Understanding brain pattern complexity and interactivity in naturalistic processing

Lucy L. W. Owen and Jeremy R. Manning
Dartmouth College

For questions, comments, or reprints, please visit our website: www.context-lab.com

This work was supported in part by NSF EPSCoR Award Number 1632738

Overview

- What is the relationship between the richness of thoughts and the complexity of brain patterns?

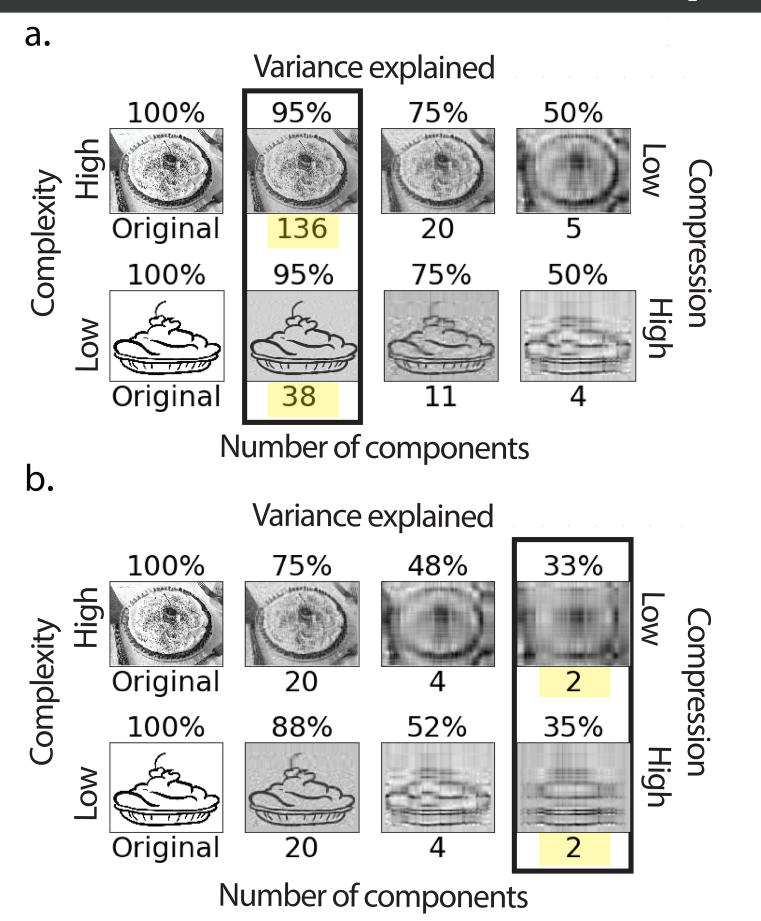
- To understand the 'dimensionality' of the neural patterns, we trained classifiers using more and more principle components to decode.

We tested two hypotheses:

1) As our thoughts become more complex, they supported by more complex brain patterns, and require more components to decode.

2) When are thoughts are deeper and more complicated, units of neural activity carry more information, and would require fewer components to decode.

Compression



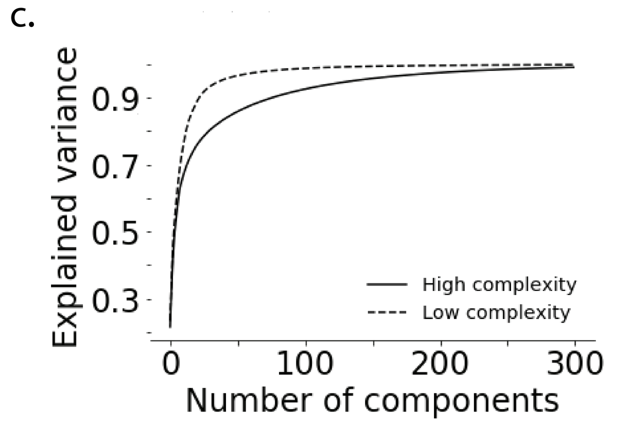


Fig 1. Visual analogy for neural compression. Here are 2 images of pies, one more complex than the other. a. It takes fewer components to reach the same percent variance explained in the less complex pie, which corresponds to higher compression. b. However, with very few components, similar variance is explained in both pies. c. Plots the cumulative explained variance for more and more components.

