Contribution of slow, brain-wide patterns of activity to ongoing experience in resting-state fMRI

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INTRODUCTION

- Ongoing experience and spontaneous thought contribute to neural activity in resting state data and can be predicted using Connectome Predictive Modeling (CPM).[1]
- Complex Principal Component Analysis (CPCA) can be used to identify slow, spatiotemporal patterns in BOLD activity that explain a third of the variance.[2]
- Removal of slow spatiotemporal patterns from resting state significantly changes functional connectivity (FC).[3]

Hypothesis: By removing slow spatiotemporal patterns, smaller fluctuations may start to emerge that are more closely tied to spontaneous thought.

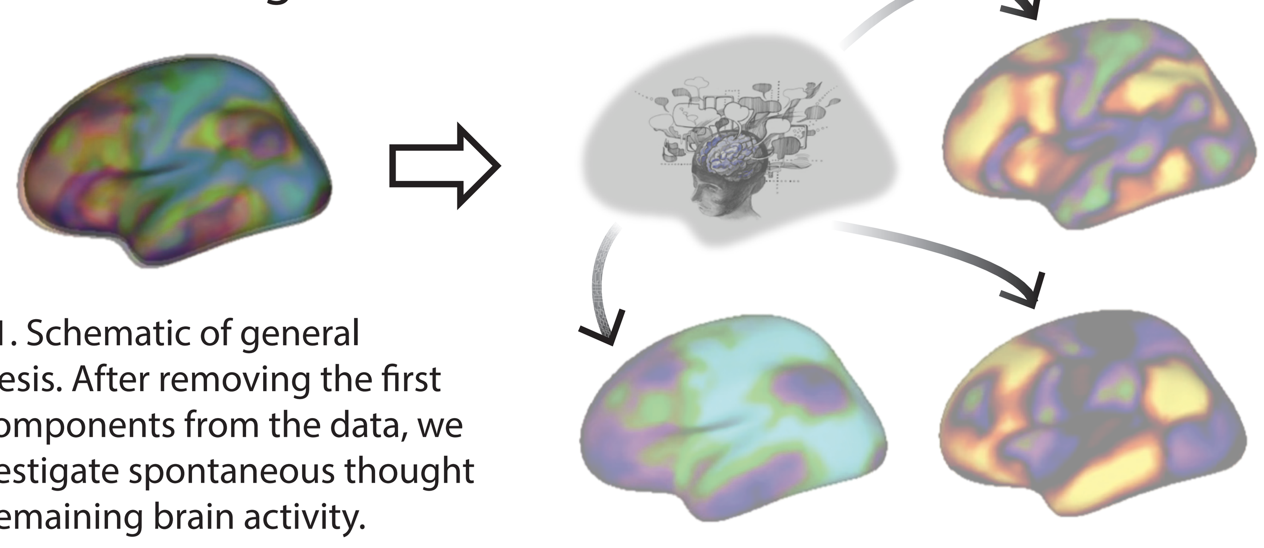


Figure 1. Schematic of general hypothesis. After removing the first three components from the data, we will investigate spontaneous thought in the remaining brain activity.

DATA

Data Set: Mind, Brain, Body[4] - Max Plank Institute
- 15 mins of rest (TR: 1.4s, voxels: 2.3mm^3)
- Experience report (Figure 2)
- 471 Scans after QA
  - 133 subjects; 1-4 scans each

FORM
- F1 | My thoughts were intrusive 0 ... 100
- F2 | My thoughts were more specific than vague 0 ... 100
- F3 | My thoughts were in the form of words 0 ... 100
- F4 | My thoughts were in the form of images 0 ... 100

CONTENT
- C1 | I thought about my environment / surrounding 0 ... 100
- C2 | I thought about other people 0 ... 100
- C3 | I thought about myself 0 ... 100
- C4 | I thought about past events 0 ... 100
- C5 | I thought about future events 0 ... 100
- C6 | I thought about something negative 0 ... 100
- C7 | I thought about something positive 0 ... 100

