Cognitive MRI of AI Conversations: Analyzing AI Interactions through Semantic Embedding Networks

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Abstract. Through a single-user case study of 449 ChatGPT conversations, we introduce a *cognitive MRI* applying network analysis to reveal thought topology hidden in linear conversation logs. We construct semantic similarity networks with user-weighted embeddings to identify knowledge communities and bridge conversations that enable cross-domain flow. Our analysis reveals heterogeneous topology: theoretical domains exhibit hub-and-spoke structures while practical domains show tree-like hierarchies. We identify three distinct bridge types that facilitate knowledge integration across communities.

1 Introduction

Linear conversation logs conceal rich cognitive structure. Our *cognitive MRI* uses network analysis to transform sequential traces into topological maps, revealing knowledge navigation patterns in AI dialogue. We analyze 449 ChatGPT conversations, revealing heterogeneous topology: theoretical domains exhibit hub-and-spoke patterns while practical domains show tree-like structures.

Building on distributed cognition [4] and transactive memory [6], we model human-AI dialogue as externalized cognitive networks. Contributions: (1) user-weighted embeddings (2:1 ratio) validated through 63-configuration ablation study, (2) empirical characterization revealing modularity 0.750 with 15 communities, (3) taxonomy of three bridge types with distinct structural signatures.

2 Methods

Dataset. 1,908 ChatGPT conversations (Dec 2022–Apr 2025), filtered at $\theta = 0.9$ yielding 449 nodes.

Embeddings. `nomic-embed-text` [5] with user-weighted aggregation: $\vec{e}_{conversation} = \frac{\alpha \times \vec{e}_{user} + \vec{e}_{AI}}{\|\alpha \times \vec{e}_{user} + \vec{e}_{AI}\|}$ where $\alpha = 2$.

Ablation Study. 63-configuration sweep (9 weight ratios $\times$ 7 thresholds) revealed phase transition at $\theta \approx 0.875$ (Figure 1). The 2:1 ratio maximizes modularity (0.750) at $\theta = 0.9$ without distorting topic structure.

Analysis. Louvain detection [1], centrality measures, core-periphery structure.

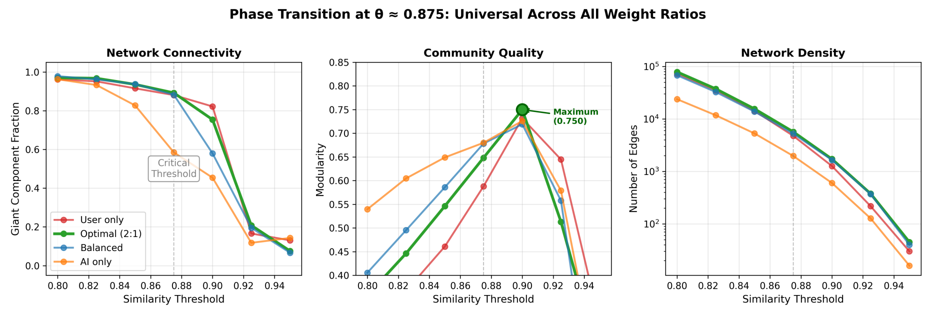

Fig. 1. Phase transition at $\theta \approx 0.875$. The 2:1 ratio achieves maximum modularity (0.750) at $\theta = 0.9$.

3 Results

3.1 Network Topology

Network: 449 nodes, 1,615 edges, degree 7.19, clustering 0.60, path length 5.81. High clustering with long paths indicates "cognitive distance" between domains.

Figure 2 reveals heterogeneity: theoretical communities (*M.S. Math*, *Stats & Probability*, *ML/AI*) exhibit hub-and-spoke structures; *Metaprogramming* shows tree-like branching; *Practical Programming* has dispersed structure without hubs. This contrasts with citation networks' consistent scale-free structure. Core-periphery structure: 25.6% dense core (degree 18.94), sparse periphery (degree 3.15).

3.2 Community Structure

15 communities emerged: *ML/AI* (23%, 103 nodes), *Stats/Probability* (18%, 82), *Philosophy/AI Ethics* (14%, 65), *M.S. Math* (10%, 44), *Programming* (10%, 45). Varying structure: *M.S. Math* shows high core membership (59.1%) and clustering (0.576); *Programming* shows sparse connectivity (degree 3.78, core 8.9%).

3.3 Bridge Conversations

Three bridge types [3, 2]: *Evolutionary* (high-degree, topic drift, e.g., degree=61, betweenness=45,467), *Integrative* (moderate-degree, deliberate synthesis, degree=10, betweenness=36,909), *Pure* (low-degree critical links, degree=2, betweenness=9,775). Figure 3 shows mechanisms. Hub nodes exhibit lower clustering (0.224 vs. 0.436).

