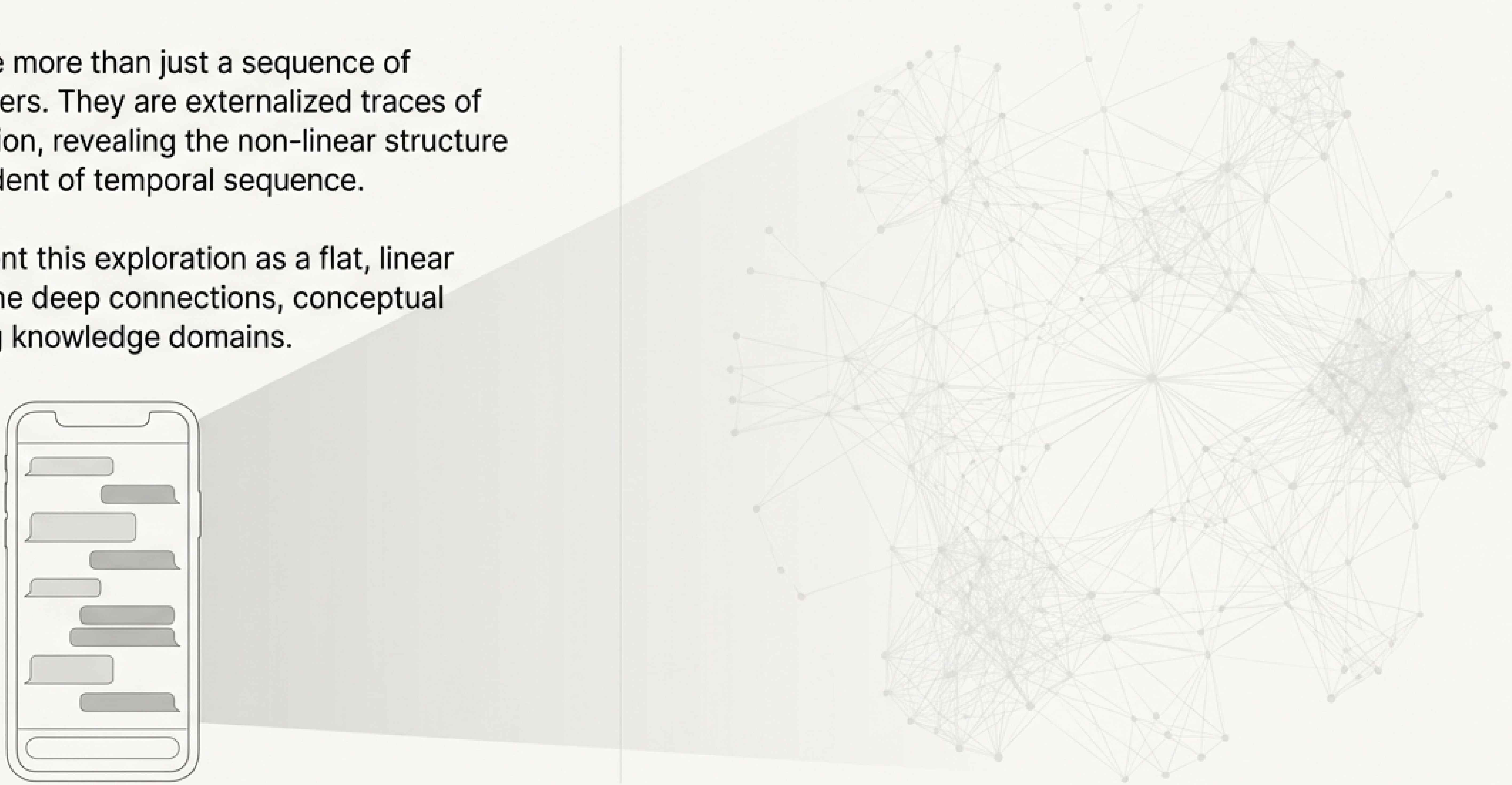
Linear conversation logs conceal the rich, non-linear structure of human thought.

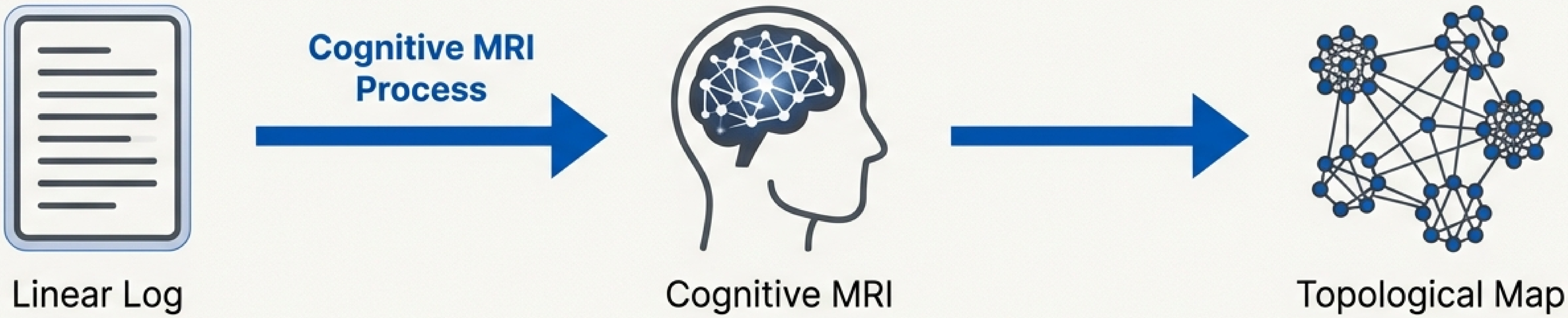
AI conversations are more than just a sequence of questions and answers. They are externalized traces of knowledge exploration, revealing the non-linear structure of thought independent of temporal sequence.

