

# ML Systems

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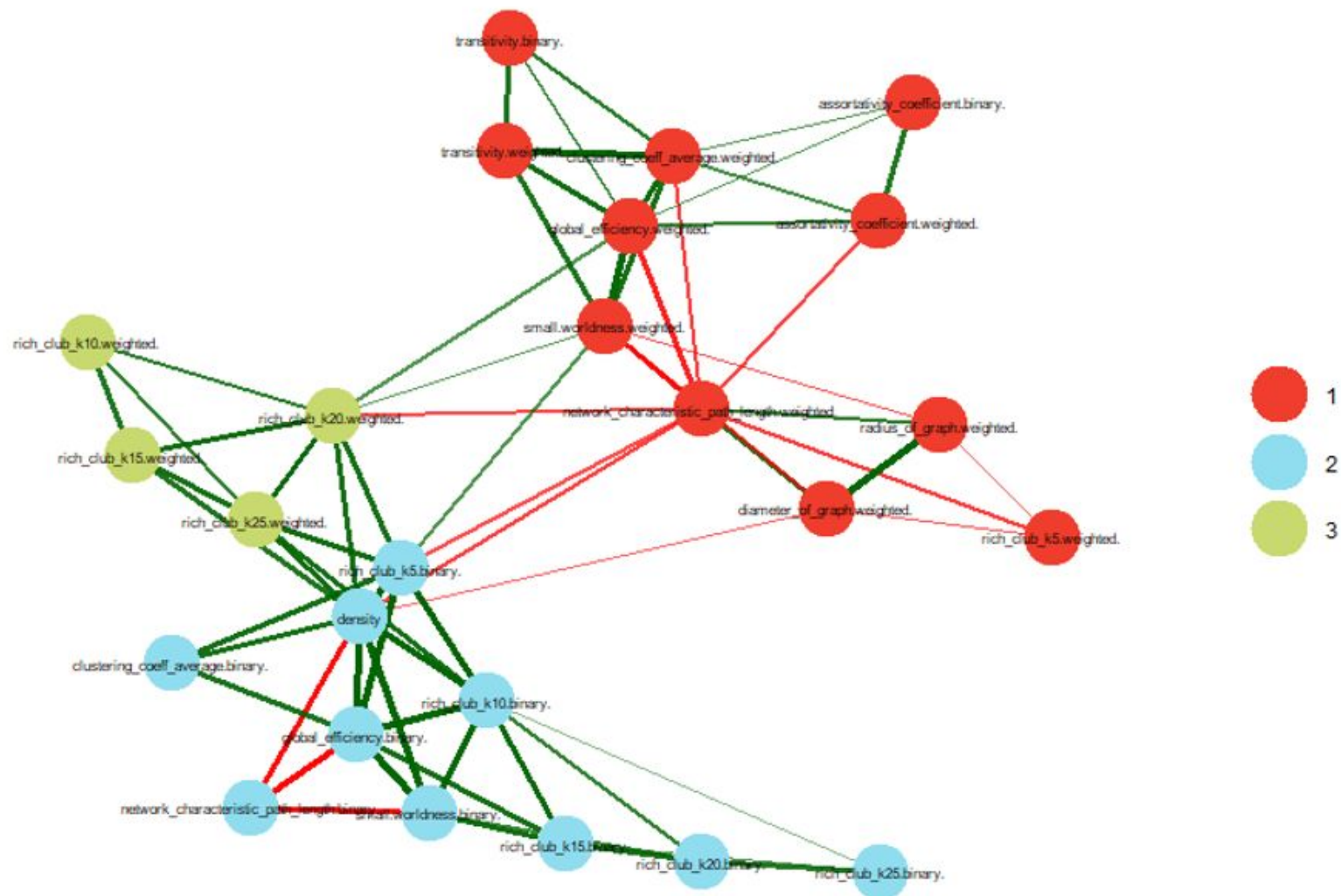
# Image Processing

- Current neuroimaging processing pipelines utilize parallelization
- Raw signal to usable image transformation is resource intensive
  - K-space to brain-space
  - Per-subject basis
  - One node per subject scan; often many scans
- Entire compute clusters dedicated to neuroimaging research

# Secondary Post-Processing

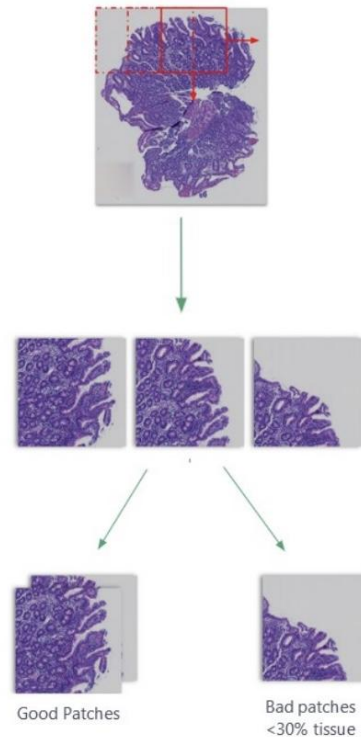
- Results in hundreds of features from a single scan
  - Network efficiency, isolated brain region metrics, functional connectivity
- Usually way fewer subjects than features ( $p \gg n$ )
- Compute clusters are not often leveraged for feature engineering
  - Most dimensionality reduction uses 'region of interest'-type narrowing
  - Eliminating the signal in the brain that depends on other regions
- Proposal: data-centric feature engineering on public, large-scale neuroimaging projects
  - Human Connectome Project ( $n > 2000$ ), UK Biobank ( $n > 50,000$ ), ABCD ( $n > 10,000$ )





# Problem

- Medical images can be very high resolution (50,000 X 50,000 pixels on average).
- Modern GPUs cannot fit images of this size in their memory.
- Have to break up images into patches for training - we lose context of the larger image.



# Proposed solutions and project ideas

- Distributed data parallelism: Can we develop a method to efficiently distribute the data across multiple GPUs
- Use data compression techniques to compress the image while preserving context of the larger image.
- Use mixed precision training and look at memory consumption.