When Stories Sync Our Minds: EEG-fMRI Insights into Narrative vs. Non-Narrative Brain Dynamics

PSYC 42350 Final Project Presentation

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Introduction

Why Do Narratives Matter for Brain Synchrony

- Narratives as a Universal Human Tool
  - Humans in all cultures rely on stories—from ancient myths to modern films—to share experiences, transmit knowledge, and foster empathy.
  - Theory: Stories bind attention, emotions, and mental models, often leading to synchronized neural responses across different individuals.

- Prior Findings
  - Hasson et al. (2008) showed that narrative films can drive inter-subject correlation (ISC) in higher-order brain areas like the Default Mode Network (DMN) and frontoparietal regions.
  - Mechanism: A coherent plot provides temporal and emotional structure, aligning when viewers anticipate plot twists, empathize with characters, etc.

Introduction

Contrasting Non-Narrative Stimuli

- Rationale for Non-Narrative
  - Helps us see if high-level neural synchrony truly stems from narrative structure or merely from shared perceptual input (color, motion, etc.).
  - If non-narrative yields lower synchronization in high-level networks, that supports the notion that plot coherence drives inter-subject alignment.

- Why EEG & fMRI Together
  - fMRI: High spatial resolution, captures which brain regions are engaged.
  - EEG: High temporal resolution, revealing rapid neural dynamics.
  - Cross-modal representational similarity (RSA) asks if both modalities reflect the same underlying process (e.g., narrative comprehension).

Introduction

Research Questions

1. Do narratives evoke stronger inter-subject correlation in fMRI?
2. Does cross-modal EEG–fMRI RSA differ between narrative vs. non-narrative? Additionally, can multimodal signals classify if a segment is narrative or not?

Dataset

- Source & Participants
  - Open-access dataset (Telesford et al., 2023).
  - 22 healthy adults (ages 23–51), balanced gender, no major psychiatric/neurological issues.
- Tasks & Stimuli
  - Narrative: [“Despicable Me”] (10-min clips).
  - Non-Narrative: [“Inscapes”] (10 min abstract animation).
  - Additional stimuli: short film “The Present,” rest scans, etc. (not the focus here).
- Data Collection
  - Simultaneous EEG-fMRI at 3T (Siemens TrioTim) + 64-channel Brain Products EEG.
  - fMRI: TR=2.1 s, preprocessed (motion correction, MNI alignment).
  - EEG: ~5000 Hz sampling, artifact removal (gradient, BCG).

Session	Recording Location	Scan	Run Length (s)
Day 1	Outside	Checkerboard (12 Hz)	200
	Scanner OFF	Checkerboard (12 Hz)	200
	Scanner ON	Checkerboard (12 Hz)	200
		Rest	600
		Inscapes	600
		The Present [Run 1]	258
		PEER	90
		Monkey 1 [Run 1]	300
		Despicable Me (English) [Run 1]	600
		MPRAGE	600
		The Present [Run 2]	258
		Monkey 1 [Run 2]	300
		Despicable Me (English) [Run 2]	600
Day 2	Outside	Checkerboard (12 Hz)	200
	Scanner OFF	Checkerboard (12 Hz)	200
	Scanner ON	Checkerboard (12 Hz)	200
		Rest	600
		Inscapes	600
		Monkey 2 [Run 1]	300
		PEER	90
		Despicable Me (Hungarian) [Run 1]	600
		Monkey 5 [Run 1]	300
		MPRAGE	600
		Monkey 2 [Run 2]	300
		Despicable Me (Hungarian) [Run 2]	600
		Monkey 5 [Run 2]	300

Analysis 1 Method (ISC)

- Goal: <u>Measure how similarly each voxel's activity fluctuates across participants when viewing the same stimulus.</u>
- **Load & Mask fMRI**
  - For each subject, extract voxel-wise time series in MNI space (3 mm resolution).
  - Leave-One-Subject-Out
    - For each subject S:
      - Compute the mean of the remaining subjects' time series.
      - Correlate S's voxel time course with that "all-other" average → ISC map per subject.

Analysis 1 Method (ISC)

- **Combine into Yeo 17 Networks**
  - Each subject's ISC map is averaged within 17 large-scale brain networks (e.g. Visual, Control, Default Mode).
- **Statistics**
  - Permutation Test (label-flip) for narrative vs. non-narrative (within-subject difference).
  - Effect size (Cohen's d) to assess magnitude.
  - Repeated-Measures ANOVA to see if the effect differs across networks.

Analysis 1 Results (ISC)

- Permutation Test (Yeo 17 Networks)
  - 16 out of 17 networks showed a significant increase in ISC for narrative vs. non-narrative (all FDR-corrected $p < 0.05$).
  - Only Network 3 was not significant.
- Effect Sizes (Cohen's d)
  - Largest difference in Network 14 (d = 3.04), which is extremely large.
  - Other prominent networks:
    - Network 4 (d = 2.25)
    - Network 5 (d = 1.81)
    - Network 17 (d = 1.42)
    - … (Nearly all exceed d = 0.5)
- Repeated-Measures ANOVA
  - $F(16, 336) = 47.30$, $p < 0.0001$
  - Confirms a strong effect of "Network" on the ISC difference (Narrative – Non-narrative).

Analysis 2 Method (Cross-Modal RSA)

- Goal: Determine if EEG and fMRI representational structures align more for narrative vs. non-narrative.
- **Data Preparation & Segmentation**
  - EEG data loaded from .set files (time × channels) via MNE; fMRI data reshaped to (time × voxels).
  - Both modalities were segmented into equal-length windows (10 s), averaging the time points/volumes within each window → creates n_segments “patterns” for EEG and fMRI.