W1 | I was completely awake 0 ... 100

Figure 2. Short New York Cognition Questionnaire[4]

PREVIOUS WORK

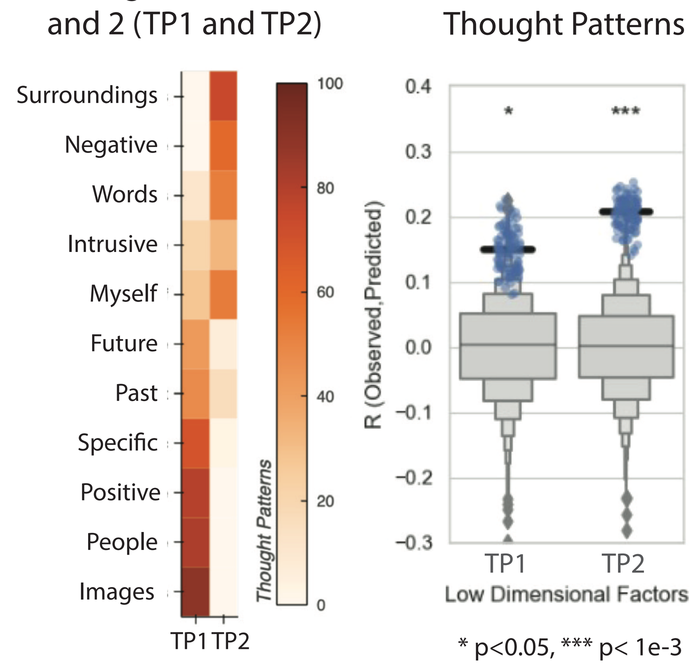
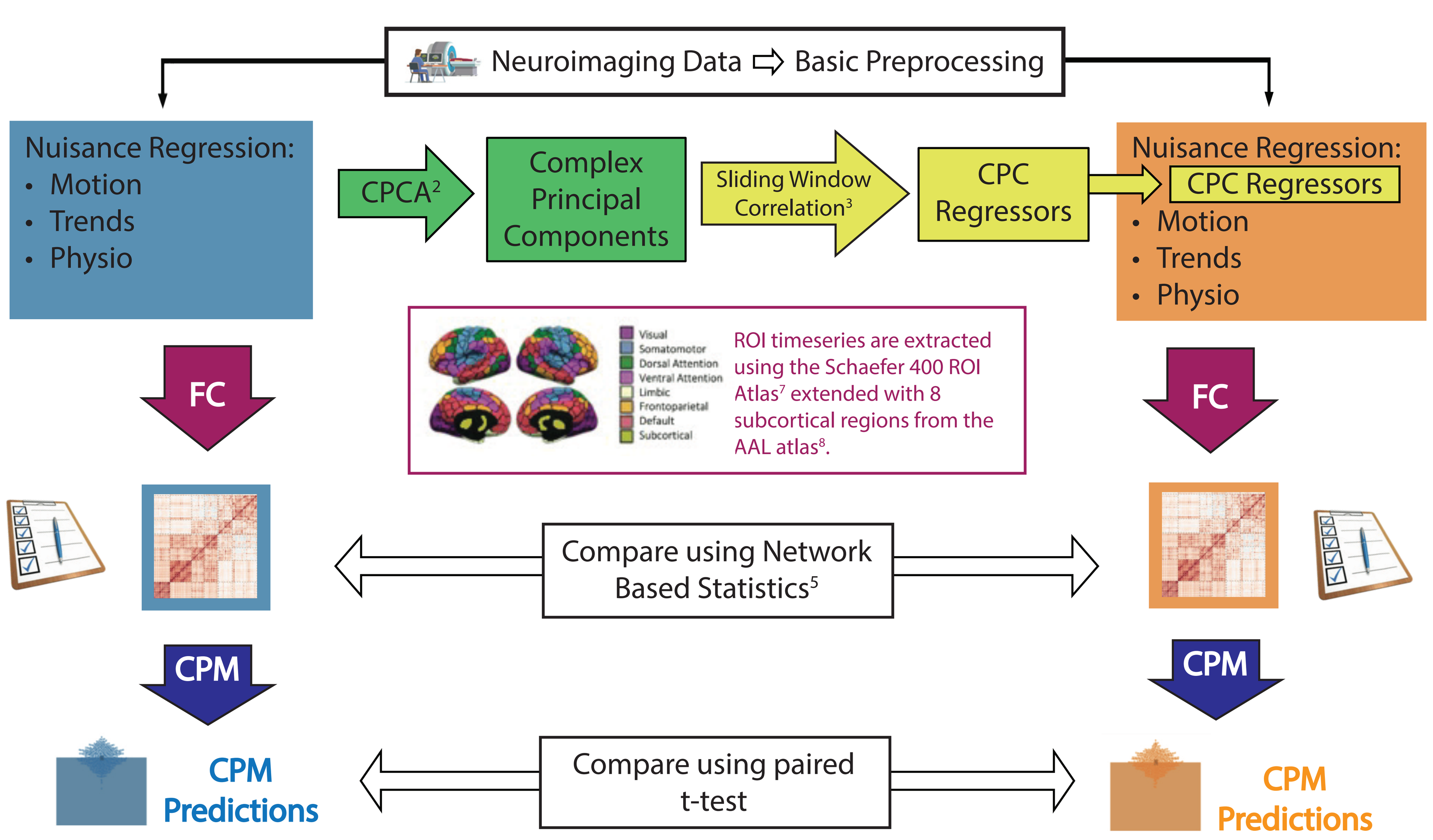
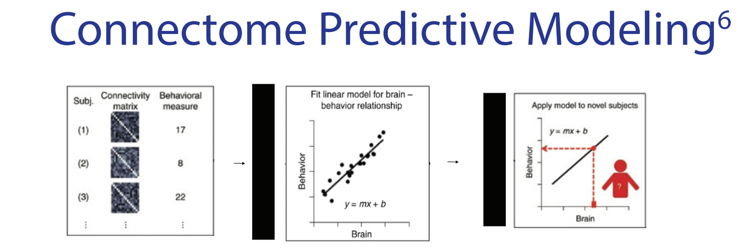


