Hierarchical Labeling of Resting State fMRI Brain Networks

Project Checkpoint

Group 9: Arden Chew

Mentors: Dr. Haris Sair and Dr. Mathias Unberath

Overview

Problem:

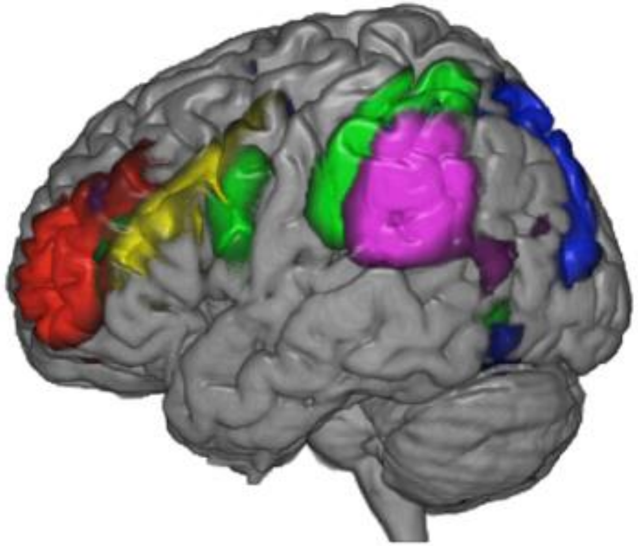
- Pre-operative brain surgery planning relies on sparse task-based fMRI
- Only handful of physicians can classify more useful resting state fMRI data

Goal:

- Automate the classification of resting state fMRI brain networks

Relevant Information

- Functional MRI
  - Measures brain activity by detecting changes in blood flow
  - Resting state fMRI is used to explore the brain's functional organization
  - Brain is organized by grouped network components
- Hierarchical network relationships
  - Variation in data clustering and underlying patient physiology make labelling difficult
  - Incorporating hierarchical data can help



