CONSTRUCTING MODEL-BASED NETWORKS

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ABCD WORKSHOP

INTRO TO NETWORK ESTIMATION

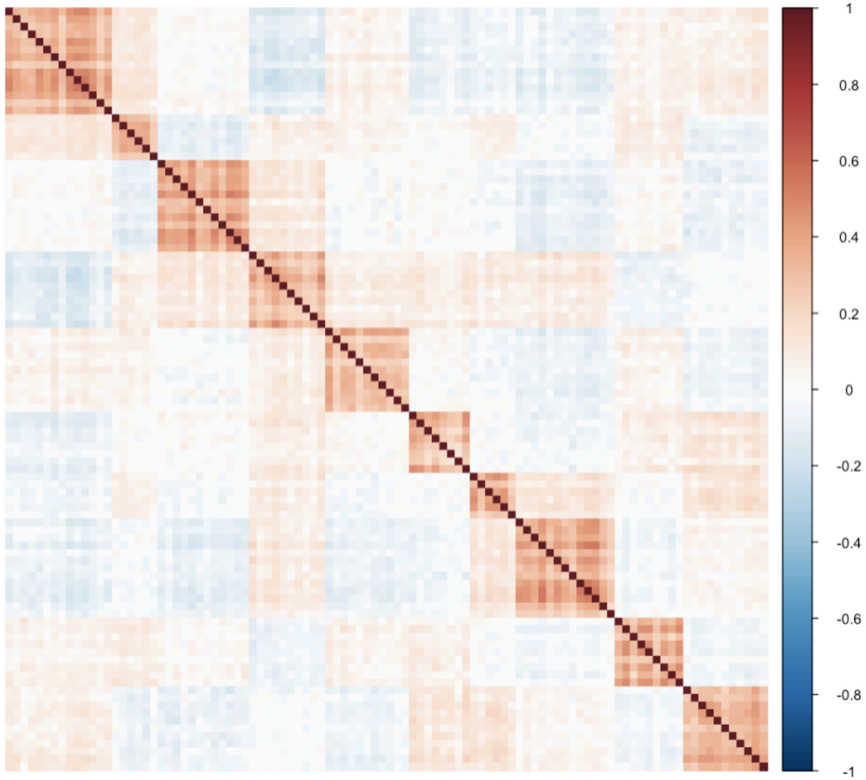
1. Goals of Network Estimation
2. Traditional Approaches
3. Estimation in an SEM framework
4. Estimation using regularized regression
5. R-packages/Resources

GOALS OF NETWORK ESTIMATION

- Uncover temporally-dependent (i.e., functional) relationships between variables (not limited to neuroimaging signals)
- Discover true relationships (i.e., no false negatives)
  - How sensitive is the estimation technique to signal in the data (i.e., power)
- Reject false relationships (i.e., no false positives)
  - Very difficult to determine in a multivariate space
  - Different estimation approaches offer different tradeoffs

