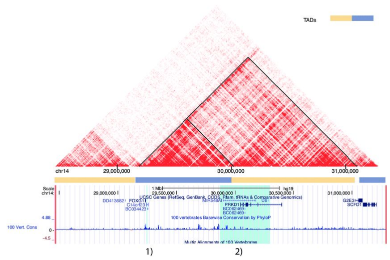
1. Write up scientific background.
    a. Theoretical frameworks that are hypothesized about brain connectivity patterns [Hypothesis]
    b. If someone else did this? What methodology did they employ? (regressions)
2. Formalize our methodology. (language wise)
3. Think of theoretical predictions. (Best case scenario - everything works (what does it mean?)
    a. At each step of analysis
4. Write section “Possible alternative outcomes” - (Worse scenarios - some confounding factor obscures our desired outcomes: what do we do then?) [The comments on the right]
5. Formalize our “controls” section on cross-validation. (language wise) [how do we make sure our model is generalizable]
6. Everyone: meaning of results.

Project proposal

- **The scientific question** - How do the functional brain connectivity patterns change as a result of a specific task?
- **Brief scientific background**
  https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5529276/ - theoretical background related to connectivity analysis (there are some beautiful hypotheses)

There are 3 main ways in which literature thinks that the brain networks interact with each other to produce cognition: spatially (spatial connections of the network), temporally (time-dependent connections), and directionally (whether networks communicate asymmetrically). In this project we will focus on directionally analysis of the parcel connectivity in the HCP dataset. Directionality of the connectivity is important as it might hint of some “top-down” actions performed by higher-brain regions like the frontoparietal cortex. (Mill et al. 2017)

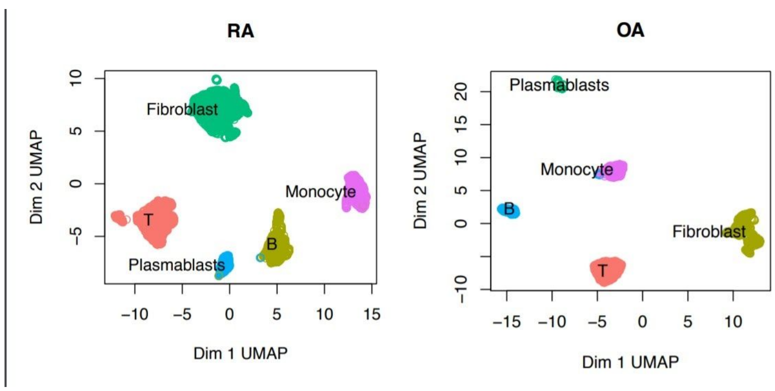
- **Data set (used to select mentors!)** - HCP dataset: social, language, gambling tasks, resting state.
- **Proposed analyses:**
  Firstly, we will do pairwise correlation analysis among different parcels of the brain using Pearson coefficient. We can create a diagram that will represent this data (looks similar to those in genome topology)



Then we select those pairs of parcels which correlate significantly and proceed to regression-based models. We will choose the “threshold” of correlation coefficients experimentally (which works best). At this step we might use the dimensionality reduction algorithms to subdivide the data to the most significant clusters and perform further analysis on them.

Regression-based models will give us the directionality of connections between different parcels. We will train and validate this model using a cross validation method. For this part of our project we will use the scikit-learn Python package.

Then we are going to perform the dimensionality reduction using PCA or umap algorithm to clusterize our parcels based on their activity, and then make comparisons between the results of this clusterization for different tasks.
How the results of clusterization can be plotted:



pairwise correlation analysis => create functional connectivity maps
- find pairs of parcels that are strongly correlated through some dimensionality reduction technique (e.g. PCA)
- use regression-based methods to find the direction between a pair
  - Genji’s analogy to U.S. stock market
  - how 1 parcel can help us predict the timeseries BOLD signal in another parcel - if the regression model one parcel is helpful in predicting the BOLD signal of another parcel, then they are linked by causality (these parcels affect each other)

- **Theoretical predictions**

    - Based on our hypothesis, we expect that parcels in brain regions that are associated with a task will have more significant correlations during a task than at the resting-state. For instance, during language task, parcels within the language processing area, auditory area and executive function area are likely to exhibit stronger correlations, as a subject is attempting to comprehend auditory stories.
    - We assume that regression-based analysis would reveal the directionality of information flow from lower-level regions (e.g. sensory/language processing) to higher-level regions (executive function) because we need to gather necessary information to perform tasks well.
    - Dimensionality reduction might find the clusters of parcels that are supporting different functionalities such as a language processing unit and auditory information processing unit.
    - We might be able to see individual differences in the strength of directionality from lower-level to higher level, the number and size of clusters, which might explain why some subjects perform tasks better.
- **Possible alternative outcomes**
- **Controls** - Can our model predict the functional connectivity on validation data? (Cross validation method) Subjects divide into two parts (7:3), the part of seven is the train data, the part of three is the test data to get the model is correct or not. (the specific task or general task)
- **What would results mean if predictions were true**

Read-up:
Granger causality: https://en.wikipedia.org/wiki/Granger_causality
Some-technic(highCorrelated) :
https://www.frontiersin.org/articles/10.3389/fnins.2019.00585/full

Check CCA analysis
Pairwise interaction analysis
Dimensionality reduction later

Left as notes:

- method
    - pairwise correlation analysis => create functional connectivity maps
    - find pairs of parcels that are strongly correlated through some dimensionality reduction technique (e.g. PCA)
    - (functional parcel? Anatomical parcel ?)
    - use regression-based methods to find the direction between a pair

- Genji’s analogy to U.S. stock market
- how 1 parcel can help us predict the timeseries BOLD signal in another parcel - if the regression model one parcel is helpful in predicting the BOLD signal of another parcel, then they are linked by causality (these parcels affect each other)

WHAT WE ARE GOING TO SEND!!!

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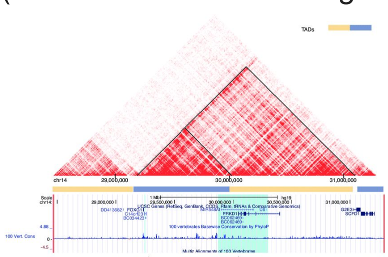

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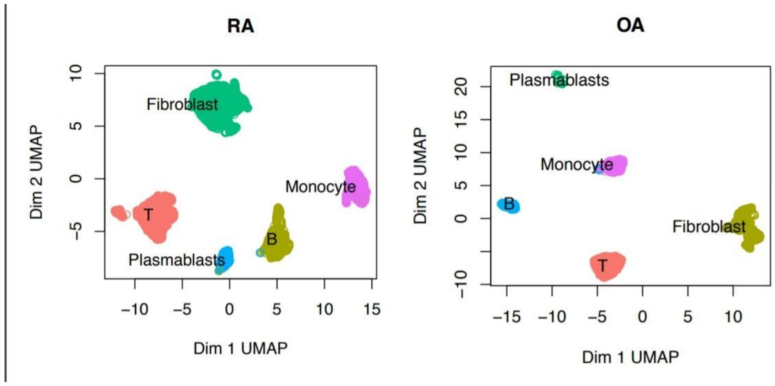

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