Cognitive MRI of AI Conversations: A Single-User Case Study

Revealing the Hidden Topology of Thought

Alex Towell John Matta

Southern Illinois University Edwardsville

{atowell, jmatta}@siue.edu





Why Now? The Scale of the Opportunity

$\sim \! \! 1$ Billion ChatGPT Users



Chat logs capture something different:

- Citations → papers (outputs)
- Social networks → connections
- Chat logs → the process

How ideas develop. The back-and-forth. *Today: one case study.*

The Big Picture: Externalized Cognition

Al conversations are not just chat logs.

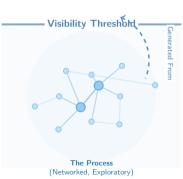
We view them through the lens of **Distributed Cognition**:

- Thinking Out Loud: The user offloads cognitive load to the machine.
- The Iterative Loop: Ideas aren't just "retrieved"; they are constructed through dialogue.

The "Cognitive Dark Matter"

Standard archives preserve the *result* (the paper). LLM logs capture the *process*—the false starts, synthesis, reasoning.





From Chat Logs to Network

Your Chat History

Python Error (Jan)

Banana Bread (Feb)

Debugging (Mar)

Just a timeline

The Transformation

Nodes: Each conversation → vector (embedding)

Edges: Connect if similarity $> \theta$ (cosine) (similar direction = similar meaning)

The Network

Coding



Grouped by meaning

The Key Insight

 $\mbox{Close in } \textbf{time} \neq \mbox{close in } \textbf{thought}.$ Jan and Mar snap together. Banana bread floats alone.

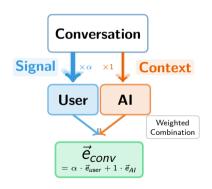
Whose Voice Matters?

The Challenge: Al responses are verbose and generic.

The Intuition: User prompts carry the intent. But by how much?

Separating Signal from Context

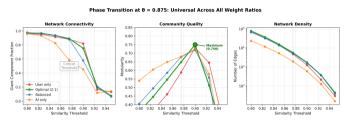
- We separate User Prompts from Al Replies.
- Weighting: Introduce parameter α (user-to-Al ratio).
- Question: Does prioritizing the user actually improve structure?



^{*}Embeddings generated via nomic-embed-text (8k context).

Rigorous Parameter Tuning: 2D Ablation Study

We ran a 63-configuration parameter sweep to maximize *Modularity* (Q).





Two-Dimensional Sweep

1 Threshold (θ) :

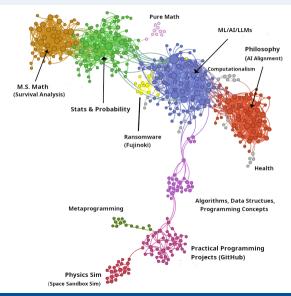
- Phase transition at $\theta = 0.875$
- Choice: $\theta = 0.9$ (optimizes modularity)
- Below: hairball; Above: fragmentation

2 Weight Ratio (α):

- ▶ Confirmed: Peak at $\alpha = 2:1$
- User voice matters more \rightarrow **Q** = **0.750**

Data-driven validation of design choices.

The Cognitive MRI: 15 Knowledge Domains



Insight 1: Structural Heterogeneity

Knowledge isn't uniform. Theoretical and practical thinking have distinct shapes.

Theoretical Domains (Math, Philosophy, ML Theory)



Practical Domains(Programming Projects, Debugging)



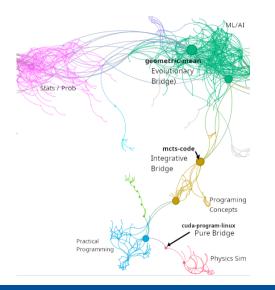
"Small-World" Structures

- **Dense Clustering** ($C \approx 0.58$): Concepts are highly interconnected.
- **Recursive:** Frequent backtracking to refine core definitions (e.g., axioms, ethics).

Tree-Like Expansion

- Branching ($C \approx 0.39$): Task-based exploration without backtracking.
- Independent: Projects form isolated silos (e.g., Metaprogramming vs. Physics Sim).

Insight 2: A Taxonomy of Bridges



The network reveals three distinct bridging mechanisms.

