Hierarchical Labeling of Resting State fMRI Brain Networks
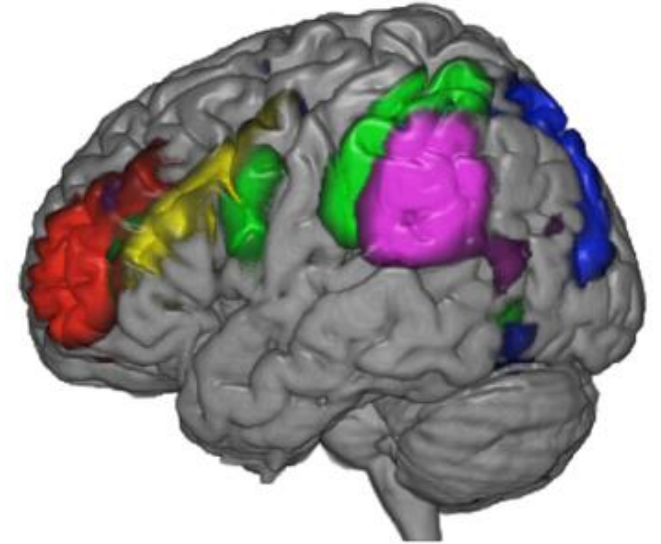
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Background

- Functional MRI
  - Measures brain activity by detecting changes in blood flow
  - Resting state fMRI is used to explore the brain's functional organization

- Hierarchical network relationships
  - Variation in data clustering and underlying patient physiology make labelling difficult
  - ICA successful in differentiating networks but unable to label or identify network relationships

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Medical Motivation

- Diagnostic value
    - Diagnosing brain tumors, brain neoplasms, arteriovenous malformations and other vascular malformations
    - Understanding severity, location, and cause with high specificity

- Pre-operative value
    - Improved pre-surgical mapping
    - Precise outcome recognition

- Improved Accessibility
    - Limited expertise in brain networks

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Specific Aims

1. Develop automated tool for precise and consistent rsfMRI networks components labeling in healthy individuals

2. Extrapolate tool for patients with brain lesions

3. Generalize tool for hierarchical rsfMRI component recognition in all patients

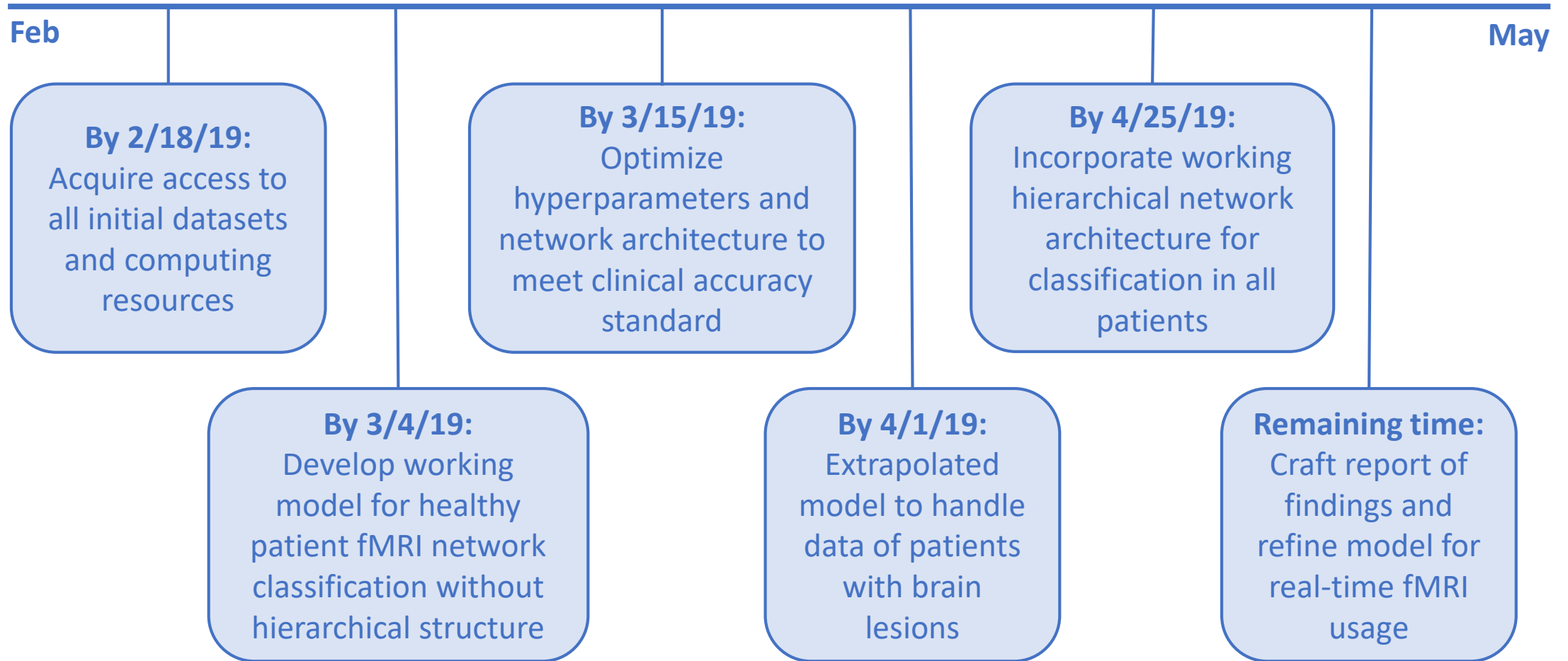4. Refine tool for real-time implementation in fMRI scanners

