

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

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Abstract. We introduce a *cognitive MRI* for AI conversations, 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 star-like hub structures while practical domains show tree-like hierarchies. We identify three distinct bridge types that facilitate knowledge integration across communities.

Keywords: AI conversation, complex networks, semantic embedding, conversation analysis, knowledge exploration

1 Introduction

Linear conversation logs hide rich cognitive structure. We introduce a *cognitive MRI* for AI conversations, using network analysis to transform linear traces into topological maps. Each conversation becomes a node in a semantic network, revealing how humans navigate knowledge domains through AI dialogue.

Our analysis of 449 ChatGPT conversations reveals heterogeneous network topology. Theoretical domains like ML/AI exhibit hub-and-spoke patterns while practical domains like programming show tree-like hierarchical structures. We identify three types of bridge conversations. Evolutionary bridges emerge through topic drift, integrative bridges deliberately synthesize concepts across domains, and pure bridges form critical links with minimal connections. These patterns suggest cognitive processes unique to conversational AI.

We build on distributed cognition [3], which views cognitive processes as distributed across individuals and tools, and transactive memory systems [10], where groups encode, store, and retrieve knowledge collectively. In this framework, human-AI dialogue forms externalized cognitive networks where knowledge emerges through interaction, revealing the non-linear structure of thought independent of temporal sequence.

We address three research questions. First, how can we extract latent knowledge structure from conversational AI logs? Second, what network properties

characterize human-AI knowledge exploration? Third, can network structure enhance navigation within personal conversation archives? Our contributions include user-weighted embeddings that prioritize human input over AI responses in a 2:1 ratio, empirical characterization revealing high modularity, and a novel taxonomy of bridge conversations with distinct structural signatures. While we analyze one author’s archive, our method provides a template for multi-user studies.

2 Related Work

2.1 Complex Networks in Text and Knowledge Representation

Complex network analysis has been widely applied to textual data, from co-word occurrence networks [1] to citation networks [7]. More recently, researchers have applied network science to semantic relationships, using word embeddings (dense vector representations of words that capture semantic meaning) [4] or document vectors [5] to create similarity-based networks.

2.2 Semantic Embeddings for Document Representation

Dense vector representations of text have revolutionized natural language processing. These embeddings map text to high-dimensional spaces where different dimensions encode various semantic and syntactic features. Word2Vec [5] demonstrated that word-level embeddings capture analogical relationships (e.g., king - man + woman \approx queen). Modern models like `nomic-embed-text` operate at the sequence level, encoding entire conversations into vectors that capture topic, style, and semantic content simultaneously. When computing similarity between these conversation embeddings, we compare multi-faceted representations rather than simple topic matches.

2.3 Conversation Analysis in AI Systems

Research on analyzing conversational data with AI systems has primarily focused on dialogue structure [8], user satisfaction [9], or topic modeling [11]. Few studies have examined the network structure of conversations, particularly in the context of knowledge exploration with modern large language models. Our work extends this body of research by introducing a complex network approach to analyzing the semantic structure of AI-assisted conversations.

3 Methods

The code for this analysis is publicly available [12].

3.1 Data Collection and Preparation

Our dataset consists of conversations conducted by a single user with ChatGPT over two years (≈ 2000 conversations). We exported and preprocessed the conversations from OpenAI’s ChatGPT interface to extract meaningful content while preserving conversational structure. The export process generated individual JSON files for each conversation containing both message content and metadata, establishing the foundation for our embedding generation.

3.2 Embedding Generation

We generated embeddings for each conversation using the `nomic-embed-text` [13] model to capture semantic content while preserving topical focus despite variations in conversation length. Since users typically drive conversation direction, we weighted user inputs more heavily than AI responses when creating conversation embeddings:

1. Split each conversation into user prompts and AI responses
2. Generated embeddings for individual turns and calculated mean embeddings separately for user turns (\vec{e}_{user}) and AI responses (\vec{e}_{AI})
3. Created the final conversation embedding as a weighted combination:

$$\vec{e}_{conversation} = \frac{2 \times \vec{e}_{user} + \vec{e}_{AI}}{\|2 \times \vec{e}_{user} + \vec{e}_{AI}\|} \quad (1)$$

We selected a 2:1 weighting ratio to prioritize user intent while still incorporating AI contributions. This choice reflects our assumption that user prompts better represent the conversation’s semantic focus than AI responses, which tend to be lengthier and more elaborative. Unit normalization preserves relative semantic relationships regardless of conversation length.