Methods

- 85 participants in an fMRI study listened to a 10 minute story with different listening conditions: intact, paragraph-scrambled, word-scrambled, as well as rest (Simony et al., 2006).

- Assessed model with cross validated timepoint decoding using more and more principle components.

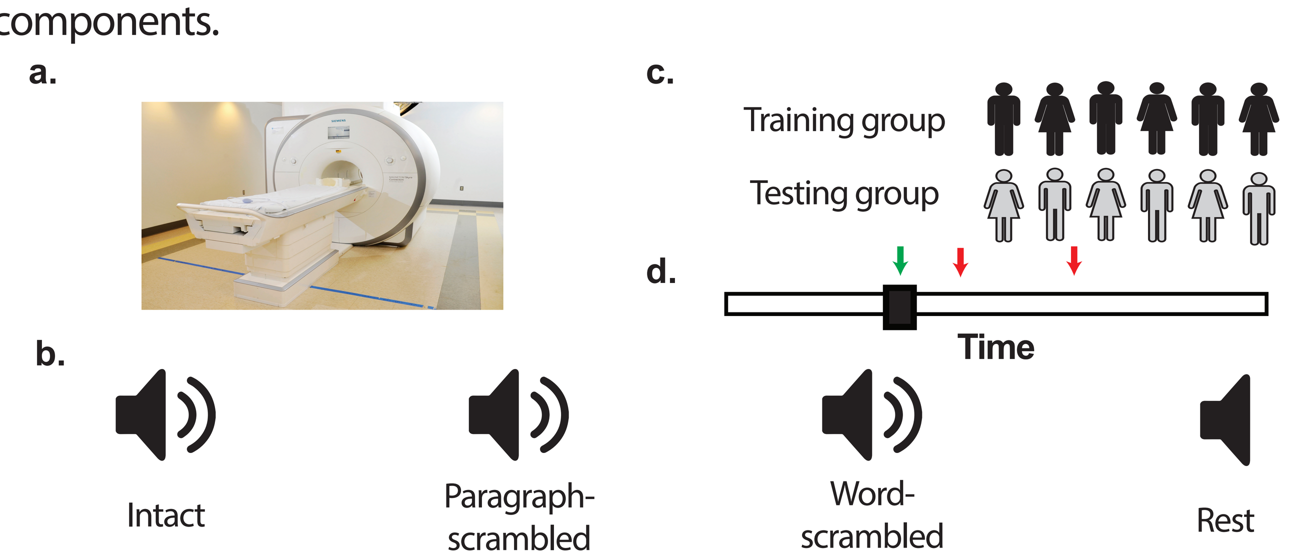


Fig. 2. Experimental methods. a. Participants lay in the scanner for ~10 minutes while functional data were collected. b. Participants were randomly assigned to1 of 4 experimental conditions. The experimental conditions varied systemically in cognitive "richness." In the intact, paragraph-scrambled, and word-scramble conditions, participants listened to an (intact or scrambled) audio recording of the story Pie Man by Jim O'Grady. We applied HTFA (Manning et al., 2018) to obtain 700 node activities for every participant. c. We randomly assigned participants in each condition to two groups. We applied dimensionality reduction (Incremental PCA) for each group. d. We then compared the groups' activity patterns (using Pearson correlations) to estimate the story times each corresponding pattern using more and more principle components.

Results: part 1

- Using more and more principle components, how well can we decode?

- As complexity of the stimuli increases, decoding accuracy increases.