Figure 3. Previous work done by our group.[1] (a) SNYCQ responses (Fig. 2) cluster by thought pattern across participants. (b) These patterns are predictable based on fMRI data. Blue dots are predictions, the black bars are the mean, and gray boxes are a null distribution. These results indicate that spontaneous thought contributes to resting state activity.

METHODS

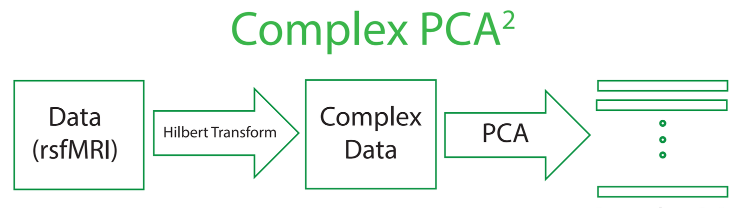


Connectome Predictive Modeling[6]



Based on Shen et al. 2017, linear models are fit to brain-behavior relationships. Accuracy is calculated by doing 500 iterations of CPM, and compared to 10,000 null permutations for significance.

Complex PCA[2]



As described in Bolt et al. 2022, CPCA allows for components that have both magnitude and phase, which generate spatiotemporal maps. The CPCs we get from these data are ~20 seconds long.

Figure 4. Outline of methods. This produces two forms of the data: the original data with preprocessing and denoising (blue), and the same data with the complex principal components removed (orange). These two forms of the data can then be submitted to the FC and CPM analyses, and we can compare them to investigate the impact of removing the CPCs.