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Dependencies

Dependency	Motivation	Method	Status
Computer	For software development	-Will use personal laptop	Complete
Authorization for access to patient data	Must access fMRI data of radiology patients from Johns Hopkins Hospital	-HIPAA training protocol -Responsible conduct of research training	Completed
Access to labelled rsfMRI component dataset	Dataset to train models on	-Receive access to shared google drive	Requested (via email to Dr. Sair) (due by 2/18/19)
Access to high powered GPU	High resolution 3D data being processed with residual layered network architecture requires GPU	-RAIL offers google cloud GPU credits -First must determine how much processing power/time is needed	Dependent on further steps (ensured access) (due by 2/18/19)

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Dependencies

Dependency	Motivation	Method	Status
Temporal rsfMRI output data	For real-time integration into fMRI usage need access to replicated data generated from actual fMRI tests	-Must discuss with Dr. Sair on arranging approval for collection -Must acquire approval to work with said data	Incomplete (Due by 4/25/19)
Matlab access (note ML development in Python)	For ICA and data visualization	-Acquired through JHU student permissions	Complete
ICA and fMRI Visualization Software Packages	For data visualization and fMRI data granularity manipulation	-Request from RAIL lab for download access	Complete

Timeline

Feb

May

By 2/18/19:
Acquire access to all initial datasets and computing resources

By 3/15/19:
Optimize hyperparameters and network architecture to meet clinical accuracy standard

By 4/25/19:
Incorporate working hierarchical network architecture for classification in all patients

By 3/4/19:
Develop working model for healthy patient fMRI network classification without hierarchical structure

By 4/1/19:
Extrapolated model to handle data of patients with brain lesions

Remaining time:
Craft report of findings and refine model for real-time fMRI usage

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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 a <u>non-hierarchical</u> network that can successfully label fMRI network components in <u>healthy</u> resting state brain • **A custom pytorch based network architecture file** for aforementioned model and associated packages for data handling, training, and testing with documentation • **Clinically actionable testing data accuracy report** (complete with testing and validation accuracies, confusion matrix of component labels, loss charting)	• **A trained pytorch model file** (.pt) for a <u>non-hierarchical</u> network that can successfully label fMRI network components in resting state brain <u>with lesions</u> • **A trained pytorch model file** (.pt) for a non-hierarchical network that can successfully label fMRI network components in resting state brain <u>of all patients</u> • **Clinically actionable testing data accuracy report**	• **A trained pytorch model file** (.pt) for a <u>hierarchical</u> network that can successfully label fMRI network components in resting state brain <u>of all patients</u> • **A custom pytorch based network architecture file** for hierarchical model and associated packages for data handling, training, and testing with documentation • **Clinically actionable testing data accuracy report** • Optimized network architecture and **implementation for real-time** • **Drafted abstract/journal report of findings**

*note that all code will be held in private RAIL github repository and accuracy reports in Neuroradiology google drive

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Technical Approach

- Available data
  - \>1000 healthy brain labeled rsfMRI files available as tensors in xml format
  - ~100 patients with brain lesions labeled rsfMRI files
    - Requires cross-validation
- Initial network choices
  - 3D CNN with residual layers allows for pattern recognition of spatially extrapolated features
  - Differing layer depths due to range of network components resolutions
  - Batch size limited by GPU constraints
  - Cross entropy loss (non-binary in multiclass scenario)
  - Considering SGD, Adam, and momentum based optimizers
  - Regularization techniques as necessary

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Technical Approach

- Hierarchical network choices
  - Brain network component relationships are dynamic and therefore unlabeled, requires an unsupervised approach
  - Deep belief network with latent variables for recognizing active and non-active components

- Real-time network choices
  - Need to limit network depth to increase speed
  - LSTM layer incorporation for temporal considerations

Logistics

- Biweekly presentations with RAIL lab for feedback

- Friday weekly check-ins with Dr. Sair

- Real-time code progress tracking via shared github repository

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Reading list

- 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.

- Hannawi Y, Lindquist M, Caffo B, Sair H, Stevens R. Resting brain activity in disorders of consciousness. Neurology. 2015 Mar. 84(12); 1272:1280.

- Kulkarni T, Narasimhan K, Saeedi A, Tenenbaum J. Hierarchical Deep Reinforcement Learning: Integrating Temporal Abstraction and Intrinsic Motivation. Conference on Neural Information Processing Systems. 2016.

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- Lee H, Grosse R, Ranganath R, Ng A. Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. ICML '09 Proceedings of the 26th Annual International Conference on Machine Learning. 2009 Jun 14. 609:616.

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