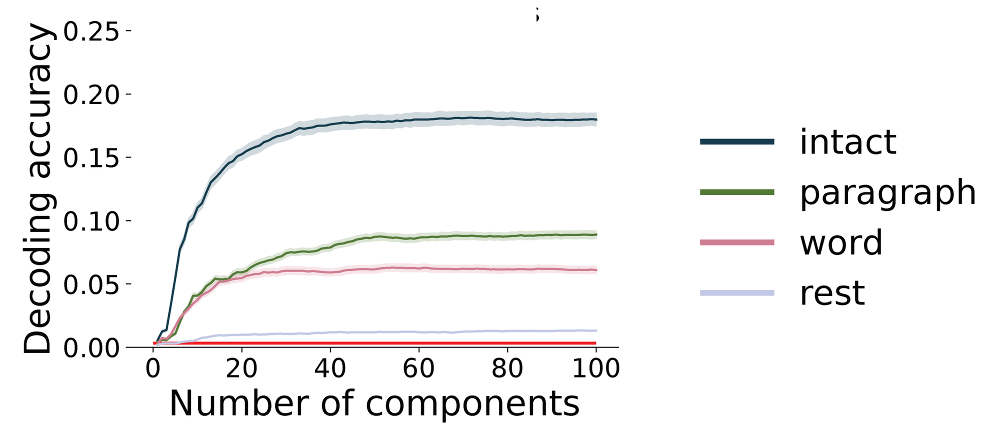


Fig 3. Decoding accuracy by number of components. Ribbons of each color display cross-validated decoding performance for each condition (intact, paragraph, word, and rest). Decoders were trained using increasingly more principle components and displayed relative to chance (red line).

- As complexity of the stimuli increases, need fewer components to decode the same amount.

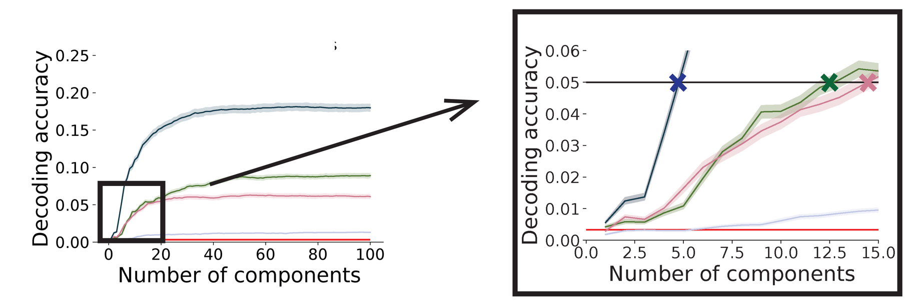


Fig 4. Fixed decoding accuracy by number of components. We zoom in on the plot shown in Fig. 3 and add a line denoting fixed decoding accuracy (.05). We plot where the intact, paragraph, and word conditions intersect.

- As complexity of the stimuli increases, more components are required to reach peak decoding accuracy.