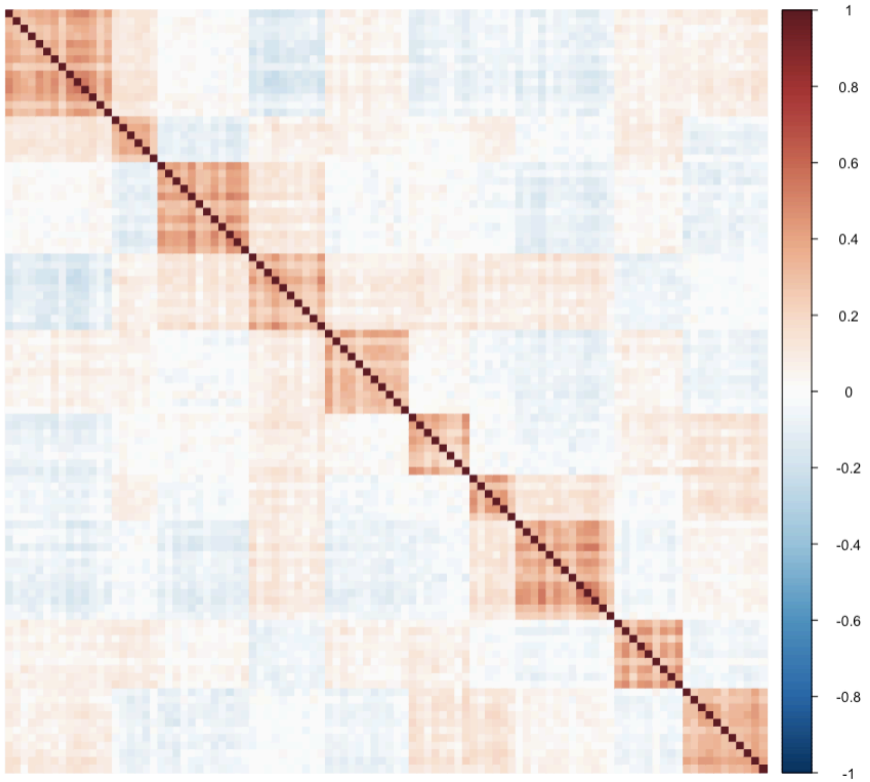
TRADITIONAL APPROACHES

- Calculate Pair-wise Zero-order Correlations (or partial correlations)
  - No time-lagged information
- Apply some sort of thresholding
  - Proportional or absolute



LIMITATIONS FOR TRADITIONAL APPROACHES

- Remove temporal information
- Problems inverting covariance matrix
- What to do about thresholds
  - Best methods?
  - Are weak relationships important?
- All relationships bi-directional and matrix is symmetric
- Individuals estimated individually or concatentated