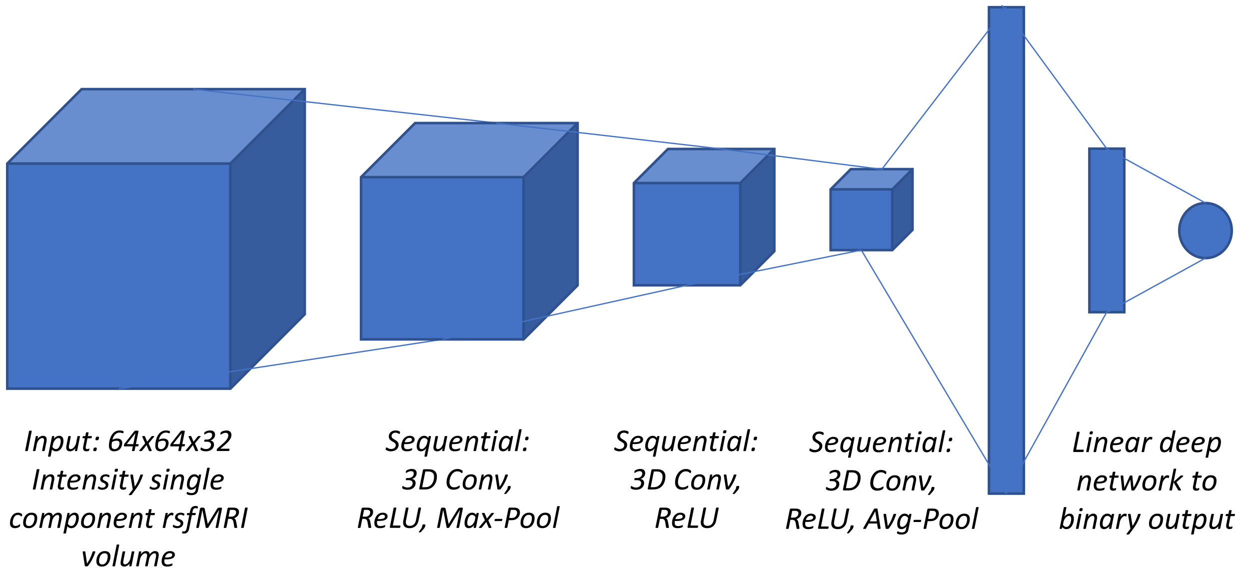
Deliverables

Minimum (expected by 3/15/19)	Expected (expected by 4/8/19)	Maximum (expected by 5/6/19)
• A trained pytorch model file (.pt) for **binary** classification of rsfMRI network components • A custom pytorch based network architecture file • Clinically actionable testing data accuracy report	• A trained pytorch model file (.pt) for **multi-label** classification of rsfMRI network components • A custom pytorch based network architecture file • Clinically actionable testing data accuracy report	• A trained pytorch model file (.pt) for **multi-label hierarchical** classification of rsfMRI network components • A custom pytorch based network architecture file • Clinically actionable testing data accuracy report • Drafted abstract/journal report of findings
COMPLETED	**COMPLETED**	**REVISING**

Deliverables: Minimum

- Binary classification of rsfMRI components (noise vs. real network)
  - Implemented custom 4-layer 3D convolutional neural network
  - Included early stopping regularization

Network Parameters for Binary Classification	
Loss function	Binary cross entropy loss
Optimization function	Stochastic gradient descent
Output activation function	Rectified linear activation
Dropout rate	0 (none)
Number of iterations	100
Epochs	1
Batch size	1
Learning rate	0.05



Deliverables: Minimum

Data comes from group ICA study of 100 rsfMRI patients from Washington University School of Medicine openNEURO dataset, labelled at Johns Hopkins Hospital

Contingency Table of Noise Classification in Group rsfMRI Study

		True	
		Network	**Noise**
Observed	**Network**	74	5
	Noise	2	19

Performance Statistics of Noise Classification in Network Separated Testing

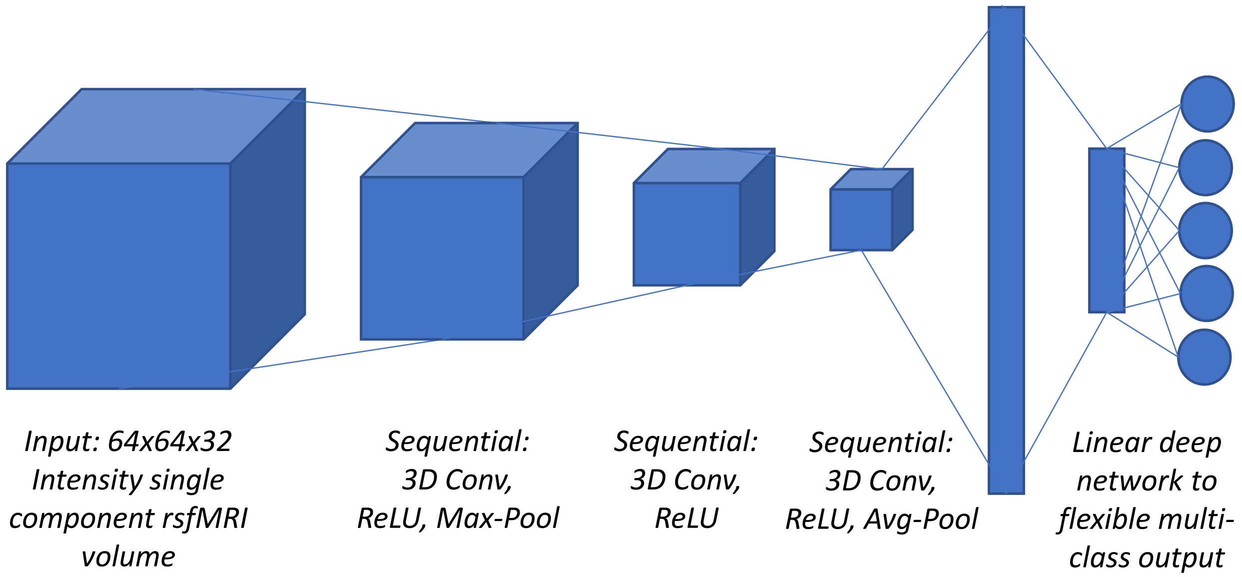
	Precision	Recall	Accuracy
Attention	0.850	0.944	0.840
Language	1.000	1.000	1.000
Default Mode	1.000	1.000	1.000
Motor	1.000	0.952	0.960
Total	**0.963**	**0.975**	**0.950**

