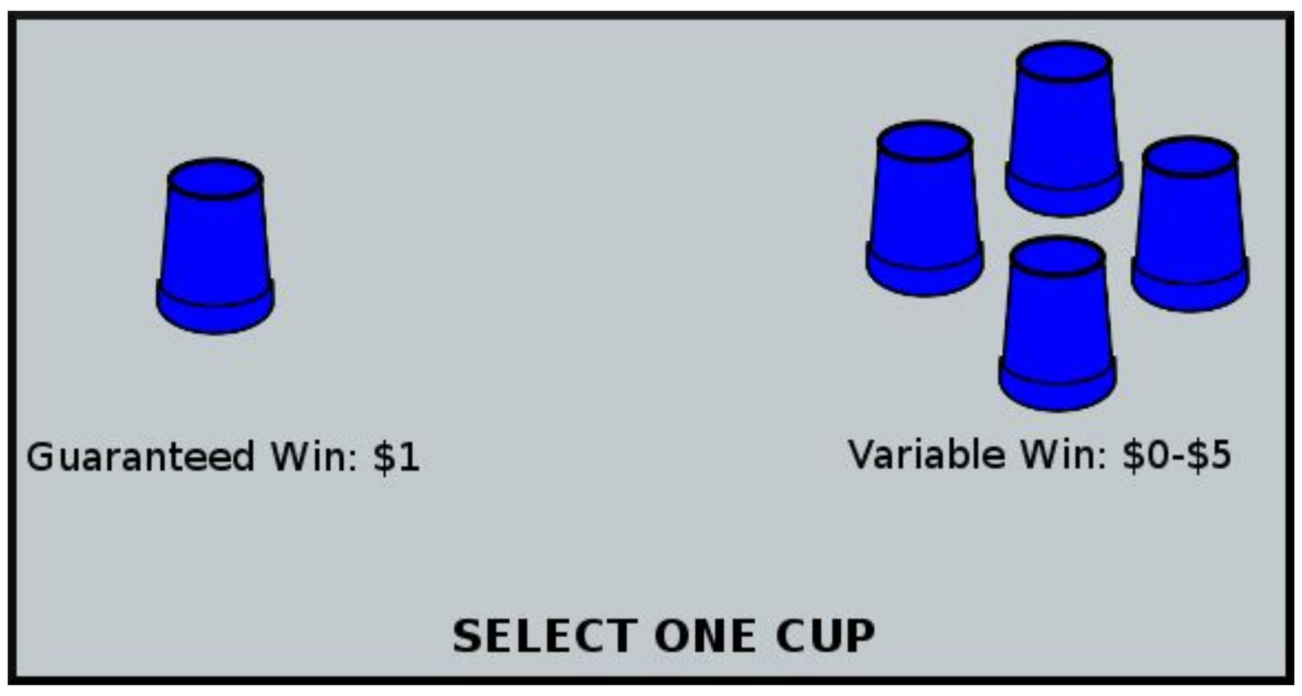
Convolution of a Signal on a Graph

Let $x \in \mathbb{R}^N$ be a signal on a graph $\mathscr{G}$ with Laplacian $L = U \Lambda U^T$, and let g_θ be a filter parameterized by $\theta \in \mathbb{R}^N$. We wish to compute the convolution $g_\theta \star x = U g_\theta U^T x$, but this is computationally expensive to do directly. Instead, approximate the convolution by

$$g_{\theta'} \star x \approx \sum_{k=0}^{K} \theta'_k T_k(\tilde{L}) x$$

with $\tilde{L} = \frac{2}{\lambda_{\text{max}}} - I_N$, and T_k the kth Chebyshev polynomial.