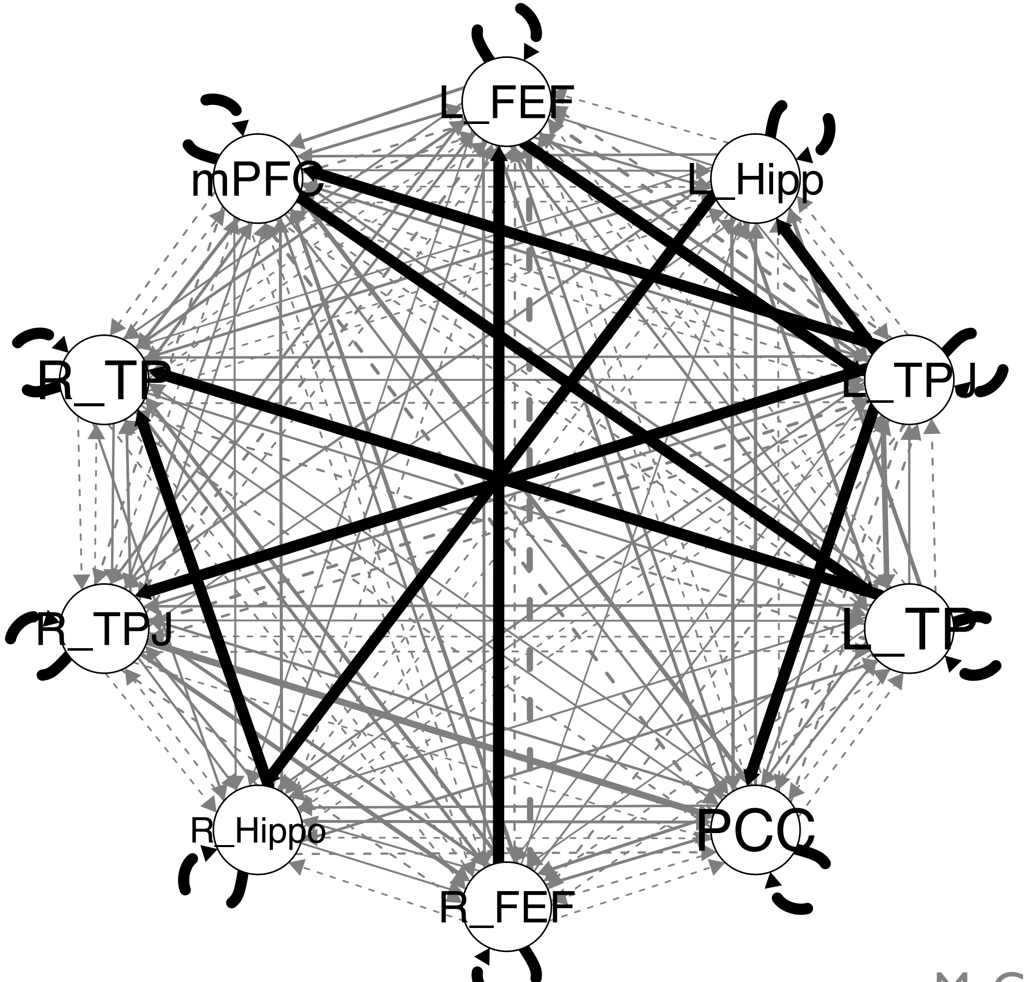
MODEL-BASED APPROACHES

- Concerned with arriving at (weakly) directed graphs on the basis of model-fit
- Incorporate additional temporal information
  - Auto-regression and cross-lagged paths
- No bi-variate estimation
- Some helpful (but not necessary) algorithmic additions
  - Utilize information across individuals to supplement individual estimation

MODEL-BASED APPROACHES (SEM)

- GIMME: Group Iterative Multiple Model Estimation
  - Utilizes structural vector auto-regression to estimate a unitary network model
  - Estimates contemporary and lagged (including autoregressive) paths
    - $\eta_t = A\eta_t + \Phi\eta_{t-1} + \zeta_t$
- Directed paths achieved through Granger causality
- Algorithmic advantages
  - Estimates group model (paths consistent across people) first
  - Group model used as starting point for individual model

MODEL-BASED APPROACHES (SEM)