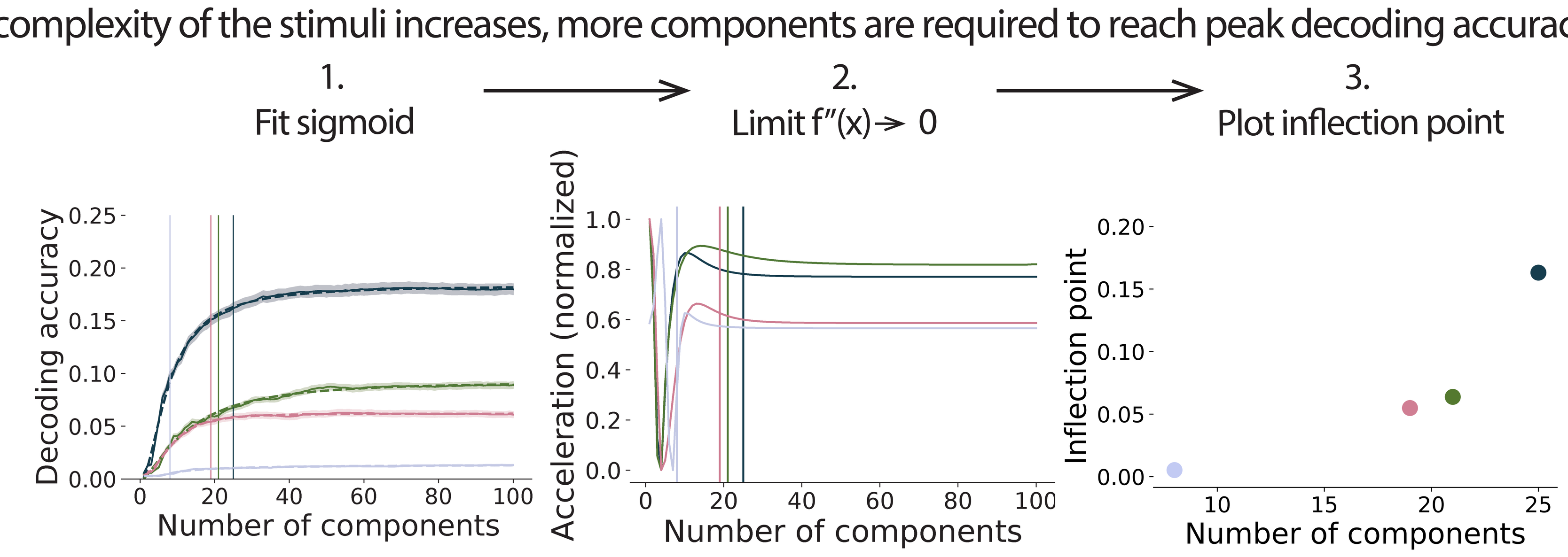


Fig 5. Explanation of inflection metric. First the we fit a sigmoid function to the decoding accuracy by number of components. Second, we found where the second derivate is both positive and less than .0001. Last, we then plot that inflection point as a single metric to capture the slope and asymptote of the curve.

- As complexity of the stimuli increases, decoding accuracy increases with higher cognitive areas. .