Deliverables: Expected

- Multi-label classification of rsfMRI components
  - Retained general network architecture of binary classification
  - Modified loss/activation function choice and hyper-parameters

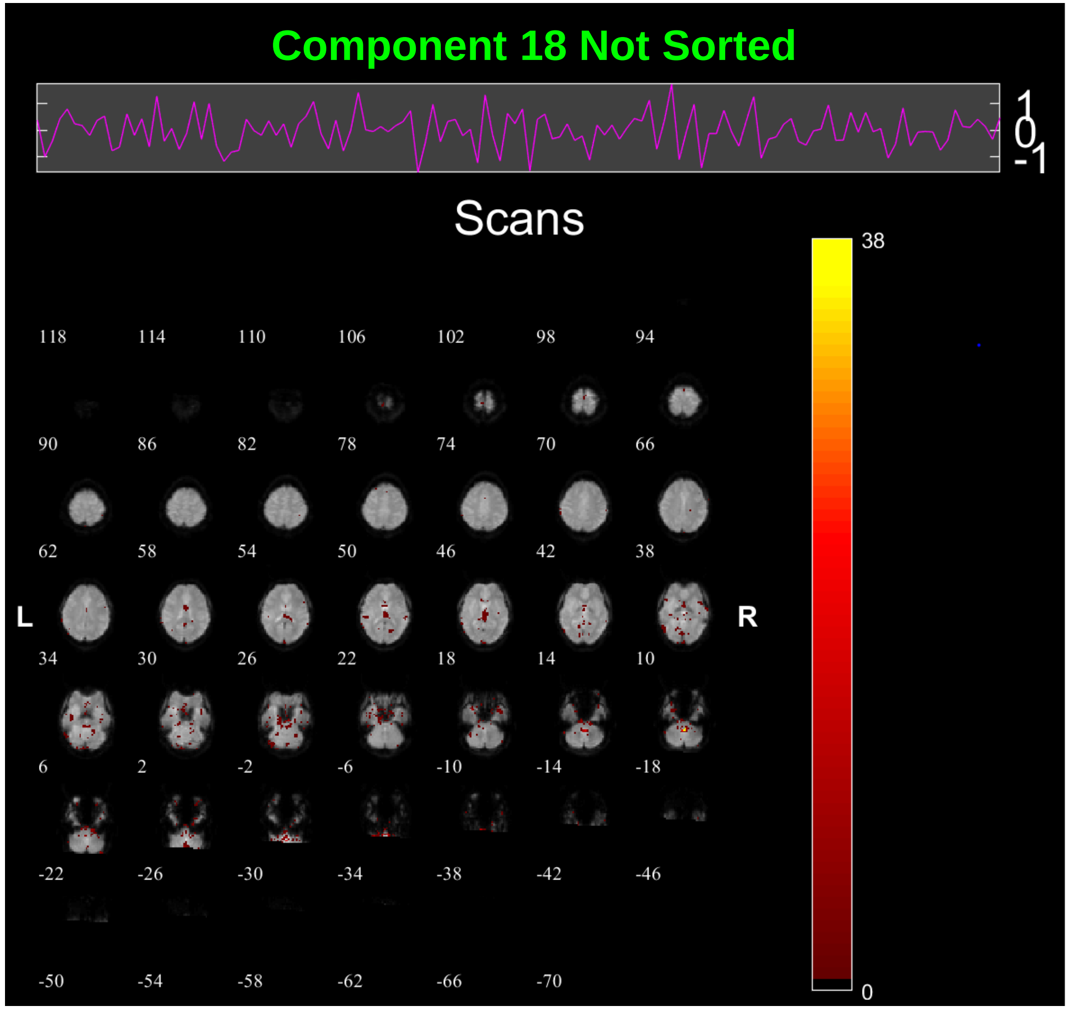
Network Parameters for Multi Classification	
Loss function	Cross entropy loss*
Optimization function	Stochastic gradient descent
Output activation function	Probabilistic softmax*
Dropout rate	0.3*
Number of iterations	100
Epochs	4*
Batch size	4*
Learning rate	0.05