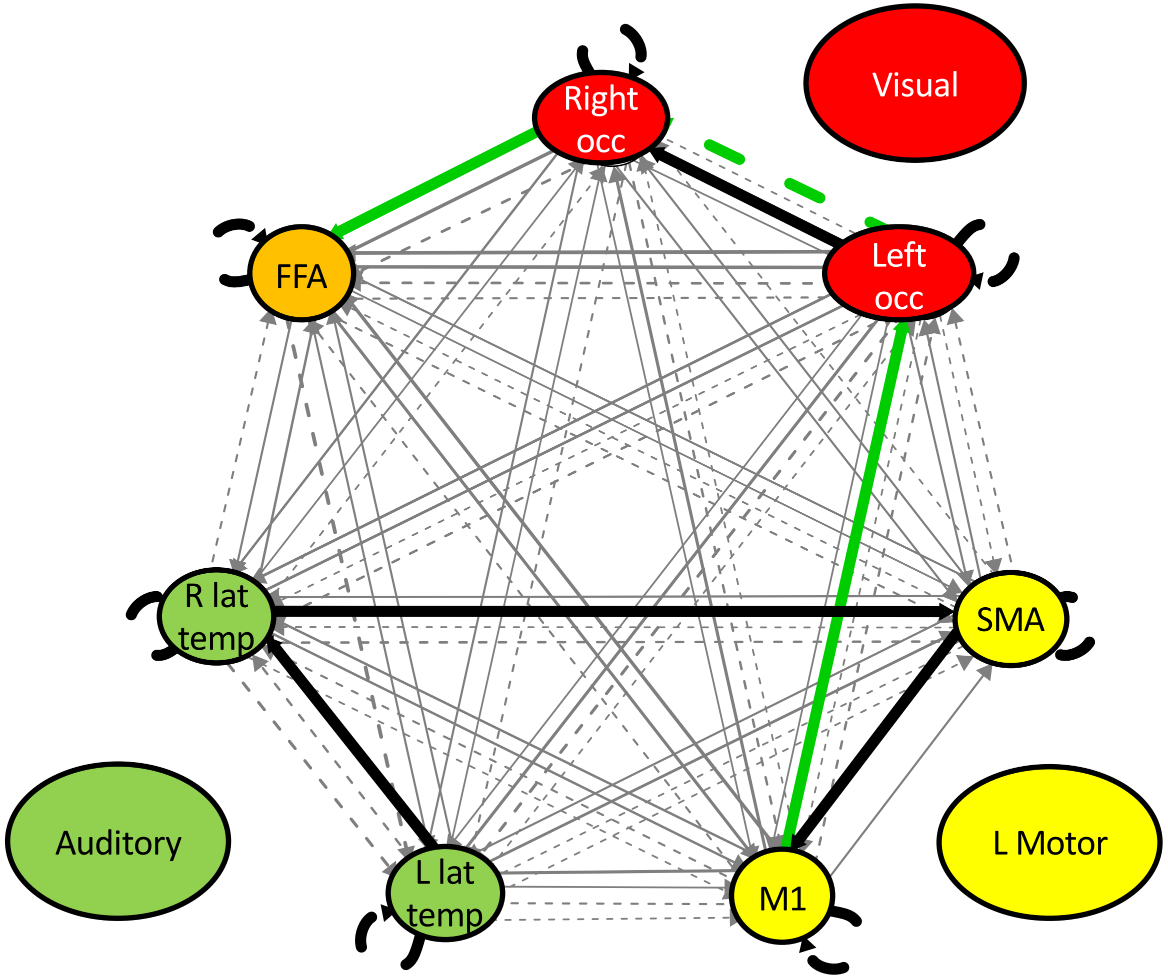
McCormick & Telzer, 2018

MODEL-BASED APPROACHES (SEM)

- GIMME: Group Iterative Multiple Model Estimation
- Subgrouping based on network features
  - Confirmatory: groups are pre-defined and provided by the user
  - Exploratory: groups are derived without user input
- Clustering options
  - Walktrap, InfoMap, Spinglass, etc.
  - All options from igraph (search “walktrap”)

Gates, Lane, Varangis, Giovanello, & Guskiewicz, 2017;
Gates, Henry, Steinley, & Fair, 2016;
Henry, Feczko, Cordova, Earl, Fair, & Gates, 2019

MODEL-BASED APPROACHES (SEM)



MODEL-BASED APPROACHES (SEM): SOME LIMITATIONS

- Limits on model estimation
  - Number of variables <20
  - Lots of parameters being estimated that are not of interest
- Third variable problem
  - Selection of variables is important
- Slow

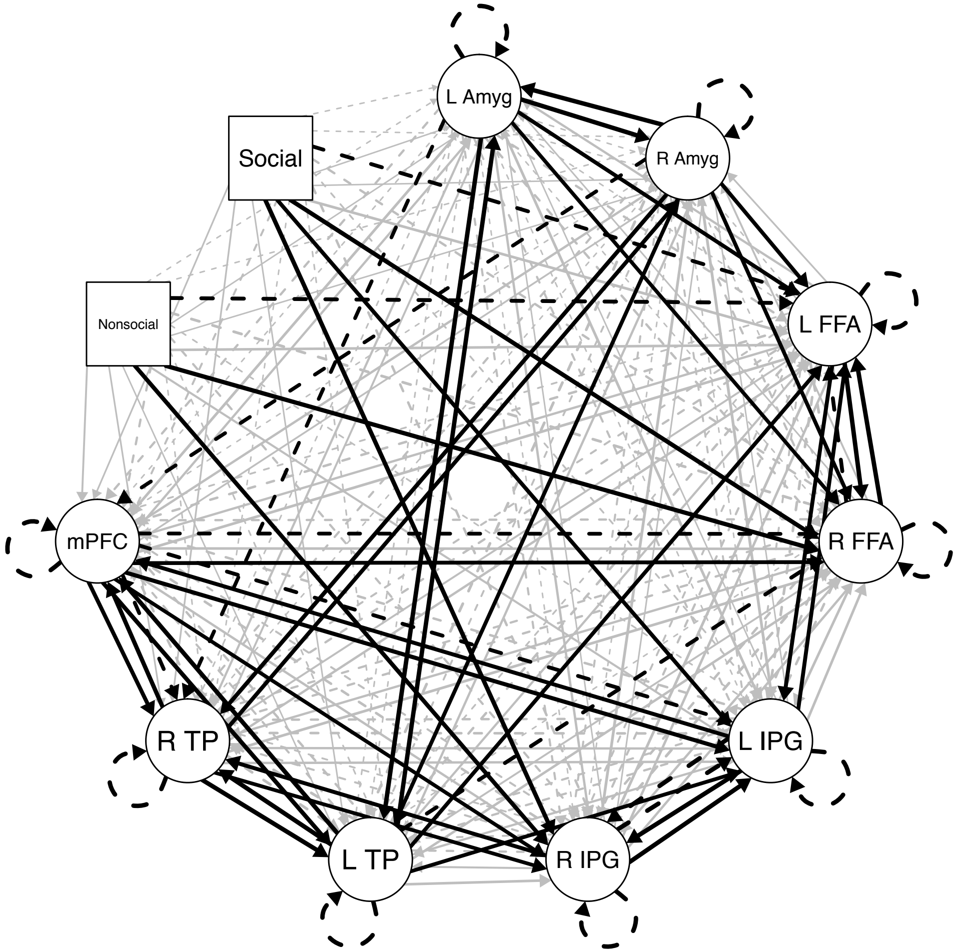
MODEL-BASED APPROACHES (REGULARIZATION)