Standard logs present this exploration as a flat, linear history, obscuring the deep connections, conceptual leaps, and emerging knowledge domains.



We developed a “Cognitive MRI” to transform these sequential traces into topological maps of thought.

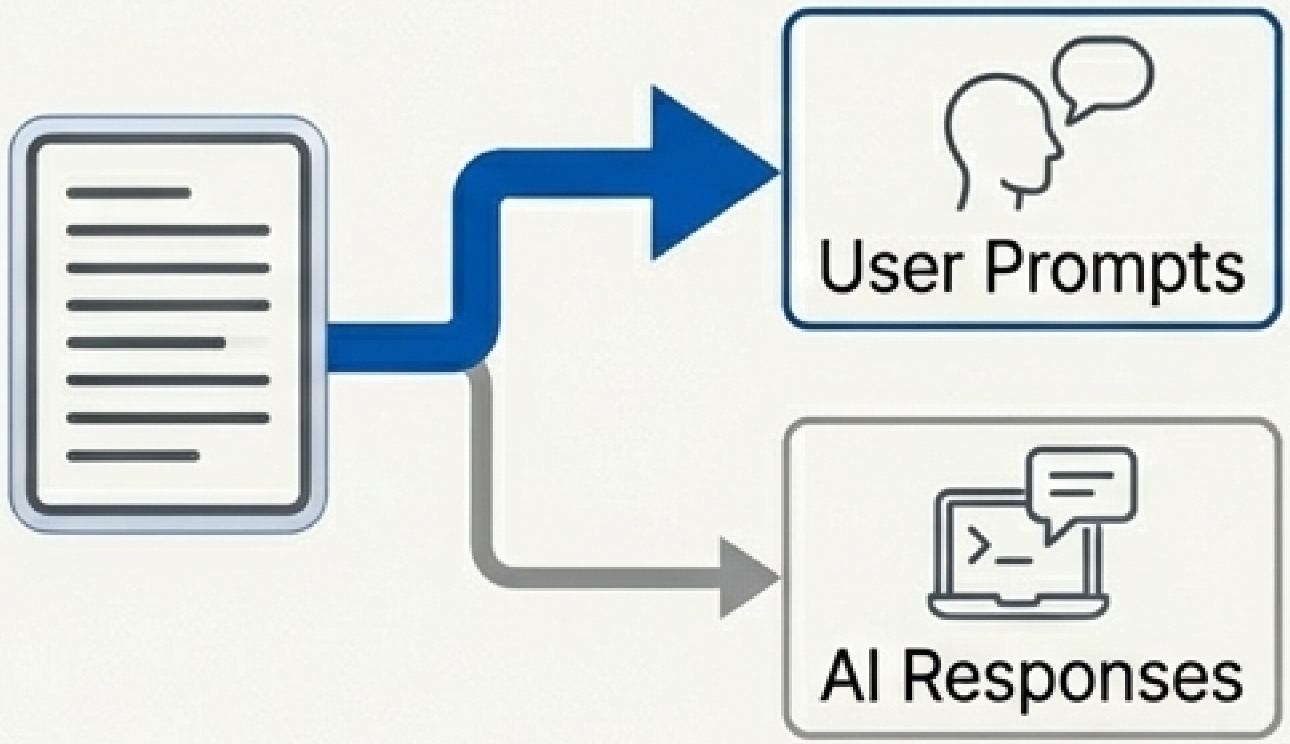
Our methodology functions like a cognitive MRI, using network analysis to reveal the latent thought structure in conversational data, just as a medical MRI reveals brain structure.



- **Nodes**: Individual conversations.
- **Edges**: Semantic similarity between conversations.
- **Result**: A topological map exposing the geometry of knowledge navigation.

User intent is the primary driver of exploration, so we weight user prompts more heavily in our model.

To capture the user's cognitive direction, we generate a weighted conversation embedding. User prompts are prioritized over AI responses, which are often lengthier and more elaborative.



$$\vec{e}_{\text{conversation}} = \frac{(\alpha * \vec{e}_{\text{user}} + \vec{e}_{\text{AI}})}{||\alpha * \vec{e}_{\text{user}} + \vec{e}_{\text{AI}}||}$$

Conversation Vector

$\vec{e}_{\text{user}}$: Mean embedding of all user messages.
$\vec{e}_{\text{AI}}$: Mean embedding of all AI responses.
α : Weight factor prioritizing user intent.