Analysis 2 Method (Cross-Modal RSA)

- **RDM Construction**
  - For each condition (Narrative vs. Non-Narrative) and each modality (EEG, fMRI), build a Representational Dissimilarity Matrix (RDM) using correlation distance among the segment patterns.
  - The resulting RDM is n_segments×n_segments.
- **Cross-Modal RSA**
  - Correlate the upper triangular entries of the EEG RDM and the fMRI RDM to obtain a single RSA value per subject, per condition.
  - This “RSA value” reflects the similarity between how EEG and fMRI represent the stimulus time segments.

Analysis 2 Method (Cross-Modal RSA)

- **Statistical Analysis**
  - One-Sample t-Tests vs. zero for each condition to see if RSA differs significantly from zero.
  - Paired t-Test (Narrative vs. Non-Narrative) to check for within-subject differences in cross-modal similarity.
  - Classification: A linear SVM attempts to distinguish Narrative vs. Non-Narrative based on the RSA feature(s).

Analysis 2 Results (Cross-Modal RSA)

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Group-Level EEG-fMRI RSA (Narrative): r=0.003, p=0.6736
Group-Level EEG-fMRI RSA (Non-Narrative): r=-0.009, p=0.02086
Paired T-test comparing Narrative vs. Non-Narrative: t=1.5057431478720822, p=0.1477643152322490З

Classification Accuracy using RSA: 0.528
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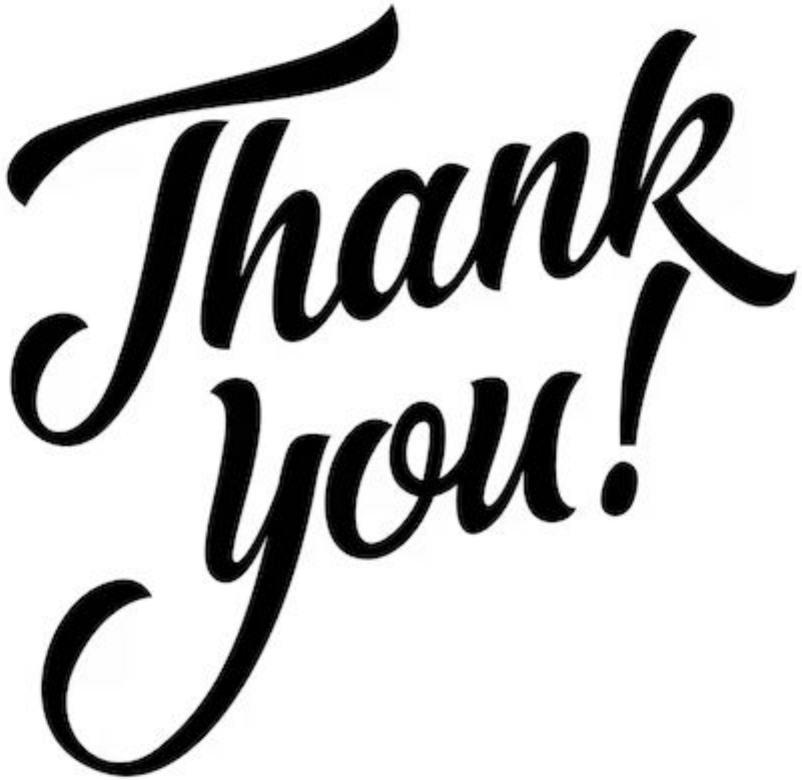
1. Although non-narrative RSA is slightly below zero (significant in one-sample terms), the direct comparison with narrative reveals no statistically significant difference.
2. Classification accuracy is only marginally above chance, indicating that EEG–fMRI representational similarity alone does not reliably distinguish the two stimulus types.
3. Possible explanations include differences in temporal resolution (fast EEG vs. slower BOLD), choice of segmentation window, and minimal alignment in the measured neural signals for these particular conditions.

Discussion

- <u>"Do narratives evoke stronger inter-subject correlation (ISC) than non-narratives in fMRI?"</u>
    - **Yes.** Analysis 1 found 16 of 17 Yeo networks showed significantly higher ISC for narrative stimuli, with large effect sizes and a strong repeated-measures ANOVA effect. This suggests that coherent stories powerfully synchronize brain activity across viewers.
- <u>"Does EEG–fMRI representational similarity (RSA) differ between narrative and non-narrative conditions?"</u>
    - **No clear difference**. Analysis 2 showed no significant difference in cross-modal RSA when comparing narrative to non-narrative (paired t-test p=0.148). So, despite high ISC in fMRI, I didn't see a corresponding boost in EEG–fMRI alignment for narrative clips.
- <u>"Can multimodal signals (RSA) classify whether a stimulus is narrative vs. non-narrative?"</u>
    - **Not robustly.** Classification accuracy hovered around 53%, barely above chance, indicating cross-modal features alone were insufficient to reliably distinguish the two conditions.

Discussion

- Temporal & Modal Mismatch:
  - Coherent narratives may unify higher-order networks in fMRI (as seen by ISC), but EEG captures faster, possibly more transient signals. Future analyses might use time-lagged or frequency-specific EEG to detect alignment.
- Methodological Enhancements:
  - Larger sample sizes or event-based segmentation might reveal subtler narrative-driven EEG–fMRI similarities.
- Takeaway:
  - While narratives strongly synchronize brain activity in fMRI across participants, these results didn’t translate into a robust cross-modal signature with my current RSA approach. This discrepancy highlights the importance of matching analysis windows and temporal resolutions to the underlying neural processes.



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