**denotes change from binary classification*



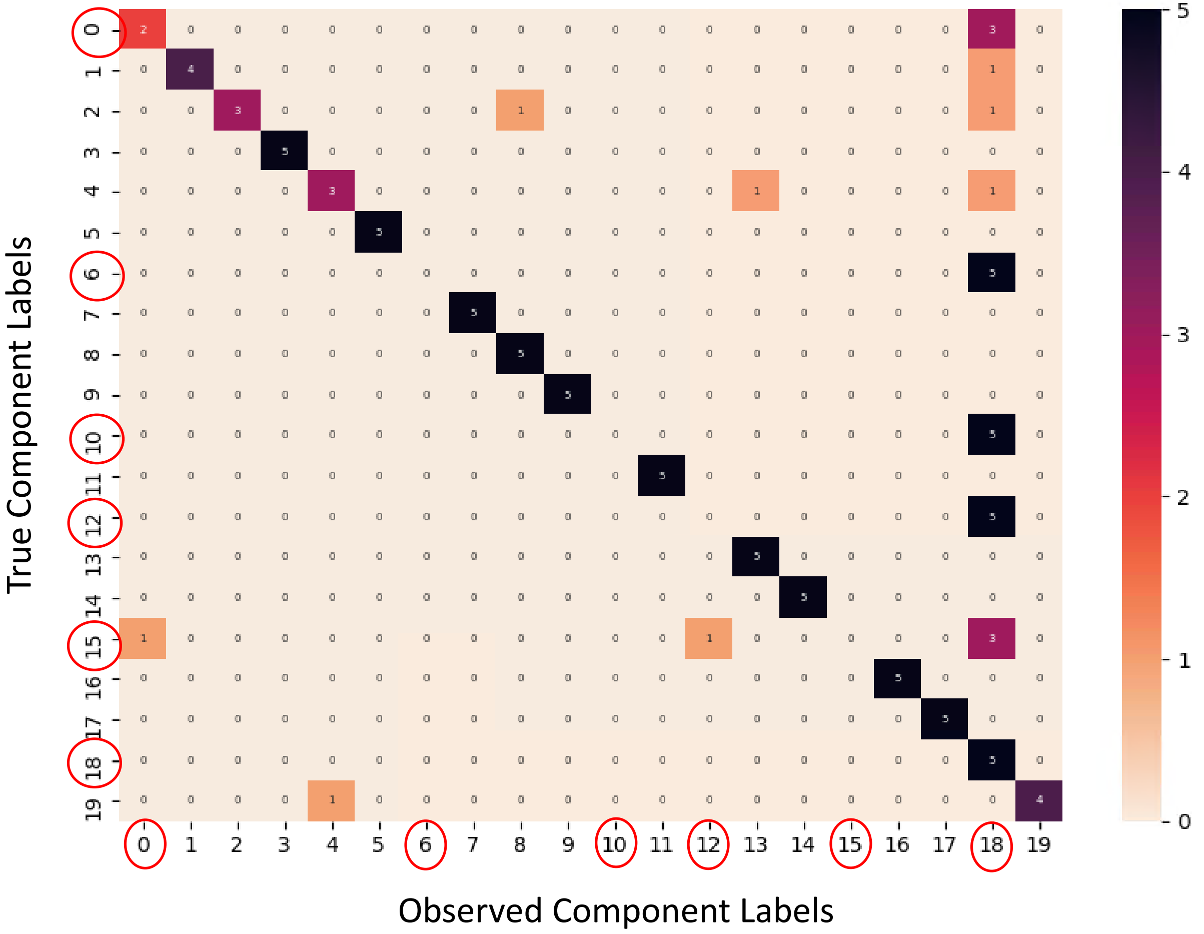
Denotes Noise Network

Deliverables: Expected



rsfMRI scan of even noise scattering on component 18

Confusion Matrix of 20 Component rsfMRI Automated Classification

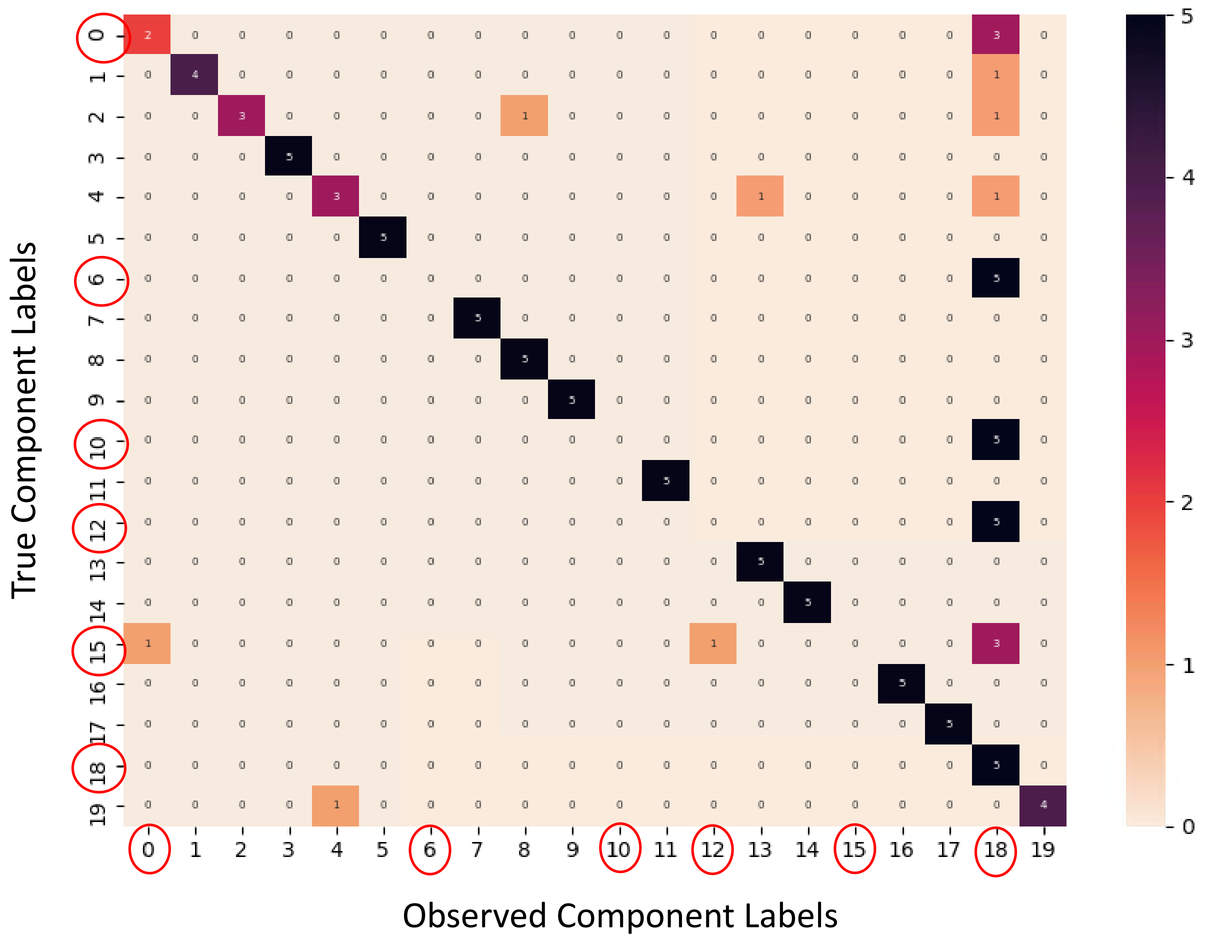


Denotes Noise Network

Deliverables: Expected

- Excluding noise groupings: 95.00% accuracy
- Initial multi-class testing only on 5 subjects (100 components)
- Requires noise filtering before neural network input

Confusion Matrix of 20 Component rsfMRI Automated Classification



Deliverables: Maximum

Two major changes impacting maximum deliverables:

1. New insights into hierarchical relationships of network components specifically in individuals alter technical approach to hierarchical labeling
2. Success at non-hierarchical multi-class labeling substantiates a push towards publication

Adapted Technical Approach

- Brain component hierarchies depend on time-series data rather than component volumes
  - Convolutional deep belief network is no longer a viable option
  - Pearson correlation matrix composite score to indicate hierarchical relationships

Noise filtering via binary classification network → Initial multi-class prediction → Prediction thresholding → Comparison to Pearson correlated predictions → Revised weighted prediction