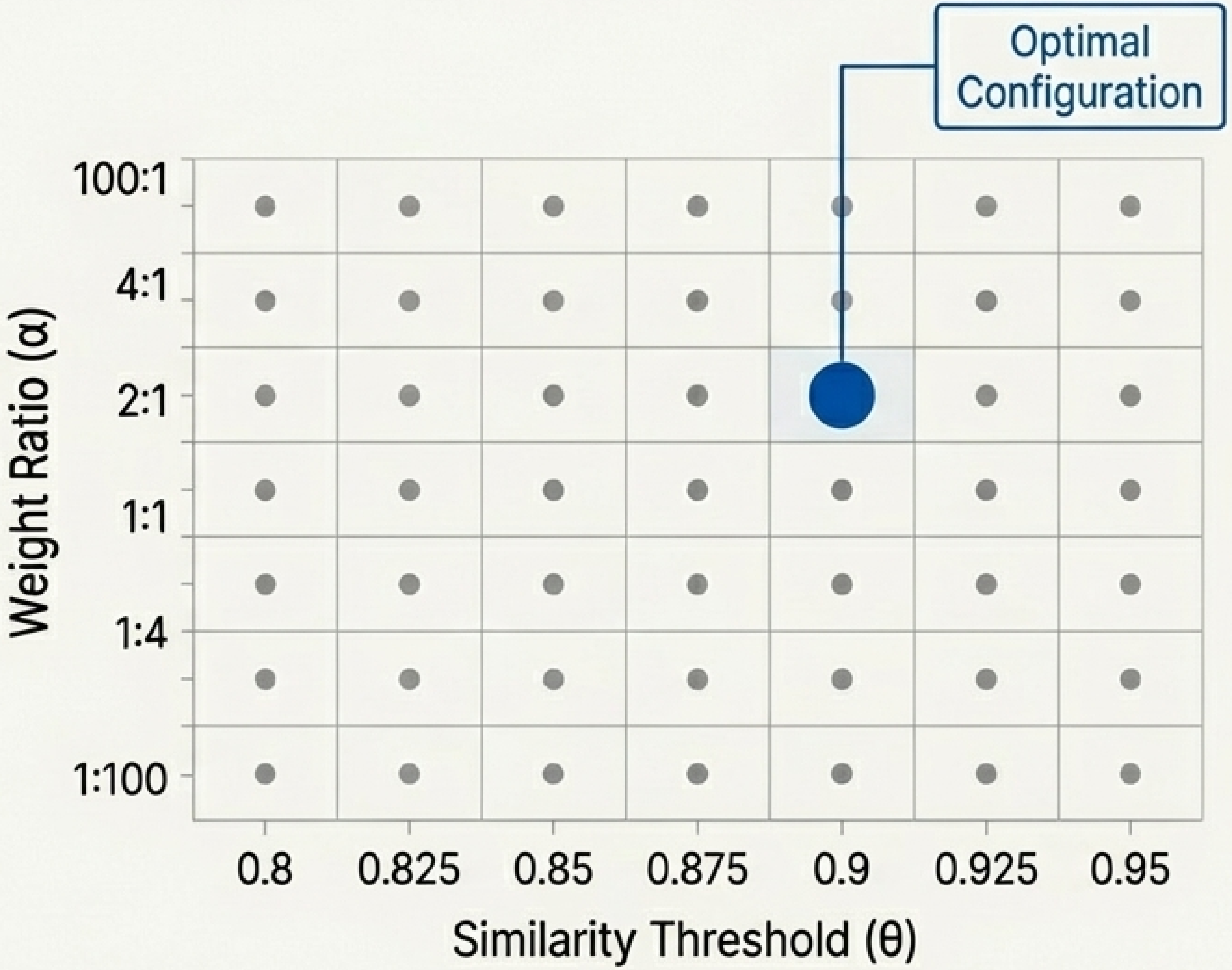
Our analysis determined the optimal weight to be **$\alpha = 2$**, a 2:1 user-to-AI ratio.

We tested 63 parameter configurations to find the optimal balance between network connectivity and semantic coherence.

To validate our choices, we conducted a complete 2D parameter sweep, systematically examining how embedding weights and similarity thresholds shape the network. This ensures our final network structure reflects genuine knowledge organization, not methodological artifacts.

Parameters Tested

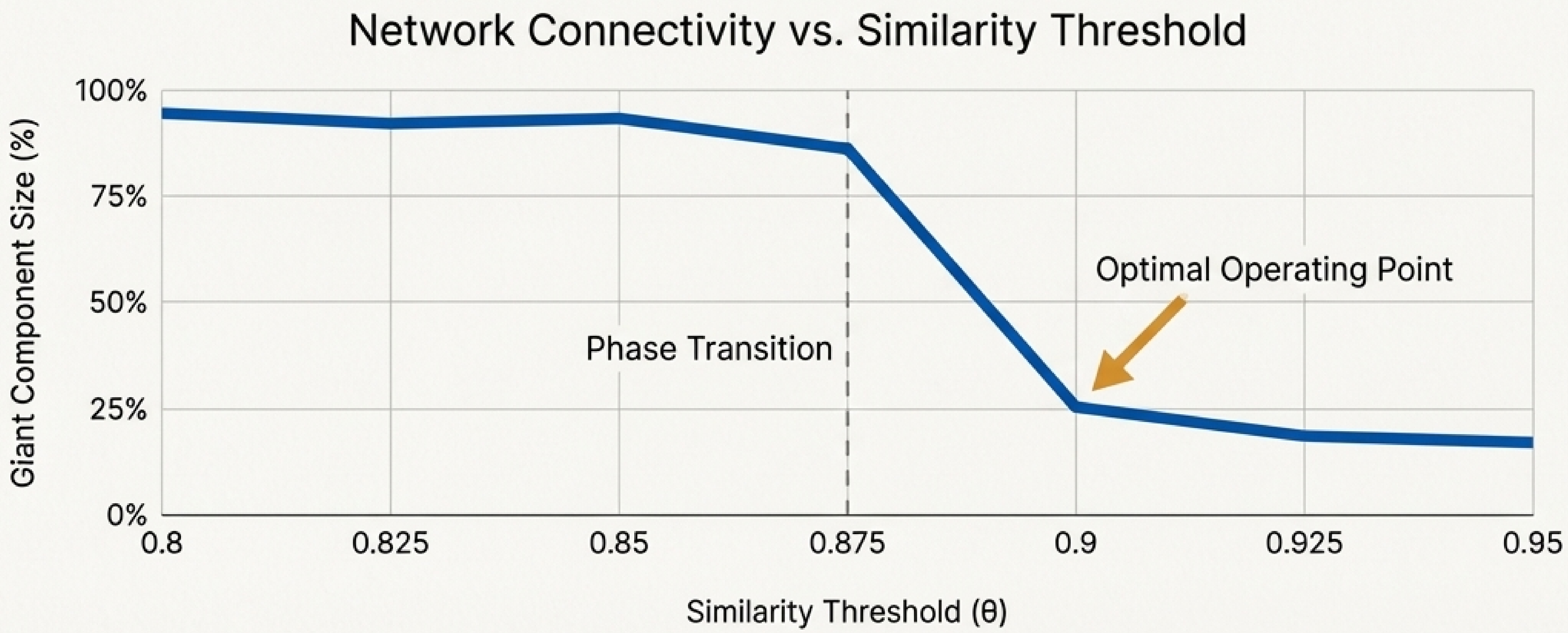
- **9 Weight Ratios** (User:AI): From 100:1 to 1:100, including 2:1, 1:1, etc.
- **7 Similarity Thresholds (θ)**: From 0.8 to 0.95.