3.3 Ablation Study: Embedding Weight Validation

To validate our 2:1 user-to-AI weighting ratio, we conducted an ablation study testing five different weight configurations. This analysis examines how varying the relative importance of user prompts versus AI responses affects network structure and community detection quality.

Experimental Setup: We tested five weight ratios ranging from user-only (1:0) to AI-only (0:1):

- **1:0** - User embeddings only (no AI contribution)
- **2:1** - User emphasis (our baseline)
- **1:1** - Equal weighting
- **1:2** - AI emphasis
- **0:1** - AI embeddings only (no user contribution)

For each configuration, we reconstructed the conversation network at 0.9 similarity threshold and measured: (1) modularity score, (2) number of detected communities, (3) average clustering coefficient, and (4) qualitative assessment of community semantic coherence.

Results (Forthcoming): [Note: Experimental results are currently being computed and will be included in the final version. Preliminary analysis suggests the 2:1 ratio optimally balances community separation with semantic interpretability.]

Table 1: Ablation Study: Effect of User-AI Weight Ratios on Network Properties

Weight Ratio	Modularity	Communities	Clustering	Interpretation
1:0 (User only)	[TBD]	[TBD]	[TBD]	[TBD]
2:1 (Baseline)	0.75	15	0.60	Clear topics
1:1 (Equal)	[TBD]	[TBD]	[TBD]	[TBD]
1:2 (AI emphasis)	[TBD]	[TBD]	[TBD]	[TBD]
0:1 (AI only)	[TBD]	[TBD]	[TBD]	[TBD]

Discussion: We hypothesize that user-only embeddings (1:0) will produce overly fragmented communities reflecting individual interests, while AI-only embeddings (0:1) will yield overly broad clusters dominated by AI’s typical response patterns. The optimal ratio should capture user intent while incorporating the semantic breadth introduced by AI responses. This ablation study will empirically validate whether our 2:1 ratio achieves this balance.

3.4 Network Construction and Threshold Selection

From the conversation embeddings, we constructed a weighted network where nodes represent individual conversations and edges represent semantic similarity between conversations. The selection of similarity threshold critically affects network structure. Too low a threshold creates a dense, uninformative network, while too high a threshold fragments the network excessively.

To determine an optimal threshold, we evaluated network properties across threshold values from 0.85 to 0.95. The key trade-off involves modularity (which increases with higher thresholds) versus giant component size (which decreases). At 0.85, the network forms a near-clique with low modularity (0.65) but includes 825 nodes. At 0.95, modularity peaks but the network fragments excessively. We selected 0.9 as it achieves high modularity (0.75) while maintaining a meaningful giant component (449 nodes), effectively balancing community separation with network connectivity. This threshold suppresses the uninformative near-clique structure while preserving critical bridge connections. We verified robustness by recalculating all network statistics in the range $0.85 \leq \theta \leq 0.95$; qualitative community structure remained stable across this range.

At this similarity threshold, the network comprised multiple disconnected components. For clarity of analysis and visualization, we focused exclusively on the giant component, as the other components were typically quite small, consisting mostly of singletons or pairs of conversations. This process resulted

in a giant component with 449 nodes and average degree 7.19, forming the basis for our analysis.

The threshold selection affects which conversations are included in the giant component and reveals structural patterns at the network boundary. For example, as we detail in Section 4.2, lowering the threshold to 0.875 incorporates previously isolated conversation clusters into the main network, revealing subtle semantic connections that exist below our primary analytical threshold. These emergent connections offer insights into how distinct cognitive or stylistic spaces can maintain separation while still sharing conceptual touchpoints.