Deliverables: Maximum

Original Maximum Deliverables	New Maximum Deliverables
• A trained pytorch model file (.pt) for **multi-label hierarchical** classification of rsfMRI network components • A custom pytorch based network architecture file • Clinically actionable testing data accuracy report • Drafted abstract/journal report of findings	• Drafted abstract/journal report of **non-hierarchical multi-label** classification of rsfMRI network component • Python script for pipelining noise filtering into multi-label classification • Python script for Pearson correlation thresholding and incorporation into full work-flow • Clinically actionable testing data accuracy report

Important to note that dependencies will not change from this shift as I will be using the same data

Updated Dependencies

Dependency	Motivation	Method	Status
Computer	Software development	Will use personal laptop	Complete
Matlab access	Independent component analysis, data processing, and data visualization	Acquired through JHU student permisssions	Complete
ICA and fMRI visualization software packages	Data visualization and fMRI data granularity manipulation	Requested from Dr. Haris Sair for downloadable packages and links	Complete
rsfMRI scan dataset of healthy patients	Training and testing of multi-label classification model	Available open source on OpenNeuro	Complete
rsfMRI scan dataset of healthy patients with binary labelled ICA	Training and testing of binary classification model	Acquired from Dr. Haris Sair hand labeling of KIRBY dataset	Complete
Graphic Processing Units with 600+ CUDA cores	Handling of high throughput volumetric data	Requested access to existing GPU enabled desktop via Pulse Secure VPN	Complete

Updated Key Dates

- **4/16** – Fine tuned network hyper-parameters and data pre-processing to achieve multi-label accuracy on enlarged testing dataset that meets Dr. Sair’s paper requirements
- **4/23** – Drafted abstract for CNN multi-label rsfMRI classification proposal
- **4/30** – Completed integration of noise filtering to data pipeline
- **5/6** – Completed integration of Pearson correlation thresholding to data pipeline and produced accuracy report of final classification model

References

- Shruti A, Sair H, Pillai J. Limitations of rsfMRI in the setting of focal brain lesions. Neuroimaging Clin N Am. 2017 Nov. 27(4); 645:661.

- Bailey P, Zaca D, Basha M, Agarwal S, Gujar S, Sair H, Eng J, Pillai J. Presurgical fMRI and DTI for the Prediction of Perioperative Motor and Language Deficits in Primary or Metastatic Brain Lesions. Journal of NeuroImaging. 2015 July 14.