- multiLASSO
  - New algorithm using the same group/individual principles of GIMME, but using regularized regression to estimate functional paths
- Estimates contemporaneous and lagged paths
  - Adds functionality for moderated paths (i.e., interactions)
- Scales up to networks of any size
- Default uses elastic net parameter (α = 0.5)
  - selects in groups of correlated predictors

McCormick, Ye, & Gates, *in prep*

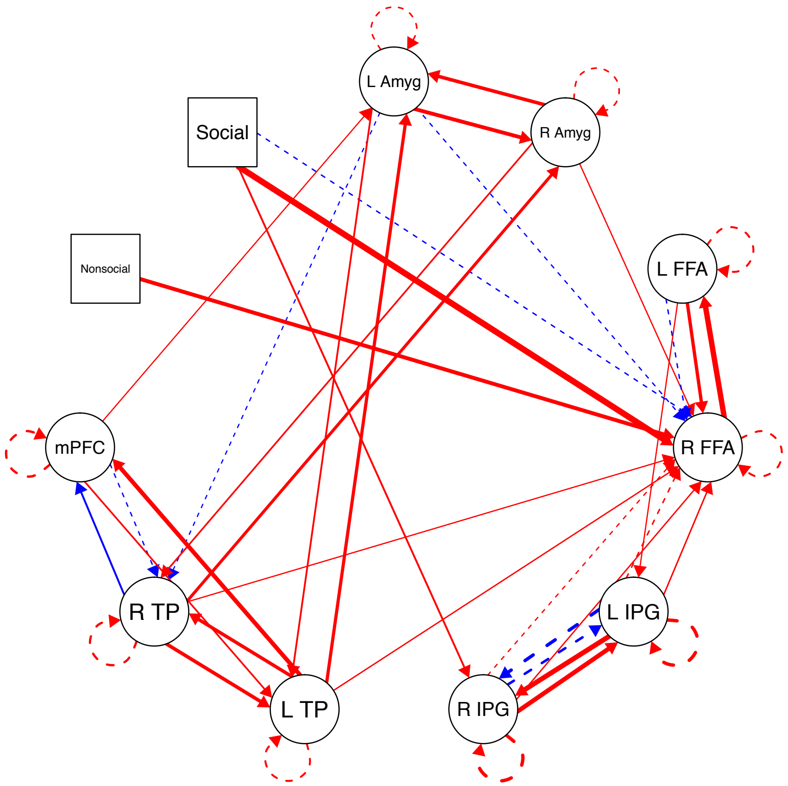
MODEL-BASED APPROACHES (REGULARIZATION)

