

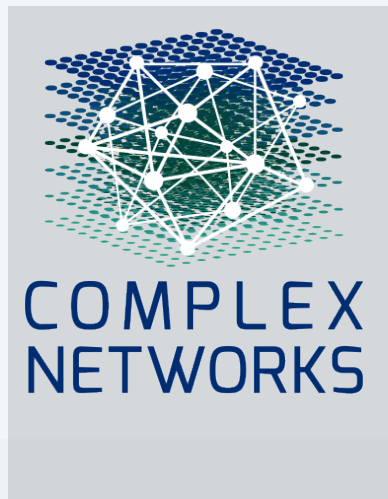
Cognitive MRI of AI Conversations: A Single-User Case Study

Revealing the Hidden Topology of Thought

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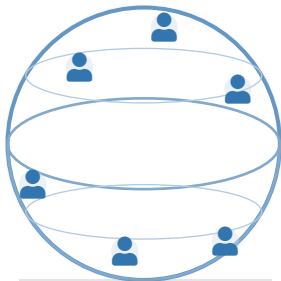
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 Code & Data: github.com/queelius/chatgpt-complex-net

Why Now? The Scale of the Opportunity

1.7 Billion ChatGPT Users



Global Scale

Unprecedented access to
cognitive processes

Why This Matters

Dataset Type		Scale	Process?
Citation Networks		10^8 papers	No
Social Networks		10^9 users	No
LLM	Conversa-	10^9 users	✓
tions			

First-Time Opportunity

Traditional datasets capture **outputs** (papers, posts).

LLM logs capture the **iterative reasoning process** at global scale.

The Big Picture: Externalized Cognition

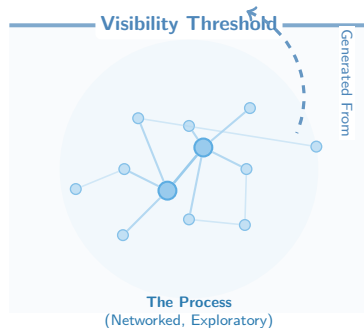
AI conversations are not just chat logs.

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

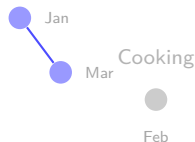


Nodes: Each conversation \rightarrow vector (embedding)

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

The Network

Coding



Grouped by meaning

The Key Insight

Close in **time** \neq close in **thought**.
Jan and Mar snap together. Banana bread floats alone.

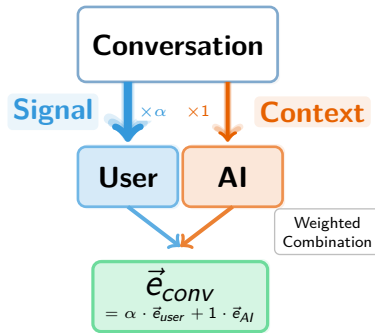
Whose Voice Matters?

The Challenge: AI 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 **AI Replies**.
- **Weighting:** Introduce parameter α (user-to-AI ratio).
- **Question:** Does prioritizing the user actually improve structure?

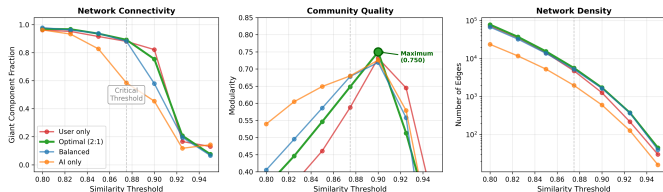


*Embeddings generated via nomic-embed-text (8k context).

Rigorous Parameter Tuning: 2D Ablation Study

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

Phase Transition at $\theta \approx 0.875$: Universal Across All Weight Ratios



Two-Dimensional Sweep

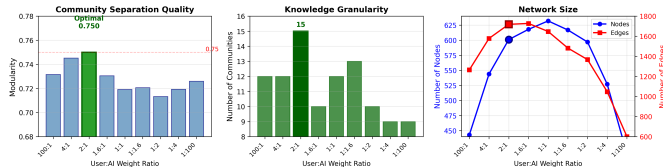
1 Threshold (θ):