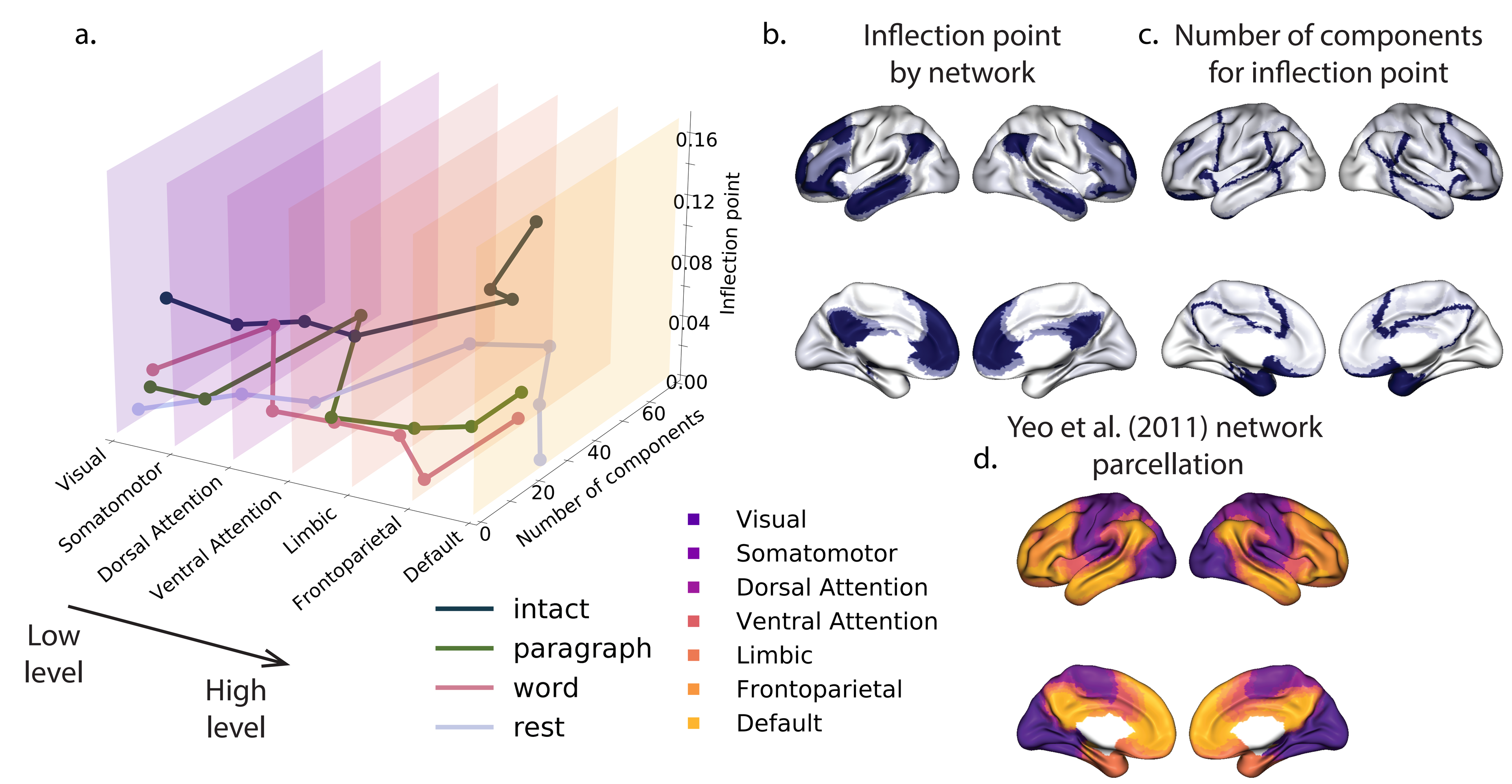


Fig 6. Inflection points by network. a. Similar to Fig 5., we limited the brain hubs by network (using the Yeo et al. (2011) parcellation) and arranged them in increasing order relative to the intact condition. b. and c. For the total time in the intact condition, we are projecting the relative inflection points (b) and corresponding number of components (c) onto the cortical surface (Combrisson et al., 2019) . d. The network parcellation defined by Yeo et al. (2011) is displayed on the inflated brain maps. The colors and network labels serve as a legend for a. and d.

Results: part 2

- If there is some understanding of the narrative that accumulates over time, we should be able to see that change.

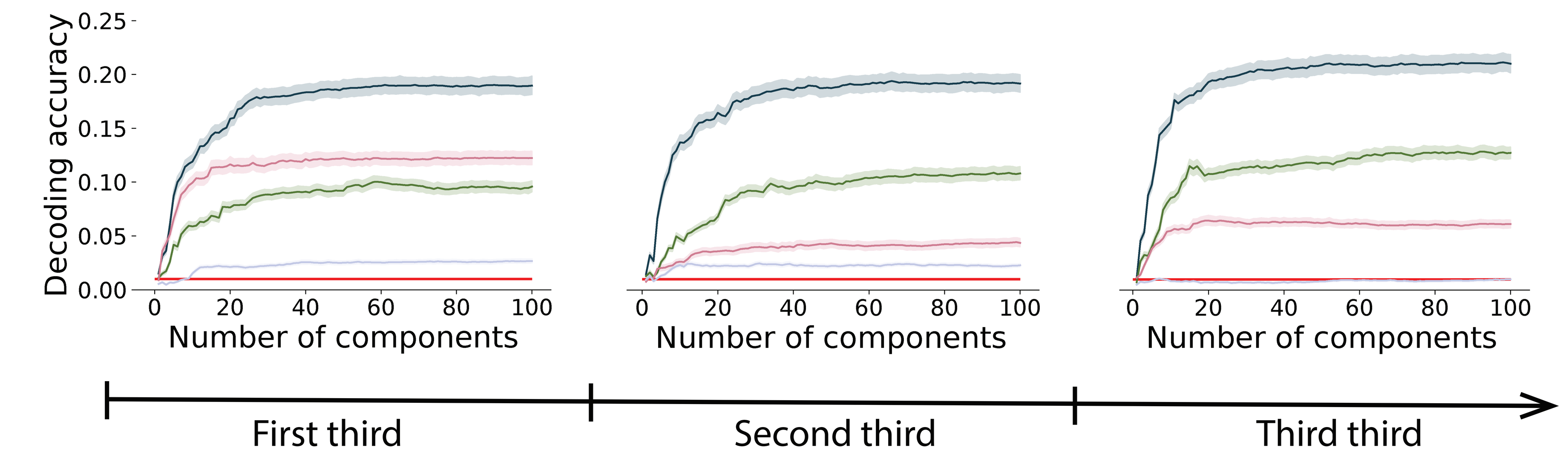


Fig 7. Decoding accuracy by number of components for each third of the scan time. We repeated the same analysis in Fig 4. but breaking the scan time for each condition into 3 intervals.