RESULTS

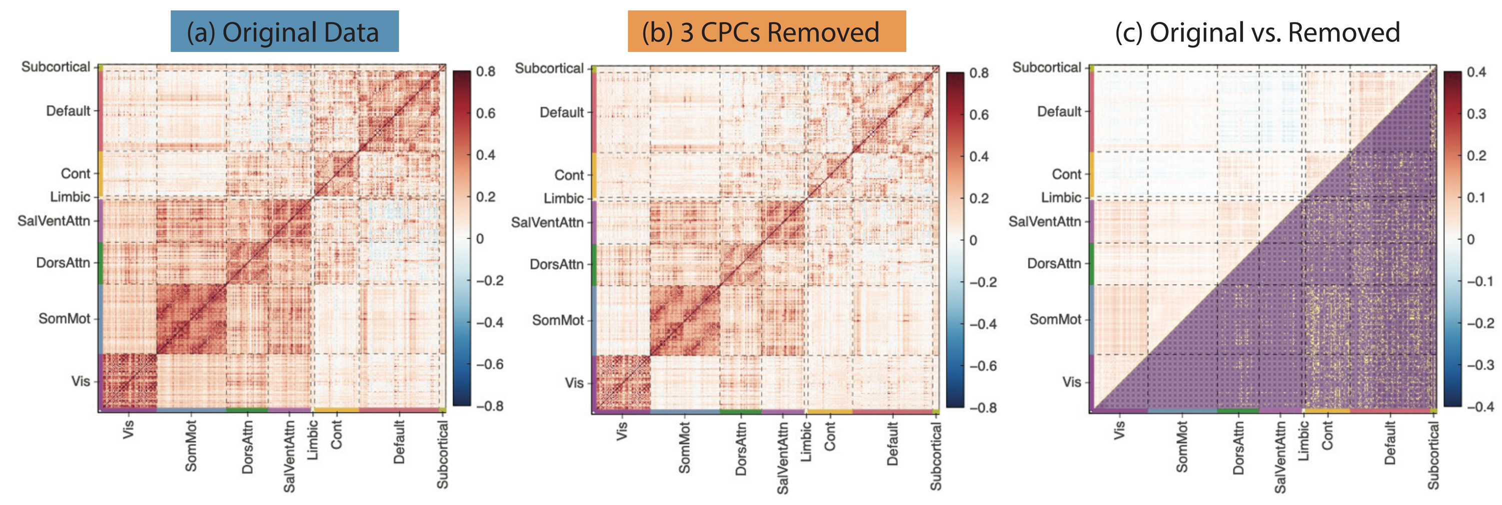


Figure 5. Functional Connectivity for data with (a) and without (b) the first three CPCs, as well as the contrast (c). We see differences in FC across networks, particularly in the control network and DMN.
Yellow: p<0.05