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

2 Weight Ratio (α):

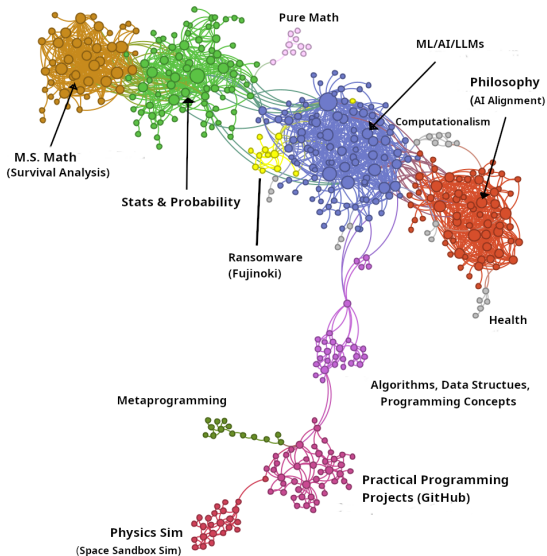
- ▶ **Confirmed:** Peak at $\alpha = 2 : 1$
- ▶ User voice matters more $\rightarrow Q = 0.750$

Weight Ratio Effects at Threshold $\theta = 0.9$



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)



“Small-World” Structures

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

Practical Domains

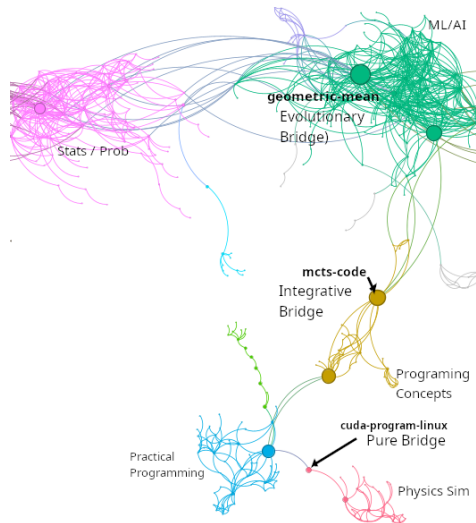
(Programming Projects, Debugging)



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 **drift**: Stats → ML/AI →
Programming.

2. Integrative Bridges

(e.g., mcts-code)

Deliberate synthesis: AI/ML ↔ Programming.

3. Pure Bridges

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

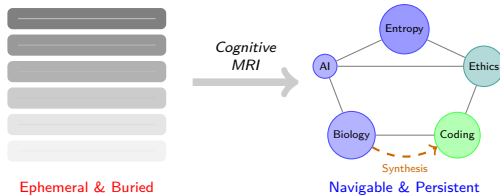
Rare shortcuts: Physics Sim ↔ Programming.

The Vision: Personal Knowledge Cartography

Why do we need this map?

Current State
"The Scroll"

Future State
"The Map"



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

Result: Network lights up connections: Biology ↔ AI Theory ↔ Coding ↔ Ethics

Problem: Insights buried
in infinite scroll

Solution: Navigate & synthesize
across your entire history

Cognitive MRI: A Proof of Concept

Key Findings



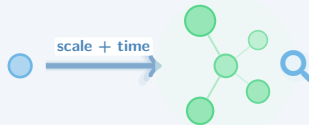
- **Method:** Tuned user-weighting (2:1) and link thresholds (for modularity).
- **Topology:** Heterogeneous (Hubs vs. Trees).
- **Bridges:** Evolutionary, Integrative, & Pure.

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-AI weighting: 2:1 ratio (validated via ablation study)

Community Detection

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

Dataset Filtering

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

Full methodology & code:  github.com/queelius/chatgpt-complex-net

Backup: Core Formulas

Weighted Embedding

$$\vec{e}_{conv} = \frac{\alpha \vec{e}_{user} + \vec{e}_{AI}}{\|\alpha \vec{e}_{user} + \vec{e}_{AI}\|}$$

$\alpha = 2$ (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_{ij} : 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 $s \rightarrow t$

Clustering Coefficient

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

e_i : 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 \neq relevance)
	Jaccard (set-based)	Semantic continuity, not just keywords
Threshold ($\theta=0.9$)	Soft/fuzzy clustering	Clear community boundaries
	k-NN graph	Ablation validated hard threshold
nommic-embed-text	OpenAI embeddings	Open weights, 8k context, reproducible
	Sentence-BERT	Better long-context handling
2:1 Weighting	Equal (1:1)	AI responses dilute user intent
	User-only	Loses conversational context

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