A critical phase transition occurs at similarity θ ≈ 0.875, where the network shifts from connected to fragmented.

Across all weight ratios, the network maintains over 90% connectivity below this threshold. Above it, catastrophic fragmentation occurs.

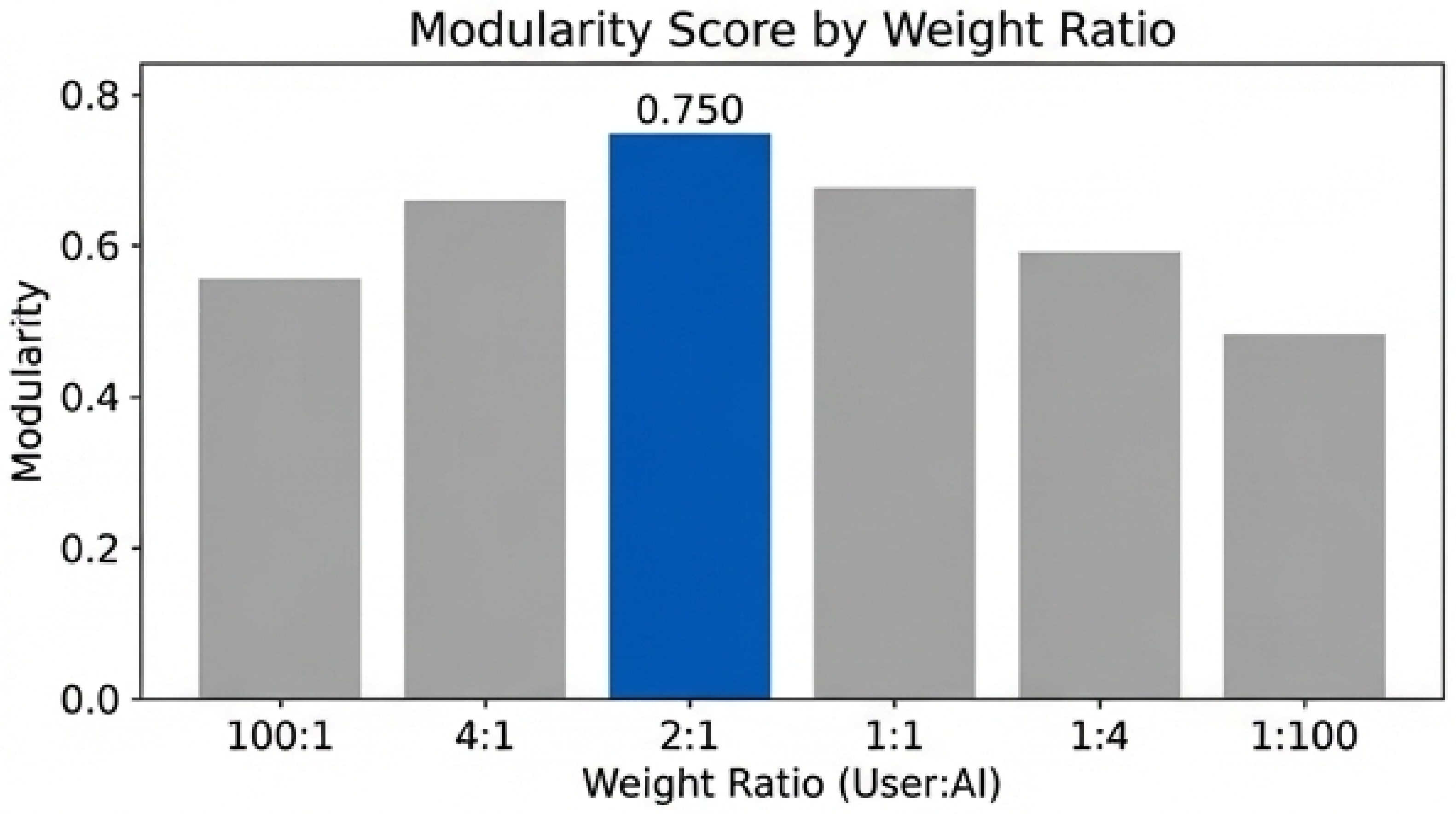
Operating just past this transition (at θ = 0.9) allows us to filter noise while preserving the 1,615 most essential semantic connections from over 100,000 possibilities.