4 Discussion and Conclusion

Unlike citation networks with preferential attachment, conversation networks show heterogeneous topology: theoretical domains form hubs, practical domains show trees. This *structural trace of thinking* reveals: *Expert domains* (dense, high clustering), *Bridging domains* (broad, lower clustering), *Task domains* (sparse, implementation-focused).

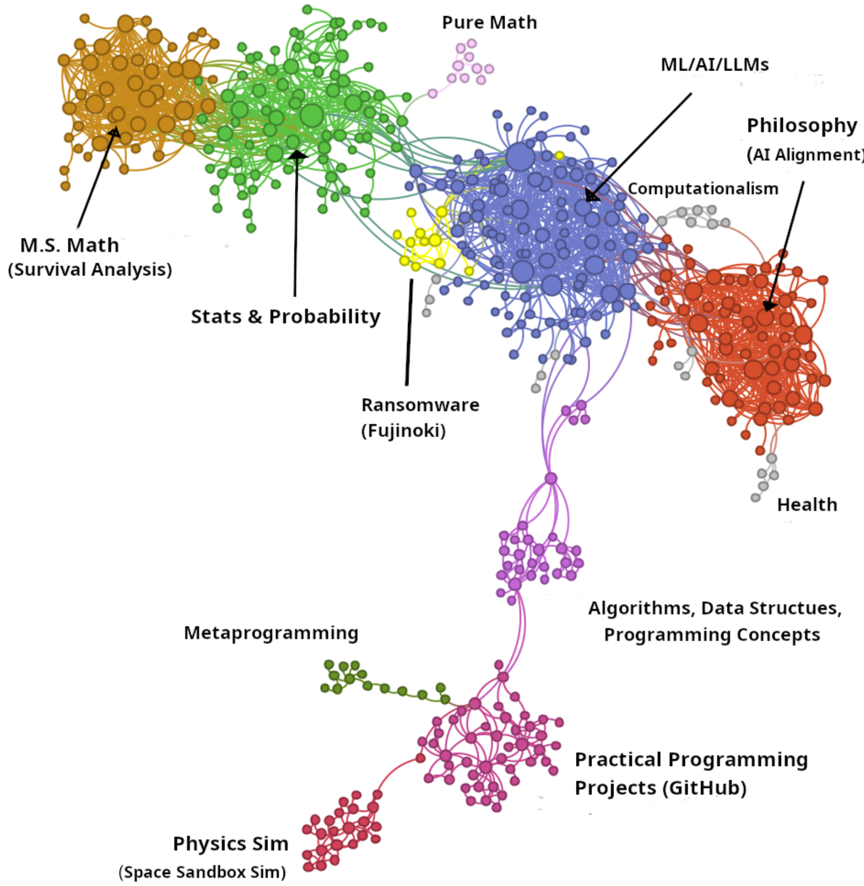

Fig. 2. 15 communities at $\theta = 0.9$ showing heterogeneous topology.

Our ablation study established 2:1 user:AI weighting optimally balances intent with semantic contributions (modularity 0.750 at $\theta = 0.9$). Three bridge types facilitate cross-domain movement. This cognitive MRI methodology provides a framework for understanding AI-assisted knowledge exploration. Limitations: single-user study; optimal weighting may vary by individual/model. Future work: multi-user analysis, temporal evolution.

References

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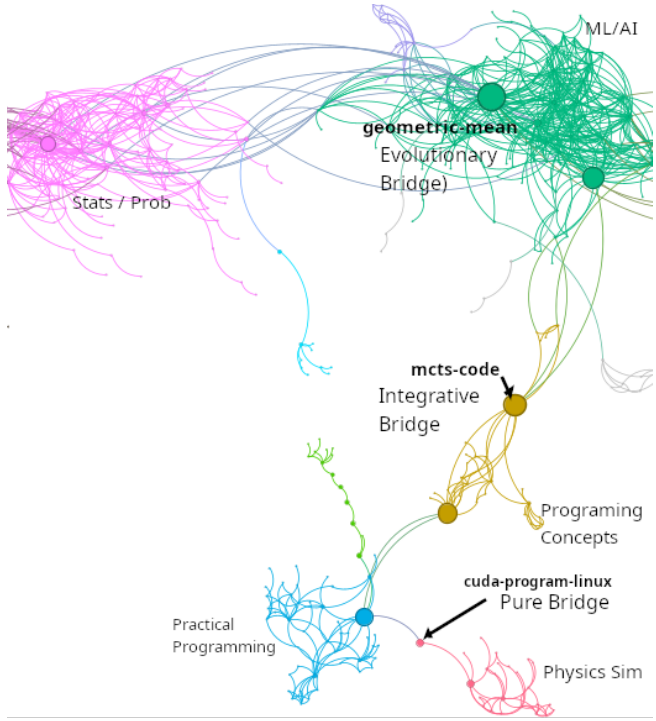

Fig. 3. Bridge types: evolutionary, integrative, and pure.

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