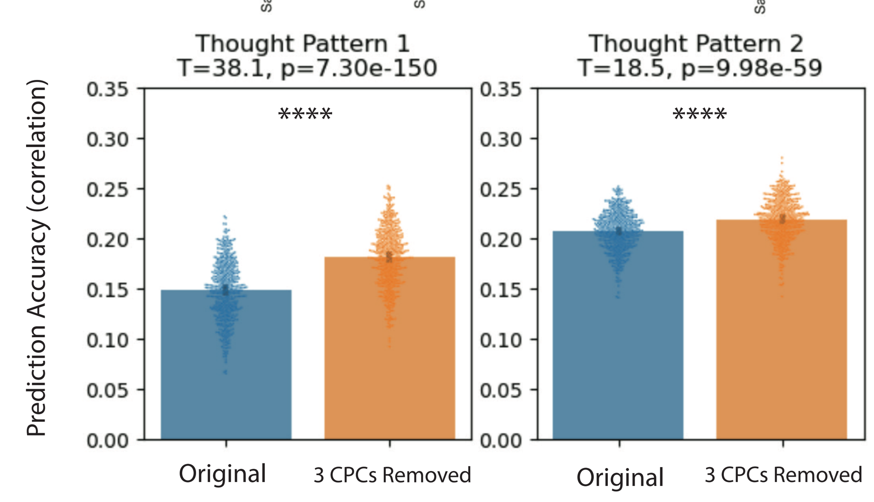


Figure 6. CPM Results. Predictions for TP1 and TP2 with original data (blue) and with the first three CPCs removed (orange). There is significant improvement with the components removed for TP1 and TP2. This suggests that the first three CPCs are not related to spontaneous thought.

**** p < 1e-4

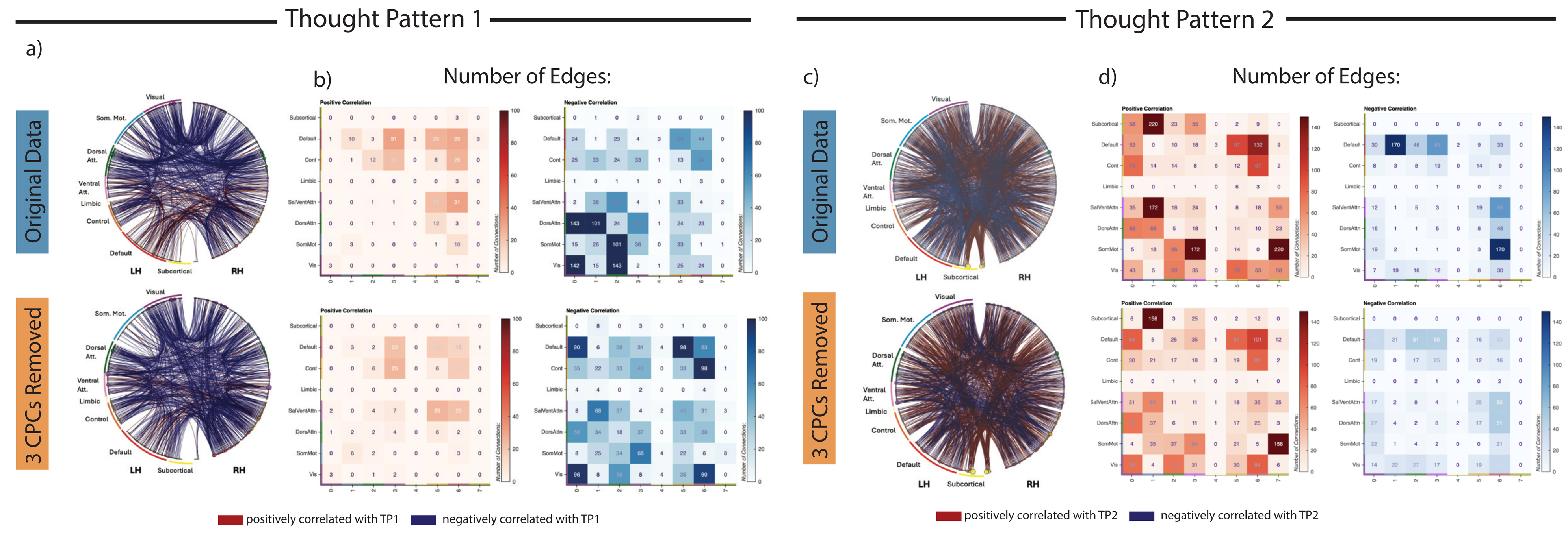


Figure 7. (a,c) Connections used in CPM. (b,d) The number of connections used in CPM summed by network. Overall, for TP1, we see a similar structure between the original data (top) and that with the first three components removed (bottom), but with a shift in the neg. correlated edges from the attention network to the DMN. For TP2, we see a shift away from the ventral attention network in the pos. correlated edges, and a shift away from the DMN in the neg. correlated edges.