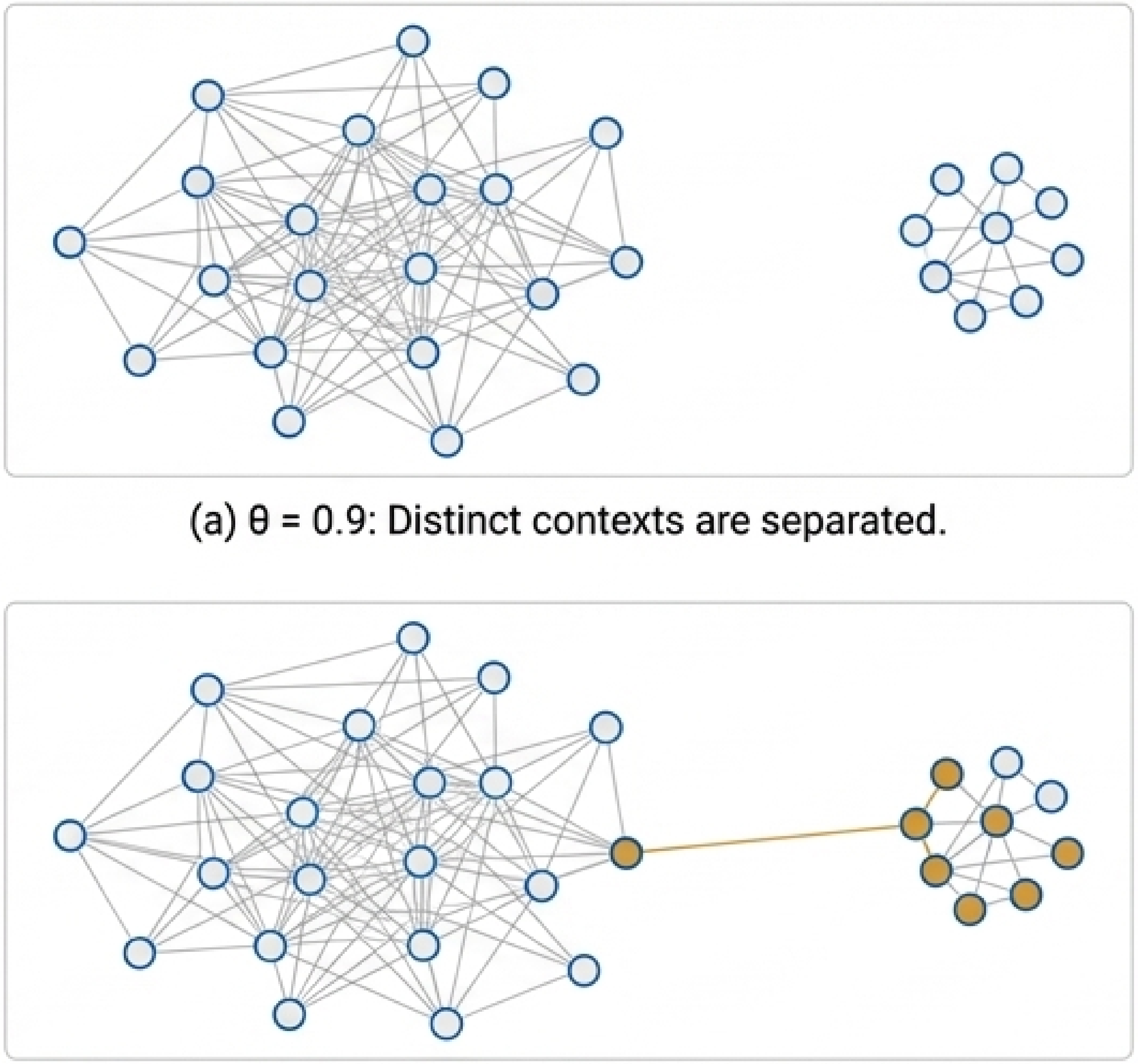


The 2:1 user:AI weight ratio maximizes community structure without distorting the underlying topic distribution.

The 2:1 ratio achieves the highest modularity score (0.750), indicating the clearest possible separation of knowledge communities.

User-heavy ratios (e.g., 100:1) over-fragment the network, while AI-heavy ratios (e.g., 1:100) merge distinct domains based on response style rather than user intent.





(a) θ = 0.9: Distinct contexts are separated.

(b) θ = 0.875: A philosophical 'bridge' conversation connects the peripheral cluster, revealing a 2.5% semantic distance.

The resulting network reveals a rich, heterogeneous topology of 15 distinct knowledge communities.

Our analysis of 449 conversations reveals a complex structure with high local clustering (0.60) and significant cognitive distance between domains (avg. path length 5.81).

The network spontaneously organizes into thematic clusters, with no explicit categorization provided.

