## Memory Maps Qualtrics Data Pipeline

**Goal**: Process data collected on Qualtrics to be ready for graph/network analysis and for correlational analysis.

1) Network analysis will yield networks of autobiographical memories based on how memories cause or were caused by other memories in the network, like a memory map of one’s own life experiences. Computing graph analysis on session one data will give us these networks.

2) Linear mixed effects modeling will allow us to determine the relationship between memory network centrality and autobiographical memory qualities such as:

* **Memory Importance** (*how important is this memory to you?*)
* Memory Clarity (*how clearly defined is this experience in your memory*?)
* Memory Recall Ease (*how easy was this memory to recall?*)
* Memory Agency (*to what extent was this experience initiated by yourself or others?*)
* **Memory Transformativeness** (*if this experience occurred differently, or never happened, to what extent do you think you would be the same?*)
* **Memory Changeability** (*to what extent did this experience change me?*)
* Memory Recency (*how long ago did this experience occur?*)

\*\* Bolded items are used for memory self-relevance comparisons.

We predict for all of these memories to relate to centrality, based on previous findings from our lab. However, we predict for memory transformativeness to be highly more effective in predicting degree centrality than the other memory qualities.

3) To corroborate the behavioral finding above, we can supplement this association between brain activity and memory recall, comparing the brain activity for memories less central to the network and for memories more central to the network. We predict for BOLD activity localized in regions highly-correlated with self-referential thinking and self-knowledge (e.g., midline core DMN regions) to be significantly higher than in memory regions (e.g., hippocampal regions and medial-temporal regions) during recall of highly network-central memories and of highly transformative memories.

Post-hoc analyses may be required to further understand the importance of directionality for centrality. In other words, we will need further analysis to determine the following: what does it mean for memories with more dependents to be more important to self-understanding? Qualitatively, how would this differ from memories with less dependents and less important to self-understanding?

### **Power Analysis**

1. *Network analysis power*

### **1. Preprocessing**

#### ***Behavioral***

##### Session One

1) Initial Data Wrangling - imported data into RStudio and organized memory data from various memory nomination stages

2) Compute relationships between memories with iGraph and connect in network space

3) Prepare data for individual differences measures

*Session Two*

1. Import processed session one data (memory nominations and relationships)
2. Organize memory rating data to be manipulable
3. Compute relationships between memory ratings and global network properties associated with the memory quality
   1. Plug these values into LME regression
4. Recode responses for individual differences measures

#### ***Neuroimaging***

1. dcm2bids → used to convert DICOM files downloaded from the MRI console into BIDS formatted files (NIFTI)

Citation:

Boré, A., Guay, S., Bedetti, C., Meisler, S., & GuenTher, N. (2023). Dcm2Bids (Version 3.1.1) [Computer software]. <https://doi.org/10.5281/zenodo.8436509>

1. FSL→ preprocessing pipeline that performs preprocessing on raw NIFTI images. The following steps were used for images (per subject) in the MM study\*:

1) Brain Extraction (BET) - image skull-stripped to extract brain voxels from the image

2) Topup FSL

* Used to estimate susceptibility-induced distortions from magnetic field inhomogeneities (signal disruptions from cavernous structures in head, like the sinuses and eye sockets) in the EPI images

3) FEAT Preprocessing

* Processing FEAT pipeline
  + MCFLIRT (motion correction)
  + B0 unwarping of corrected EPI to use with BBR cost function for structural to functional registration
  + Spatial smoothing at 6m FWHM
  + Structural registration to MNI template with guidance of corrected EPI

\* BET not completed during FEAT, completed before distortion correction/fieldmap correction

\* Slice Time Correction not used due to low amount of TRs (1.0/1.5), which would not serve the statistical power of the bold contrasts and GLMs ([Andy's Brain Book - Slice Timing Correction](https://andysbrainbook.readthedocs.io/en/latest/fMRI_Short_Course/Preprocessing/Slice_Timing_Correction.html)).