INFLUENCE OF SPATIAL BLURRING

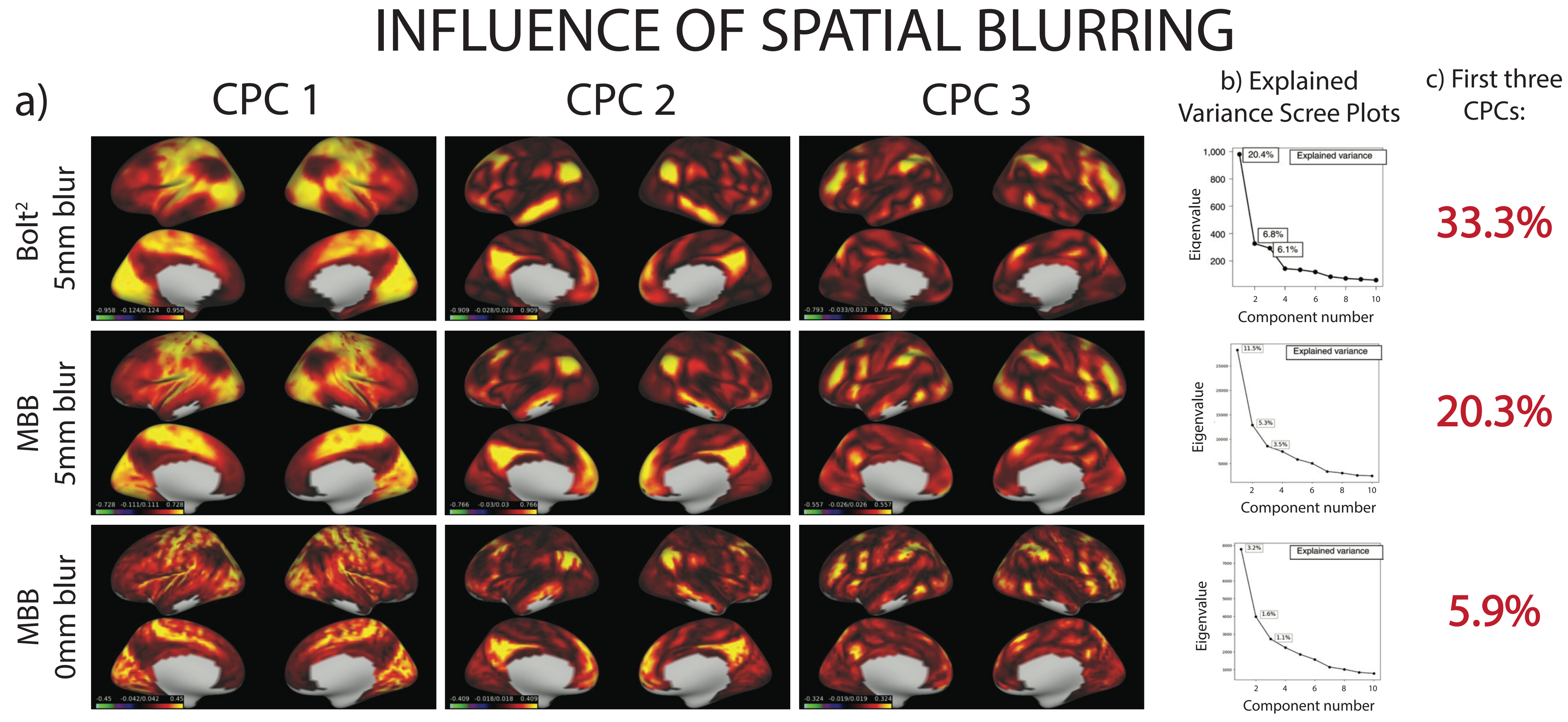


Figure 8. (a) Magnitude maps of the first three components. The top row is the previous findings[2] that we were aiming to replicate, the bottom is the patterns used in this project. (b) Scree plots of explained variance. (c) Cumulative explained variance. Blurring the data increases explained variance.