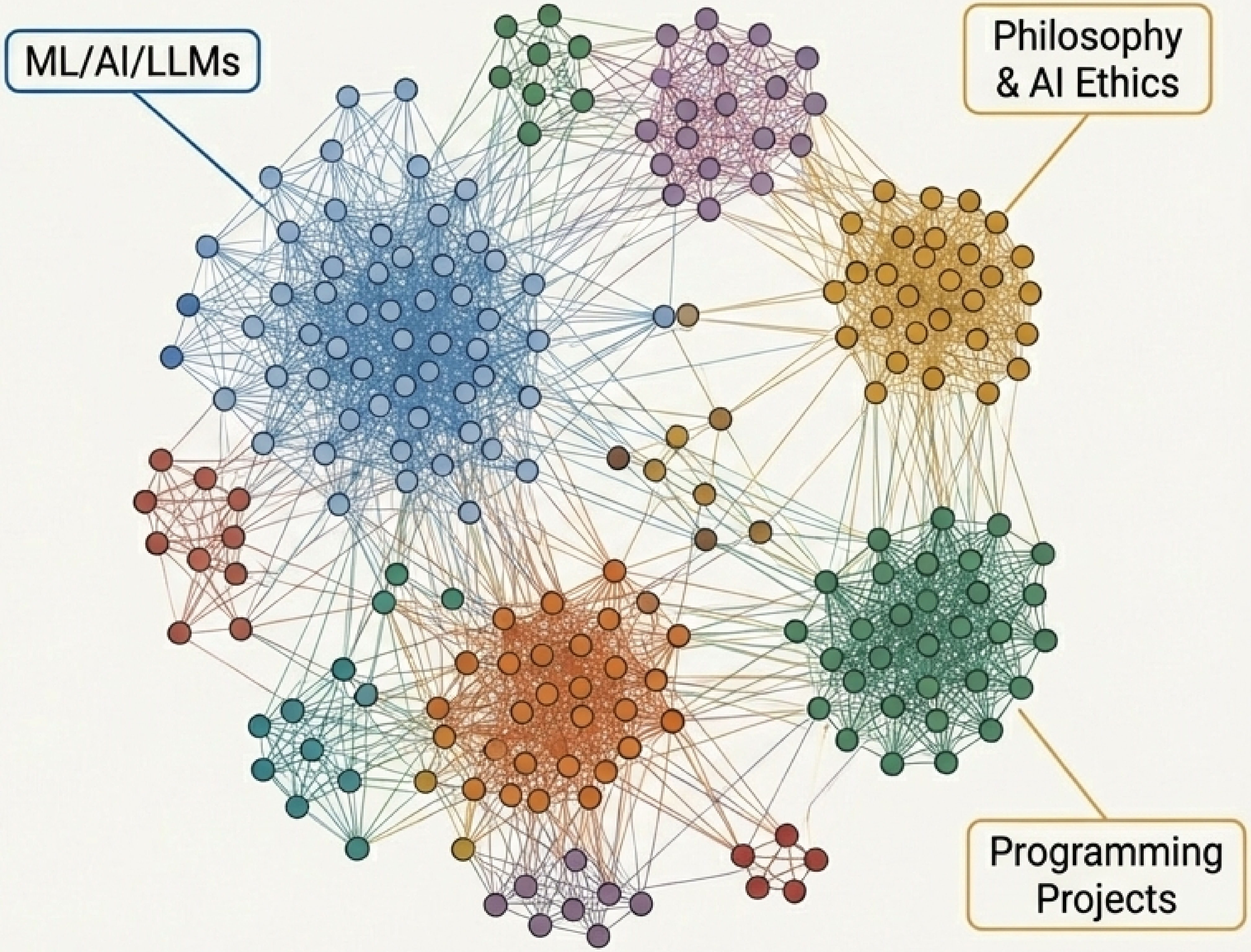
Key Network Stats:

Nodes: 449

Edges: 1,615

Average Degree: 7.19

Modularity: 0.750

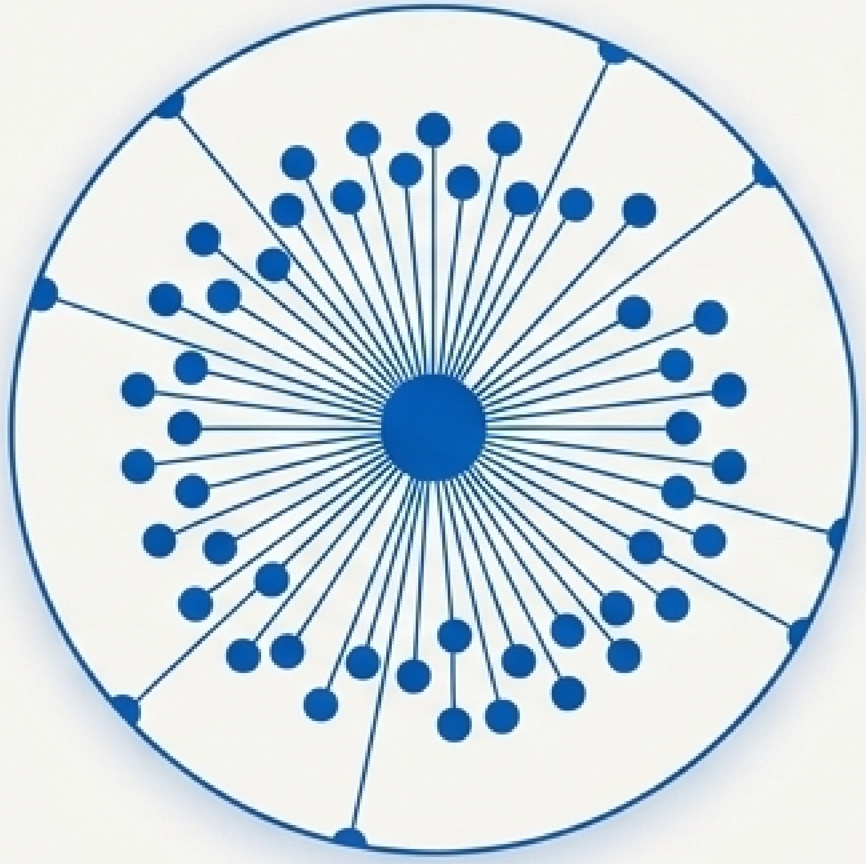


Knowledge domains exhibit distinct organizational patterns: theoretical topics form hub-and-spoke systems, while practical topics form tree-like hierarchies.

Inter

Theoretical Domains (e.g., M.S. Math, ML/AI, Philosophy)