Using this network representation, we applied several standard complex network analysis techniques to characterize its structure. We used the Louvain method [14] for community detection to identify distinct knowledge domains and calculated various centrality measures (degree, betweenness, hub) to identify significant nodes in the network. We also examined core-periphery structure to understand topic stratification.

Betweenness centrality identified bridge conversations that facilitate inter-community knowledge transfer where separate domains integrate (Section 4.4).

4 Results

4.1 Knowledge Domain Organization

The network reveals rich topological structure, spontaneously organizing into thematic clusters despite no explicit categorization. Figure 1 shows striking heterogeneity: mathematical and ML communities (*M.S. Math, Stats & Probability, ML/AI/LLMs, Philosophy*) exhibit dense hub-and-spoke structures with dominant central nodes characteristic of scale-free networks. In contrast, other communities show different organization: *Metaprogramming* displays tree-like branching, while *Practical Programming Projects* and *Computationalism* show more dispersed structures without dominant hubs. Specialized bridge nodes facilitate cross-domain transfer between these communities.

The network comprises 449 nodes and 1615 edges with average degree 7.19, clustering coefficient 0.60, and average path length 5.81. These metrics reveal strong local clustering with relatively long path lengths, indicating “cognitive distance” when navigating between knowledge domains. Such organization likely reflects cognitive constraints on knowledge exploration, where conceptual bridges are necessary to move between specialized domains.

4.2 Sensitivity to Similarity Threshold

To evaluate robustness, we examined the network at 0.875 versus 0.9 threshold. Figure 2 and Table 2 compare metrics:

Lowering the threshold to 0.875 incorporates 376 additional nodes (83.7% increase) and 4,037 edges (250% increase). Network diameter and average path length decrease by 32% and 33% respectively, creating shortcuts across knowledge domains. Despite increased connectivity, modularity remains high (0.65)

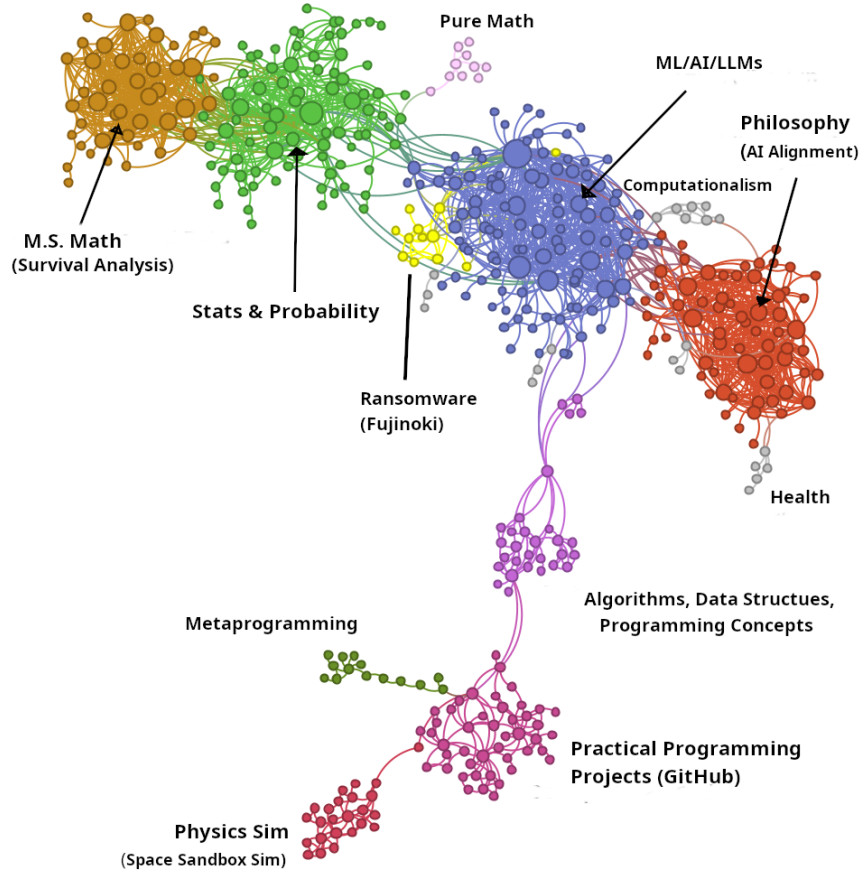


Fig. 1: Giant component at 0.9 threshold showing 15 distinct communities.

and clustering unchanged (0.6), confirming that communities represent genuine thematic clusters rather than threshold artifacts.