"Cups Task" Experiment



- Subjects are asked to choose between a cup with a fixed, guaranteed reward, or a random cup with a variable reward.
- **70 "gain" domain trials, 70 "loss" domain trials for each subject, divided into 2 blocks of gain domain, 2 blocks of loss domain.**

fMRI Data

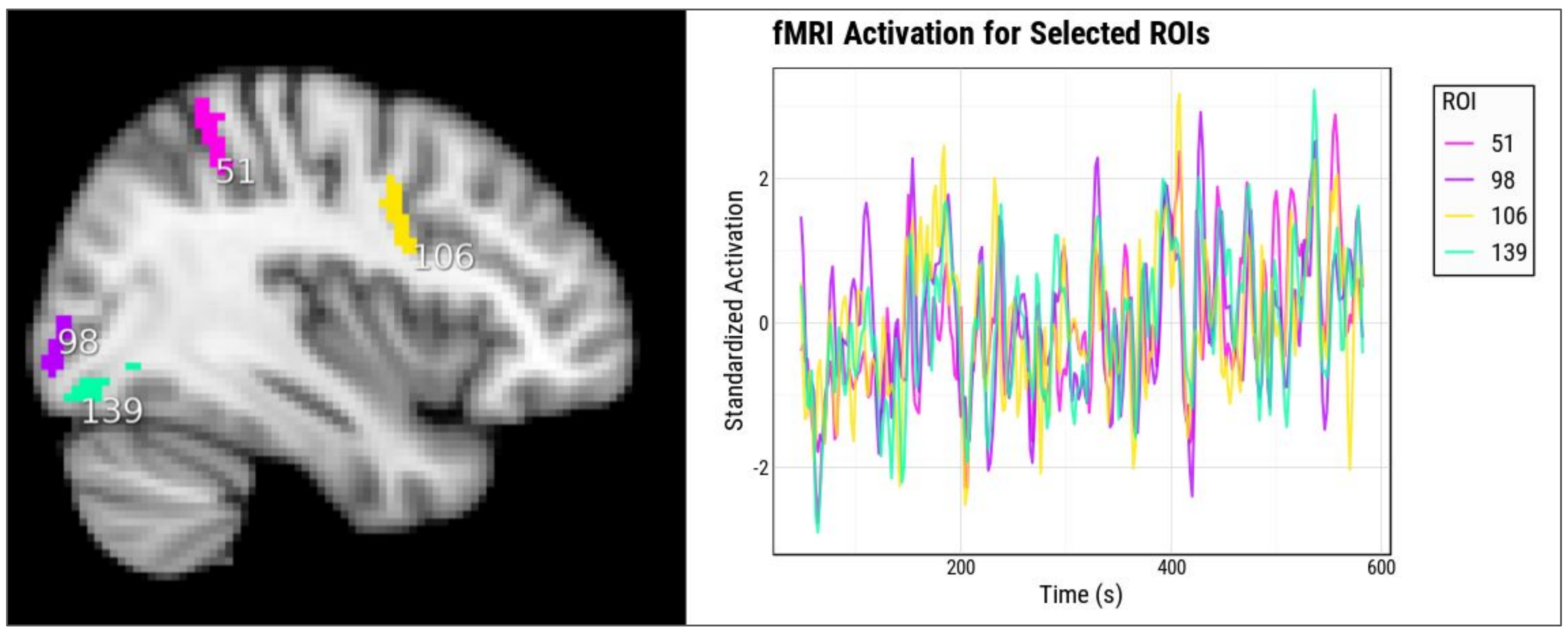
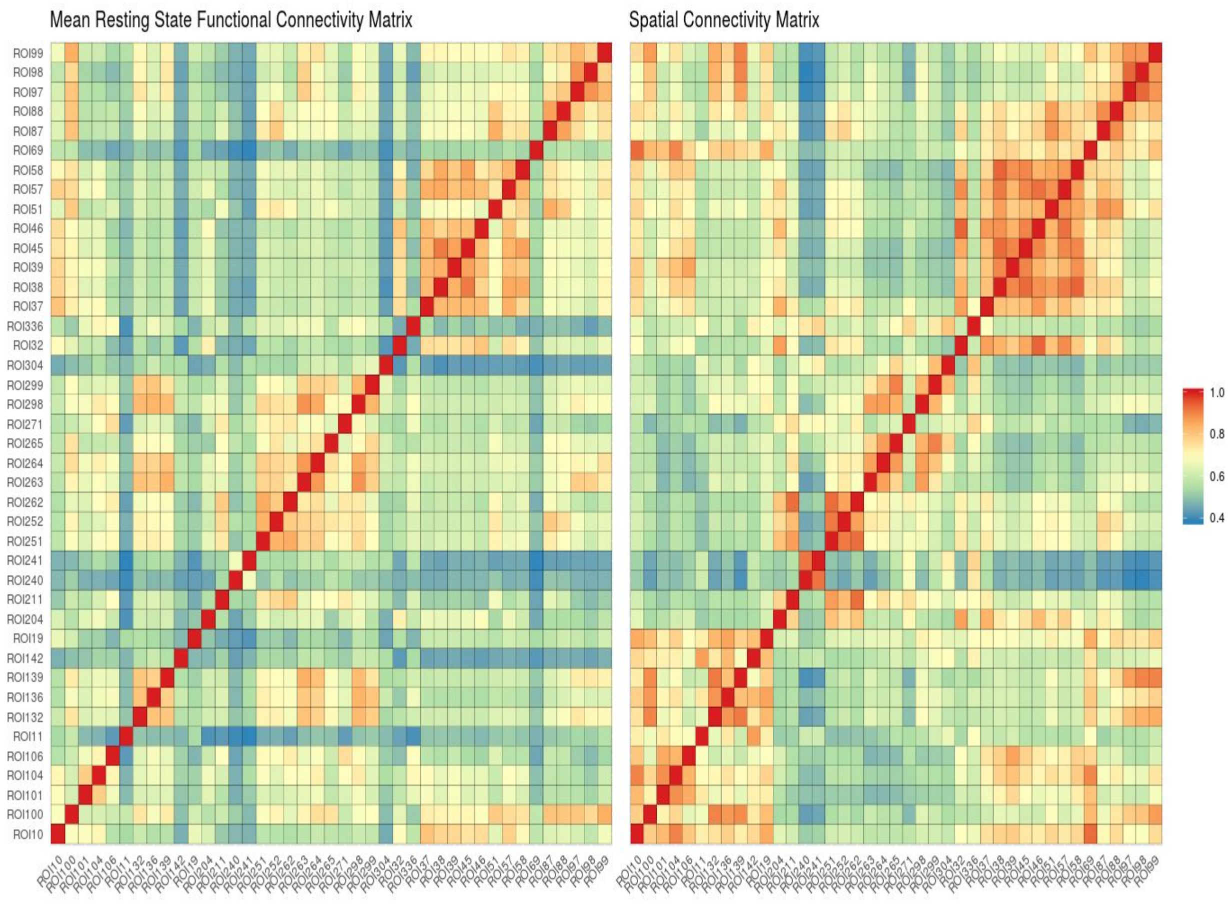