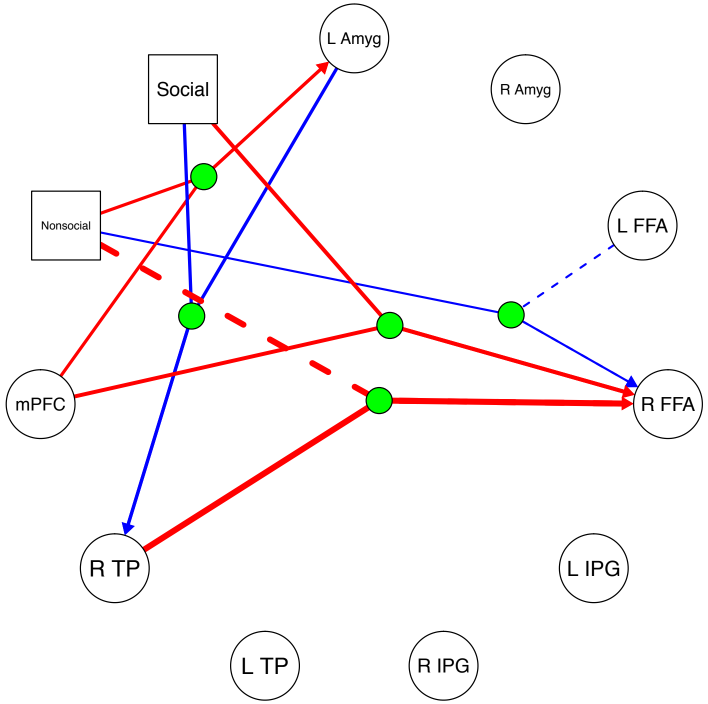
- multiLASSO



MODEL-BASED APPROACHES (REGULARIZATION)

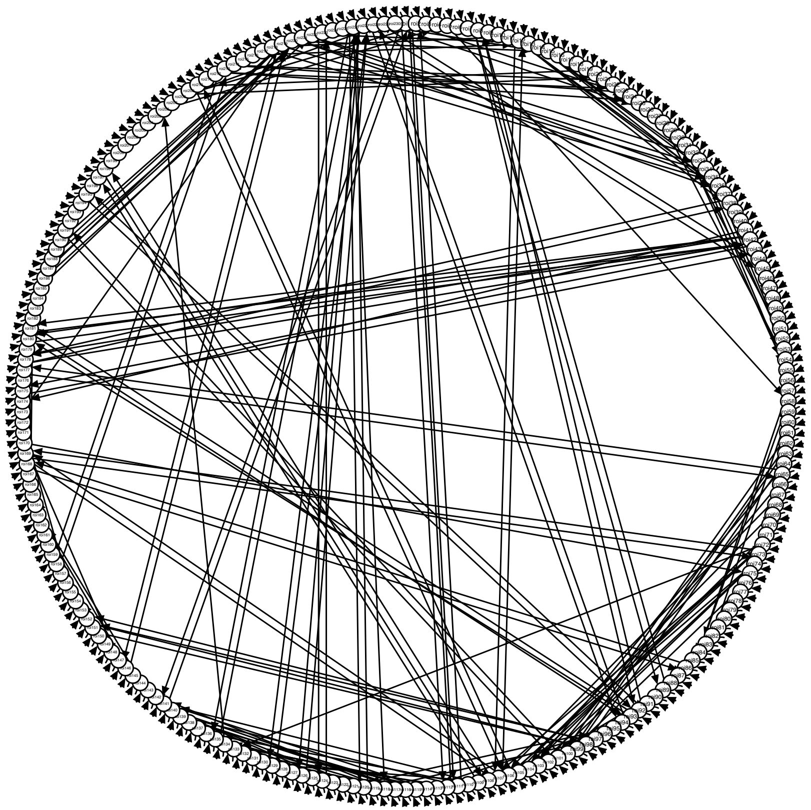
- multiLASSO: interactions





MODEL-BASED APPROACHES (REGULARIZATION)

- multiLASSO: scaling up



RESOURCES

- GIMME
  - Github: https://github.com/GatesLab/gimme
  - Website: http://gimme.web.unc.edu/
- multiLASSO
  - Github: https://github.com/McCormickNeuro/multiLASSO
- qgraph (for network visualization)
  - http://sachaepskamp.com/qgraph/examples