1. Evolutionary Bridges

(e.g., Geometric Mean)

Conversations that $\textbf{drift} \colon \mathsf{Stats} \to \mathsf{ML}/\mathsf{AI} \to$

Programming.

2. Integrative Bridges

(e.g., mcts-code)

Deliberate synthesis: $AI/ML \leftrightarrow Programming$.

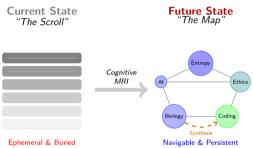
3. Pure Bridges

(e.g., cuda-program-linux)

Rare shortcuts: Physics Sim ↔ Programming.

The Vision: Personal Knowledge Cartography

Why do we need this map?



Example Query: "Show me everywhere I discussed entropy."

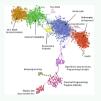
Result: Network lights up connections: Biology \leftrightarrow Al Theory \leftrightarrow Coding \leftrightarrow Ethics

Problem: Insights buried in infinite scroll

Solution: Navigate & synthesize across your entire history

Cognitive MRI: A Proof of Concept

Key Findings



- Method: Tuned user-weighting (2:1) and link thresholds (for modularity).
- Topology: Heterogeneous (Hubs vs. Trees).
- Bridges: Evolutionary, Integrative, & Pure.

Limitations



- Single User & Platform.
- Snapshot in time.
- Exploratory (No "Ground Truth").

Future Directions



- Scale: More users & cross-platform analysis.
- Longitudinal: Track knowledge evolution over time.
- Validation: User studies.

Backup: Technical Details

Embedding Details

- Model: nomic-embed-text (8k context window)
- Dimension: 768
- Chunking: 500-token windows with 50-token overlap
- User-to-Al weighting: 2:1 ratio (validated via ablation study)

Community Detection

- Algorithm: Louvain (resolution = 1.0)
- Modularity: Q = 0.750 (15 communities discovered)
- Giant component: \sim 500 nodes, \sim 1,600 edges

Dataset Filtering

- Original dataset: 1,908 conversations (2–3 years)
- After similarity threshold ($\theta=0.9$): $\sim\!500$ conversations in giant component
- Isolated nodes filtered: conversations with no semantic neighbors

Backup: Core Formulas

Weighted Embedding

$$ec{e}_{conv} = rac{lpha ec{e}_{user} + ec{e}_{AI}}{\|lpha ec{e}_{user} + ec{e}_{AI}\|}$$

 $\alpha = 2$ (2:1 weighting)

Modularity (Newman's Q)

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

 A_{ii} : adjacency, k_i : degree, m: edges

Betweenness Centrality

$$B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

 σ_{st} : shortest paths $s \to t$

Clustering Coefficient

$$C_i = \frac{2e_i}{k_i(k_i - 1)}$$

ei: edges among neighbors

Backup: Privacy & Data Handling

This Study

- Consent: Author's own conversations
- Export: Official ChatGPT data export
- Content: Exploratory/academic only
- Sharing: Aggregated statistics, no raw logs

Code Release

- Framework is open-source
- Users run locally on their own data
- No data leaves user's machine

Future Multi-User Studies

- IRB Required: Formal ethics review
- Informed Consent: Explicit opt-in
- Anonymization:
 - Remove PII (names, emails)
 - Hash conversation IDs
 - Redact sensitive topics
- Differential Privacy: For aggregate statistics

Key Principle

Designed for self-knowledge—users mapping their own thought, not surveillance.

Backup: Methodology Alternatives

Why These Design Choices?

Choice	Alternative	Why We Chose This
Cosine Similarity	Euclidean Distance	Magnitude-invariant (length $ eq$ relevance)
	Jaccard (set-based)	Semantic continuity, not just keywords
Threshold $(\theta=0.9)$	Soft/fuzzy cluster- ing	Clear community boundaries
	k-NN graph	Ablation validated hard threshold
nomic-embed- text	OpenAI embeddings	Open weights, 8k context, reproducible
	Sentence-BERT	Better long-context handling
2:1 Weighting	Equal (1:1) User-only	Al responses dilute user intent Loses conversational context

All choices validated via 63-configuration ablation study (Slide 6)