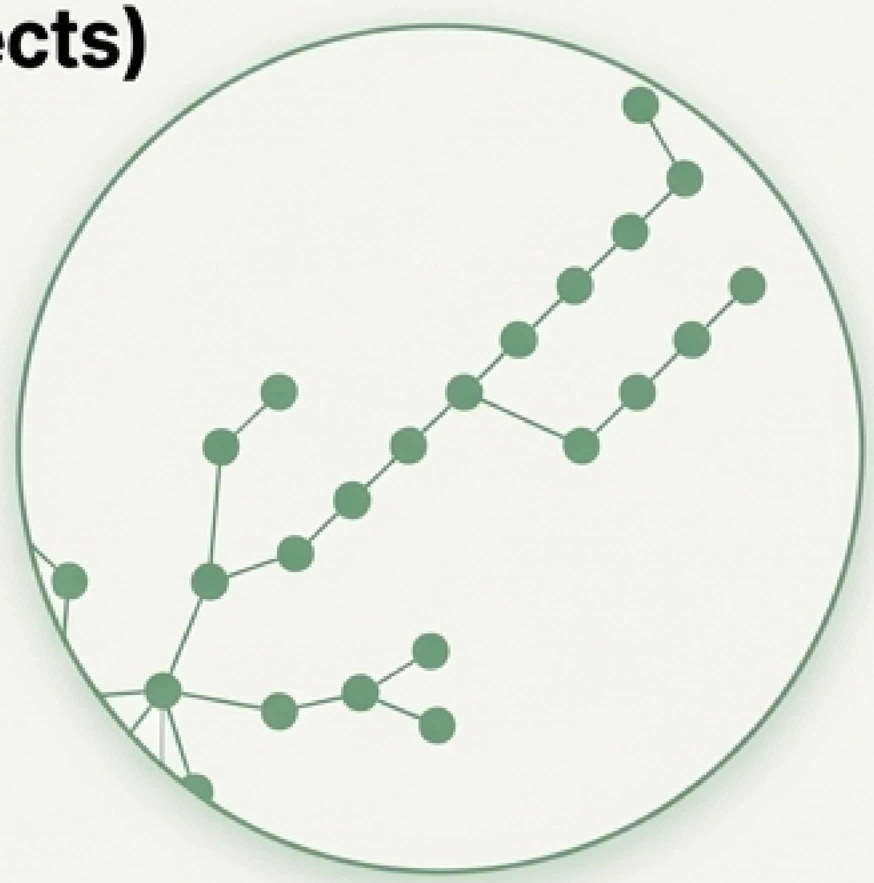
Show dense, hub-and-spoke structures characteristic of scale-free networks. A few core conversations act as central authorities.



Inter

Practical Domains (e.g., Metaprogramming, Programming Projects)

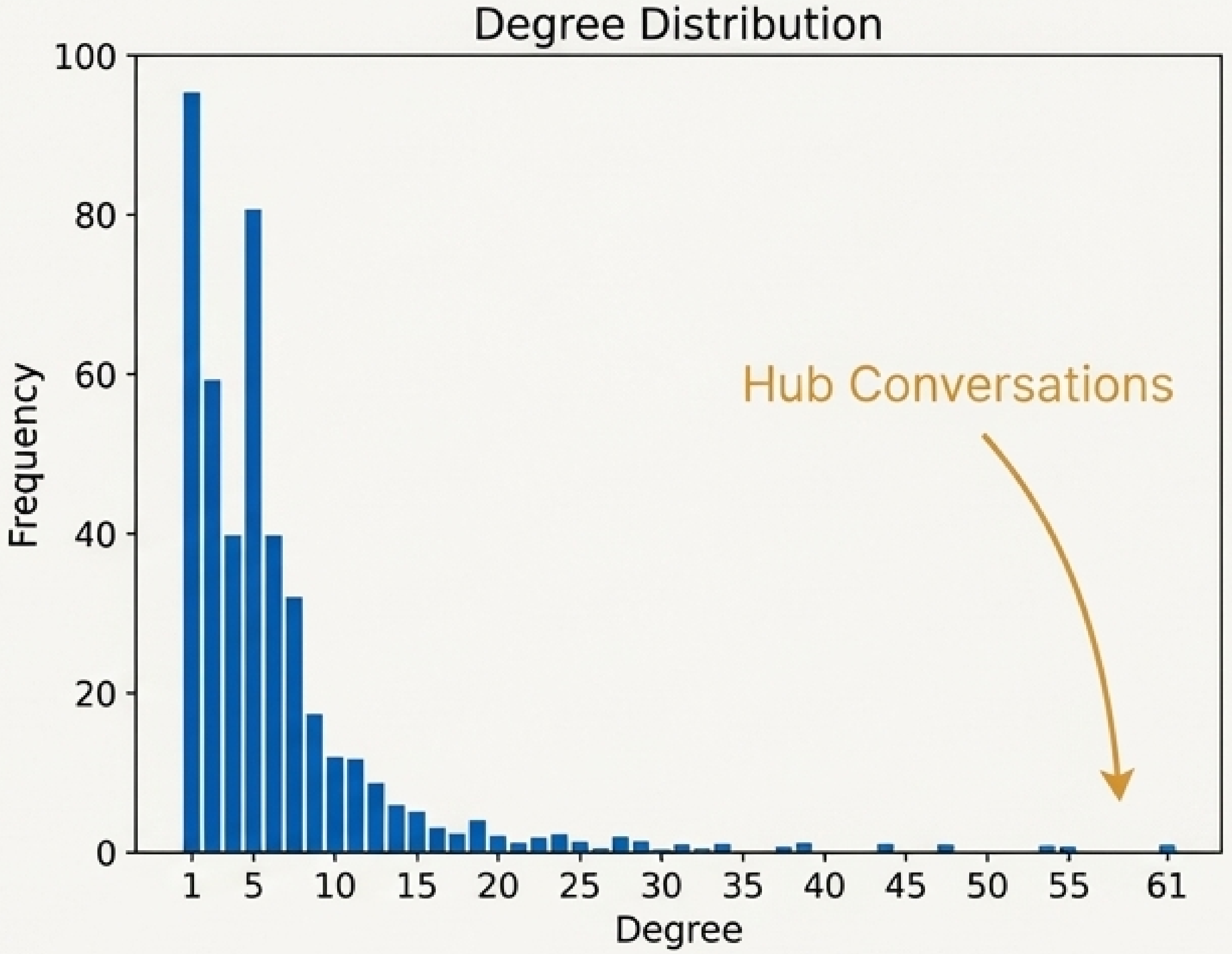
Display tree-like branching or dispersed structures. Exploration is more linear and task-focused, without dominant hubs.