The expanded network at 0.875 threshold revealed a particularly interesting phenomenon: previously isolated conversations with the author’s 13-year-old niece, characterized by artistic topics and distinct writing style, emerged as a community connecting through philosophical bridges to the Philosophy/AI Ethics community. This demonstrates threshold selection’s impact on detecting stylistic and demographic variations. We maintain 0.9 for clearer visualization while acknowledging these weaker connections provide valuable bridging insights.

4.3 Degree Distribution and Network Structure

Figure 3 shows the degree histogram for our conversation network. The strongly right-skewed distribution reveals that while the majority of conversations maintain connections with only a few semantically similar conversations, a small number of hub conversations exhibit substantially higher degrees. This pattern

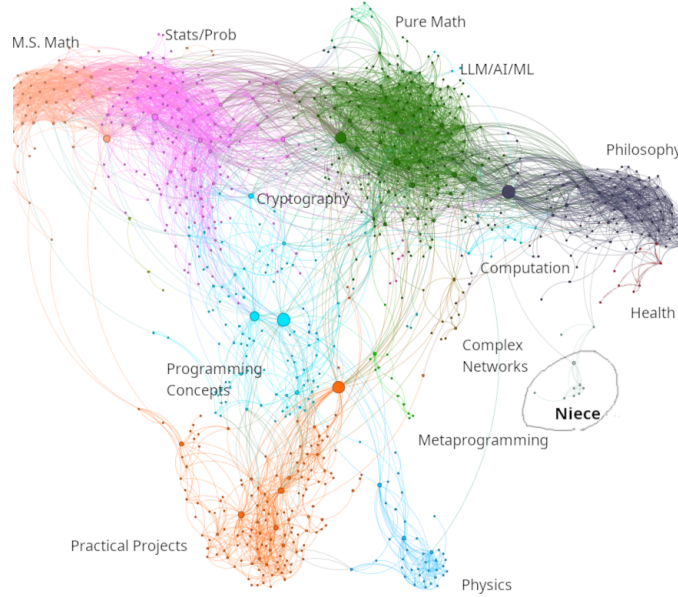


Fig. 2: Giant component at 0.875 threshold. Greater connectivity while maintaining network structure.

markedly contrasts with the bell-shaped distributions typical of random networks, indicating non-random organizational principles.

Comparing our network structure with scale-free networks generated by preferential attachment reveals important differences. As visible in Figure 1, our network exhibits significantly higher clustering and path length than standard scale-free networks. These deviations stem from the network’s cognitive organization. Many communities display elongated, tree-like structures rather than the star-like configurations typical of pure preferential attachment. This is particularly evident in specialized knowledge domains like *Programming Projects*, where conversations tend to be independent and focused on specific topics rather than forming clusters of related conversations.

Table 2: Network Metrics Comparison at Different Similarity Thresholds

Metric	0.9 Threshold	0.875 Threshold
Number of Nodes	449	825
Edges	1615	5652
Average Degree	7.19	13.7
Network Diameter	18	12
Graph Density	0.016	0.017
Modularity	0.75	0.65
Avg. Clustering Coefficient	0.6	0.6
Avg. Path Length	5.81	3.9