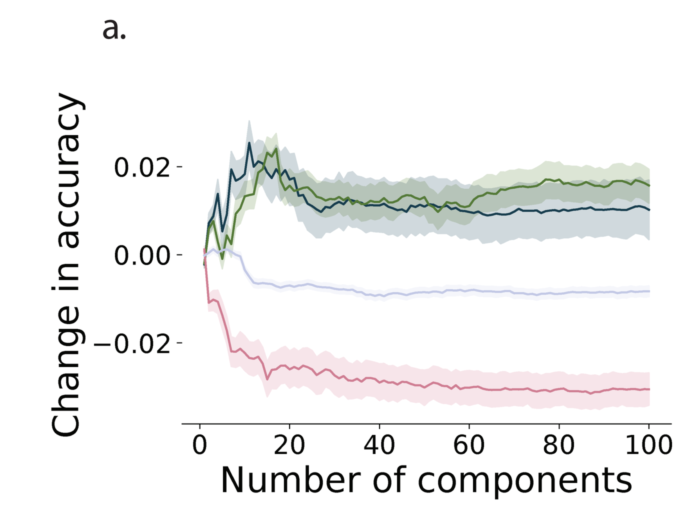
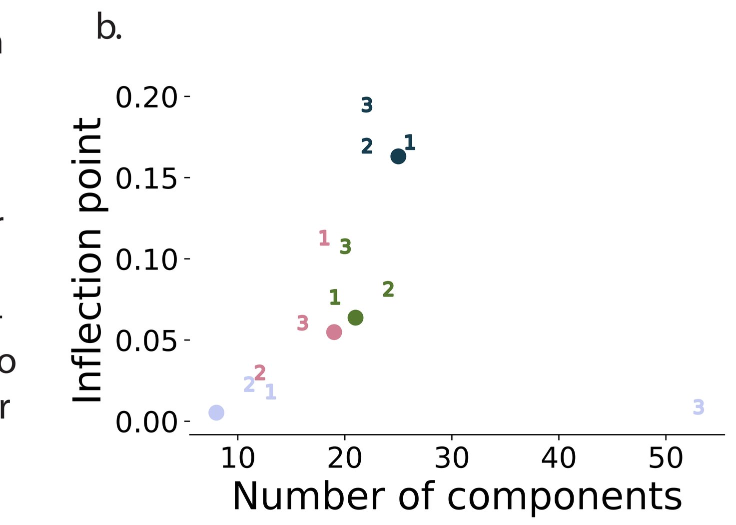


Fig 8. Quantifying changes in decoding accuracy across time. a. We calculated the slope of decoding accuracy, by fitting a regression line for each component/condition for each third. b. We also repeated the analysis in Fig 5. to obtain the inflection point for each condition and for each third.



- Increases in decoding accuracy with the same number or fewer components for more complex, cognitively rich, conditions.

- Decreases in decoding accuracy for the word-scrambled and rest condition.

Summary

- We trained classifiers using more and more principle components to decode, and compared across conditions with varying degrees of cognitive richness.

- We found that as listening conditions become more cognitively rich, decoding accuracy increased.

- Also, decoding accuracy increased as understanding of the narrative accumulated over time, in more complex listening conditions.

- Decoding accuracy also increased in higher cognitive areas, in more complex listening conditions.

- We found that as story listening conditions become more complex, more components are required to decode.

- We also found we could decode better with more impoverished data when there is the underlying structure of the narrative providing more cognitive richness.

- We posit that as the complexity of our thoughts increases, neural compression decreases. However, as our thoughts become deeper and richer, more reliable information is available at higher neural compression.

References:

Combrisson, E., et al. (2019). Visbrain: a multi-purpose GPU-accelerated open-source suite for multimodal brain data visualization. Frontiers in Neuroinformatics, 13(14), 1–14.
Mack, M.L., et al. (2020).Ventromedial prefrontal cortex compression during concept learning. Nature Communications 10(15):243-252.
Manning, J. R., et al. (2018). A probabilistic approach to discovering dynamic full-brain functional connectivity patterns. Neuroimage 46(20):243-252.
Rubin, T. N., et al. (2017). Decoding brain activity using a large-scale probabilistic functional-anatomical atlas of human cognition. PLoS Computational Biology, 13(10), e1005649.
Simony, E., Honey, C. J., Chen, J., & Hasson, U. (2016). Uncovering stimulus-locked network dynamics during narrative comprehension. Nature Communications, 7(12141), 1–13.