Figure 2: (*Left*) Locations of four selected ROIs that show significantly different activation between the gain and loss domains. (*Right*) Time series of the activation of these ROIs.

- 259 Subjects * 4 Blocks/subj. = **1036 observations**
- Randomly divided into
  - N = 700 training sample
  - N = 336 validation sample.
- **41 ROIs selected** from preliminary modeling
- After preprocessing, 268 volumes per subject scanned at 2 s resolution.
- Graph adjacency of ROIs from **resting state correlation and spatial distance.**
- First **16 Fourier coefficients** of each ROI used as model inputs.



Results: Predicting Gain/Loss Domain

Model	Design Notes	Accuracy
Graph CNN	Spatial Distance Connectivity	77.3
Graph CNN	**RS Correlation Connectivity**	**75.3**
Logistic Regression	**LASSO Regularization**	**74.7**
Feedforward NN	**3 layers**	**74.4**
CNN		**74.1**
XGBoost		**73.2**

Conclusions

- GCNN with connectivity determined by spatial distance of ROIs outperforms competing models.
- These results suggest that information on the spatial relationship of brain regions is helpful for discriminating the Gain/Loss domains in the Cups Task experiment.
- Future work will explore feature engineering and selection methods for graph structures in this context.
- Despite the difficulty of the problem, logistic regression performs relatively well compared to more sophisticated methods.

References

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2. Sofia Ira Ktena, Sarah Parisot, Enzo Ferrante, Martin Rajchl, Matthew Lee, Ben Glocker, and Daniel Rueckert. Distance metric learning using graph convolutional networks: Application to functional brain networks. In International Conference on Medical Image Computing and Computer-Assisted Intervention, 469–477. Springer, 2017.
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