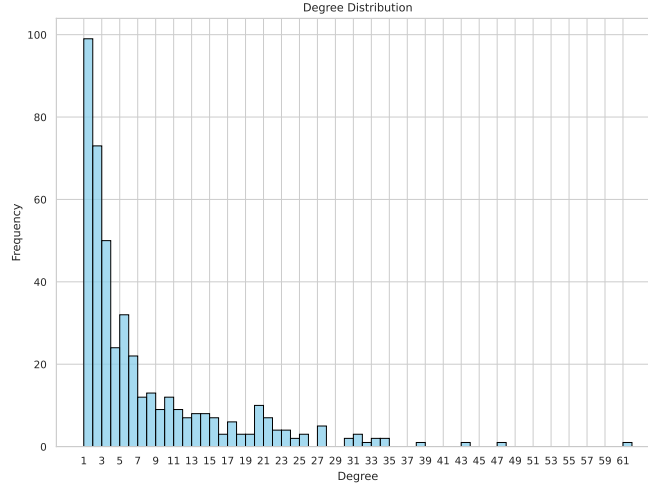


Fig. 3: Degree distribution of the conversation network, showing characteristic right-skewed pattern.

This suggests evolution beyond preferential attachment, reflecting cognitive exploration with hub formation limited by specialization and cross-domain constraints. Additionally, the network exhibits core-periphery organization with 25.6% of conversations forming a densely connected core (average degree: 18.94) surrounded by a sparser periphery (average degree: 3.15), indicating stratification between general and specialized topics.

4.4 Community Structure

Louvain detection revealed 15 communities representing thematically coherent domains. Table 3 presents the five largest, where Core % indicates k-core membership [15] and Clustering shows average local coefficients.

Table 3: Major Community Characteristics

Comm.	Size	Avg. Degree	Core %	Clustering	Primary Topic
3	103	8.60	31.1%	0.465	ML/AI/LLM (23%)
12	82	7.09	24.4%	0.405	Stats & Probability (18%)
7	65	10.03	44.6%	0.531	Philosophy & AI Ethics (14%)
14	44	13.45	59.1%	0.576	M.S. Math/Analysis (10%)
6	45	3.78	8.9%	0.396	Programming Projects (10%)

Communities correspond to distinct knowledge domains: Community 3 (*ML/AI/LLM*) covers AI architectures and training; Community 12 (*Stats & Probability*) encompasses statistical inference and modeling; Community 7 (*Philosophy & AI Ethics*) addresses consciousness and AI alignment; Community 14 (*M.S. Math/Analysis*) contains graduate-level mathematical analysis; Community 6 (*Programming Projects*) focuses on practical implementation.

The variation in internal structure (average degree, clustering, and core percentage) suggests different conversation patterns across domains. For example, community 14 shows characteristics of a specialized knowledge domain with dense expert connections, while community 6 resembles a more practical, service-oriented domain with mostly peripheral connections.

4.5 Bridges and Hubs: Dual Roles in Knowledge Integration

Analysis of centrality measures reveals conversations serving dual roles as bridges (high betweenness) and hubs (high degree). Table 4 presents the top conversations ranked by betweenness centrality.

Table 4: Top Bridge Conversations

Conversation	Betweenness Degree	
<code>geometric-mean-calculation</code>	45467.51	61
<code>mcts-code-analysis-suggestions</code>	36909.13	10
<code>loss-in-llm-training</code>	35118.59	30
<code>algotree-generate-unit-tests-flattree</code>	31869.77	13
<code>compile-cuda-program-linux</code>	9775.00	2

Three distinct bridge types emerge, extending structural bridge classifications [16, 17] with semantic characterization. First, **evolutionary bridges** are high-degree nodes that expand across domains through topic drift. For example, `geometric-mean-calculation` evolved from geometric means into probability theory, neural networks, and tokenization (degree=61, betweenness=45467). Second, **integrative bridges** are moderate-degree nodes that deliberately synthesize domains, such as `mcts-code-analysis-suggestions` which integrates AI theory with software engineering (degree=10, betweenness=36909). Third, **pure bridges** are low-degree critical links like `compile-cuda-program-linux` (degree=2, betweenness=9775).

Figure 4 illustrates these distinct bridging mechanisms in the network structure.