CONCLUSIONS

- We are able to partially* reproduce patterns on a different data set using CPCA.
  - *Blurring has a large impact on patterns and explained variance.
- Removal of CPCs from resting state data causes significant changes in FC across networks, confirming previous findings[3].
- Removing these patterns increases our ability to predict thought patterns, suggesting that they may not be related to spontaneous thought.

FUTURE DIRECTIONS

- Shift to looking at > 3 components. Preliminary results from removing the first 50 CPCs (accounting for 15% of the explained variance) (Fig. 9), suggest that the FC patterns that are involved in the prediction of spontaneous thought are in CPCs 3-50, and may be identifiable.
- Investigate contribution of individual CPCs to TPs (Fig. 10).
- Investigate activity patterns within CPCs and relate them to aspects of cognition.

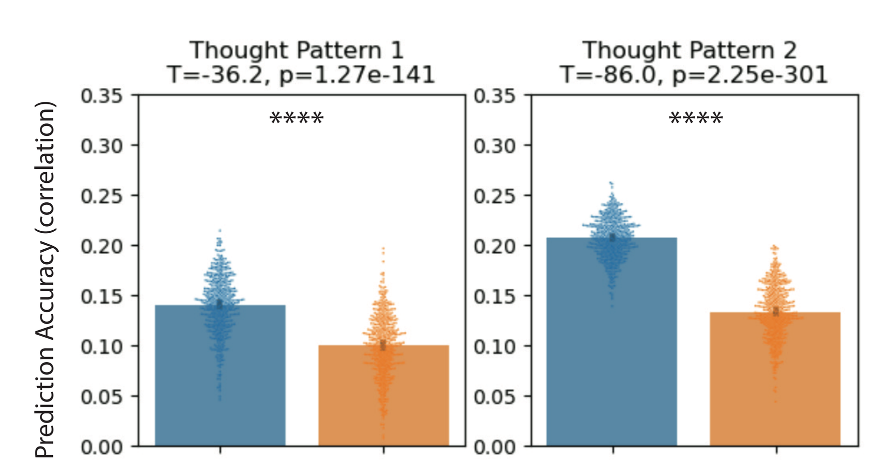


Figure 9. CPM predictions results before (blue) and after removing the first 50 CPCs (orange). TP1 and TP2 predictions significantly decrease. **** p< 1e-4

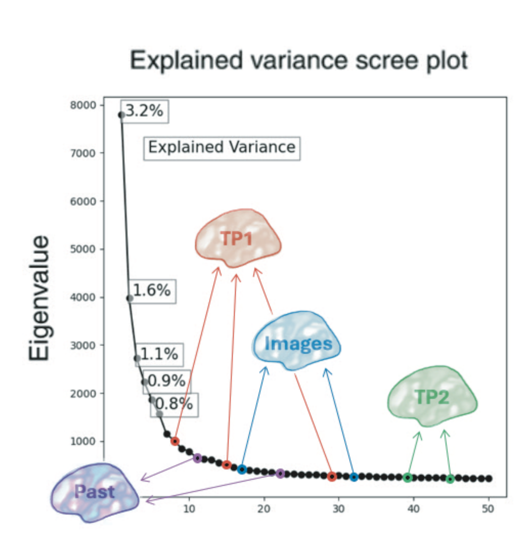


Figure 10. Schematic of new hypothesis.

[1] Gonzalez-Castillo et al. (2024) BioRxiv
[2] Bolt et al. (2022) Nature Neuroscience
[3] Abbas et al. (2019) NeuroImage
[4] Mendes et al. (2019) Scientific reports
[5] Zelesky et al. (2010) NeuroImage
[6] Shen et al. (2017) Nature Protocols
[7] Shaefer et al. (2018) Cerebral Cortex
[8] Tzourio-Mazoyer et al. (2002) NeuroImage

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