Citation: [found in output reports]

### **2. Network Analysis (Behavioral)**

[iGraph in R](https://cran.r-project.org/web/packages/igraph/vignettes/igraph.html#treating-a-graph-as-an-adjacency-matrix)

* Using iGraph, we created an adjacency matrix indicating which memories are connected (1) and which memories are not connected (0).

### **3. Linear Mixed Models (Behavioral)**

* Linear mixed effects models/linear regression will predict network metrics (degree centrality) from memory qualities such as memory transformativeness, memory changeability, memory importance, etc.
* From this analysis, we can determine which memories/nodes of a network are…
  + (1) potentially responsible for participant’s subjective feelings of self-coherence through self-report measures
  + (2) relationally/causally responsible for participant’s memory-based representation of a coherent self-concept

### **4. General Linear Model (Neuroimaging)**

1. General Linear Model (GLM)

**First-Level Analysis**

* We are estimating the beta weights/parameter estimates corresponding to the amplitude of a BOLD/HRF response relative to the ideal time-series per stimulus condition (Andy’s BB and fMRI Handbook)

Centrality GLM:

→ YBOLD-Outdegree = b0 + b1(High Outdegree Centrality) + b2(Low Outdegree Centrality)

→ YBOLD-Indegree = b0 + b1(High Indegree Centrality) + b2(Low Indegree Centrality)

Self-Relevance GLMs:

YBOLD-transformativeness = b0 + b1(High Transformative) + b2(Low Transformative)

YBOLD-changeability = b0 + b1(High Changeability) + b2(Low Changeability)

YBOLD-importance = b0 + b1(High Importance) + b2(Low Importance)

* The ideal time-series is defined by paradigm or onset files for each functional run within each subject’s respective functional directory.
  + Stimuli: Memory Cues
  + Requires ‘conditions’, ‘durations’, and ‘onsets’
    - ‘Duration’ can either be the same per subject (14.00) or equal to the subject-defined recall period, if available
    - ‘Onsets’ are all relative to the start of the acquisition and need to account for jittered inter-trial intervals (8-10s // 2-4s)
    - ‘Conditions’ would be set for each subject. *Each centrality estimate and memory quality rating are centered and scaled within subjects*.
      * High Outdegree Memory // Low Outdegree Memory
      * High Indegree Memory // Low Indegree Memory
      * High Transformative Memory // Low Transformative Memory
      * High Changeable Memory // Low Changeable Memory
      * High Importance Memory // Low Importance Memory
      * Fixation

* Consider adding nuisance regressors before second-level GLM
  + Previous fMRI/network study used…
    - Motion parameters (from fMRIprep HMC)
    - Volumes exceeding .9mm of head motion

**Second-Level Analysis**

* Average contrast estimates WITHIN-subjects
  + Jake used “a fixed effects analysis that forces random effect variance to zero”
    - Would this be where we use a random-effects analysis to account for high variance across subjects?

**Third-Level Analysis**

* Average contrast estimates BETWEEN-subjects
  + Or would THIS be where we use a random-effects analysis to account for high variance across subjects?
    - Jake’s accounted for both within- and between-subject variance using FMRIB’s analysis of mixed effects

**Multiple Comparisons ( *p > 0.05, based on Jake’s previous work )***

* Final maps were compared over multiple iterations, using permutation-based cluster mass thresholding
  + Jake used FSL randomize for this

**Representational Similarity Analysis**

* To determine trial-by-trial estimates of the hemodynamic responses
  + Used to examine how centrality/self-relevance of memories may relate to patterns of neural similarity across the brain.
* Step-by-Step (as per Mapping the Self mri analysis procedures)
  + 1) Use Least Squares (OLS?) procedure to compute a (beta estimates?) map for each stimulus onset per run
    - “Involves modeling individual task trials as separate regressors in

a single general linear model” (Jake, Mapping the Self)

* 2) Register estimated activation patterns at each stimulus onset onto standard space
  + “through FNIRT"
* 3) RSA employed to associate stimulus qualities/conditions to patterns of neural similarity throughout the brain
  + “RSA searchlight was conducted using MultiVariate Pattern Analysis in Python; PyMVPA2”