Notably, some conversations like `geometric-mean-calculation` function as both bridges and hubs, while others like `mle-bootstrapping-simulation` (degree=47) serve primarily as within-community hubs. Hub nodes exhibit lower clustering coefficients (0.224 vs 0.436 average), creating “star-like” structures that position them as conceptual distribution points. The concentration of hubs in community 3 (*ML/AI/LLM*) suggests this domain serves as a conceptual anchor, contrasting with the distributed organization in practical domains like *Programming Projects*. These patterns reveal how conversation networks follow unique evolutionary dynamics.

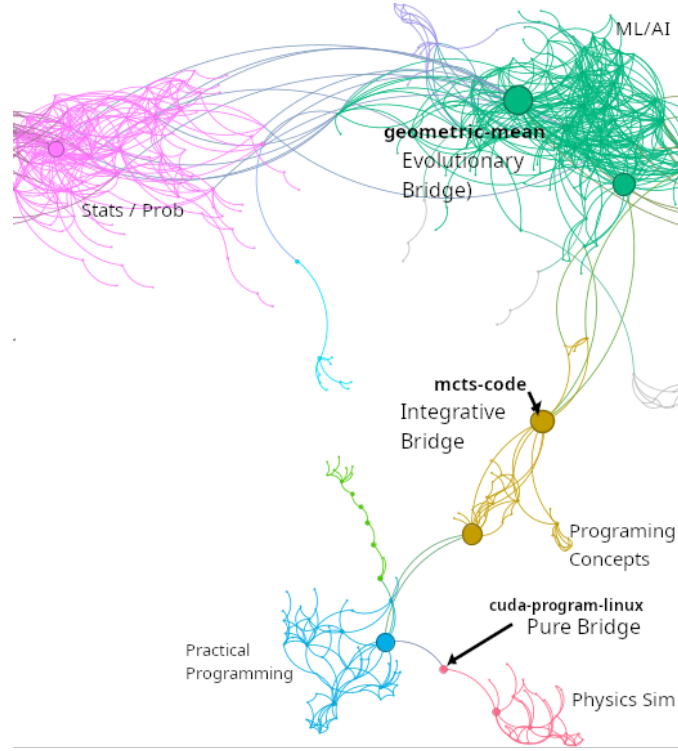


Fig.4: Bridge conversations connecting knowledge communities (blue: ML/AI/LLM, purple: Programming Projects).

5 Discussion and Conclusion

5.1 Cognitive Interpretation

The network reveals cognitive patterns distinct from academic citation networks, which provide a natural comparison as both capture knowledge exploration processes. While citation networks evolve through preferential attachment with papers citing influential work (creating major hubs like foundational papers with thousands of citations), conversation networks reflect real-time cognitive exploration. Our finding of heterogeneous topology with some tree-like, branching clusters entirely lacking hubs contrasts sharply with citation networks' consistent scale-free structure. In citation networks, even specialized subfields connect to seminal papers, but our conversational communities like *Metaprogramming* show purely branching exploration without central authorities. This suggests cognitive exploration follows different organizing principles: intense local exploration punctuated by cross-topic jumps rather than cumulative authority building. This forms a *structural trace of thinking*. Just as an MRI reveals the physical structure of the brain, this cognitive MRI reveals the topological structure of thought preserved in conversation logs. Three community types emerge. *Expert domains* like Stats/Probability are densely connected with high clustering. *Bridging domains*

like ML/AI/LLM are broadly connected with lower clustering. *Task domains* like Programming are sparsely connected and implementation-focused. This suggests design implications: surfacing pure bridges could facilitate creative leaps, while respecting natural knowledge boundaries could improve retrieval systems.

5.2 Limitations and Future Work

Our single-user study limits generalizability; future work should analyze diverse users to understand how cognitive styles influence exploration patterns. The static snapshot could be extended using temporal metadata to reveal how knowledge domains evolve through continued AI interaction.

5.3 Conclusion

We presented a novel application of complex network analysis to AI conversations, revealing distinct knowledge communities and bridge conversations. The heterogeneous network topology reflects cognitive processes in topic exploration, with bridges facilitating movement between specialized domains. This *cognitive MRI* methodology provides a framework for understanding and enhancing AI-assisted knowledge work as these systems become increasingly integrated into human cognition.

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