The network's degree distribution is highly skewed, confirming its organization around a few critical hub conversations.

The vast majority of conversations have few connections, while a small number act as hubs with substantially higher degrees. This right-skewed pattern is a hallmark of non-random, organized systems.

This structure differs from pure preferential attachment models; higher clustering and longer path lengths suggest cognitive constraints limit hub formation to specialized domains.



The five largest communities represent distinct, thematically coherent knowledge domains.

Community detection identifies domains ranging from theoretical AI to practical programming, each with a unique internal structure.

Community Topic	Size (% of Network)	Avg. Degree	Core %	Primary Characteristic
ML/AI/LLM	23% (103 nodes)	8.60	31.1%	Broadly connected bridging domain
Stats & Probability	18% (82 nodes)	7.09	24.4%	Densely connected expert domain
Philosophy & AI Ethics	14% (65 nodes)	10.03	44.6%	Specialized, dense connections
M.S. Math/Analysis	10% (44 nodes)	13.45	59.1%	Highly specialized, dense expert hub
Programming Projects	10% (45 nodes)	3.78	8.9%	Sparsely connected task domain

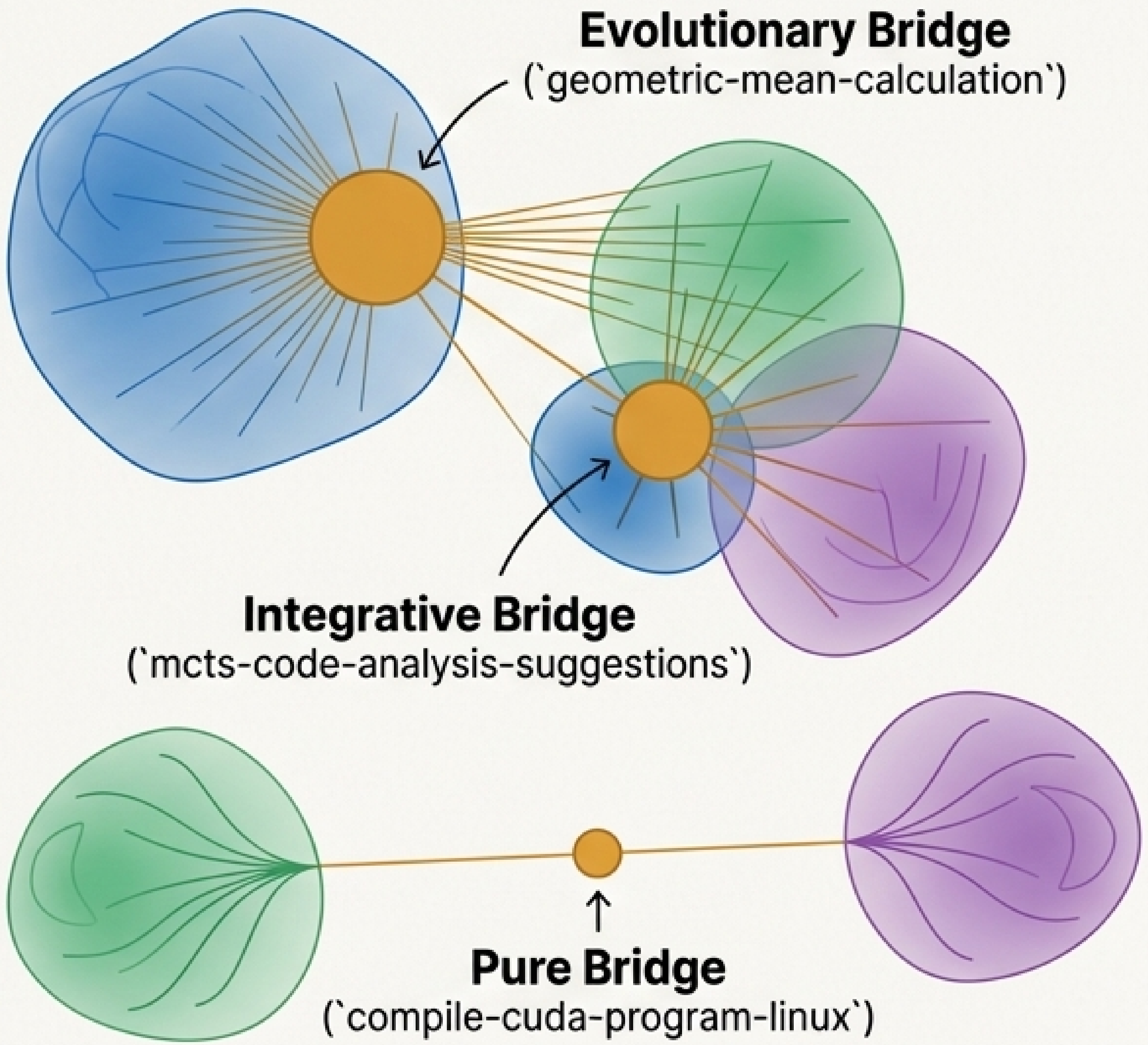
We identified three distinct types of "bridge" conversations that facilitate cross-domain knowledge integration.

Bridges are conversations with high betweenness centrality. They are critical for connecting disparate knowledge domains and enabling creative, cross-topic jumps.

Evolutionary Bridges: High-degree hubs that expand across domains through topic drift (e.g., `geometric-mean-calculation`).

Integrative Bridges: Moderate-degree nodes that deliberately synthesize concepts from different domains (e.g., `mcts-code-analysis-suggestions`).

Pure Bridges: Low-degree, critical links that form an essential, minimal connection between two otherwise separate domains (e.g., `compile-cuda-program-linux`).



Some conversations act as both hubs and bridges, while others serve as pure, critical links.

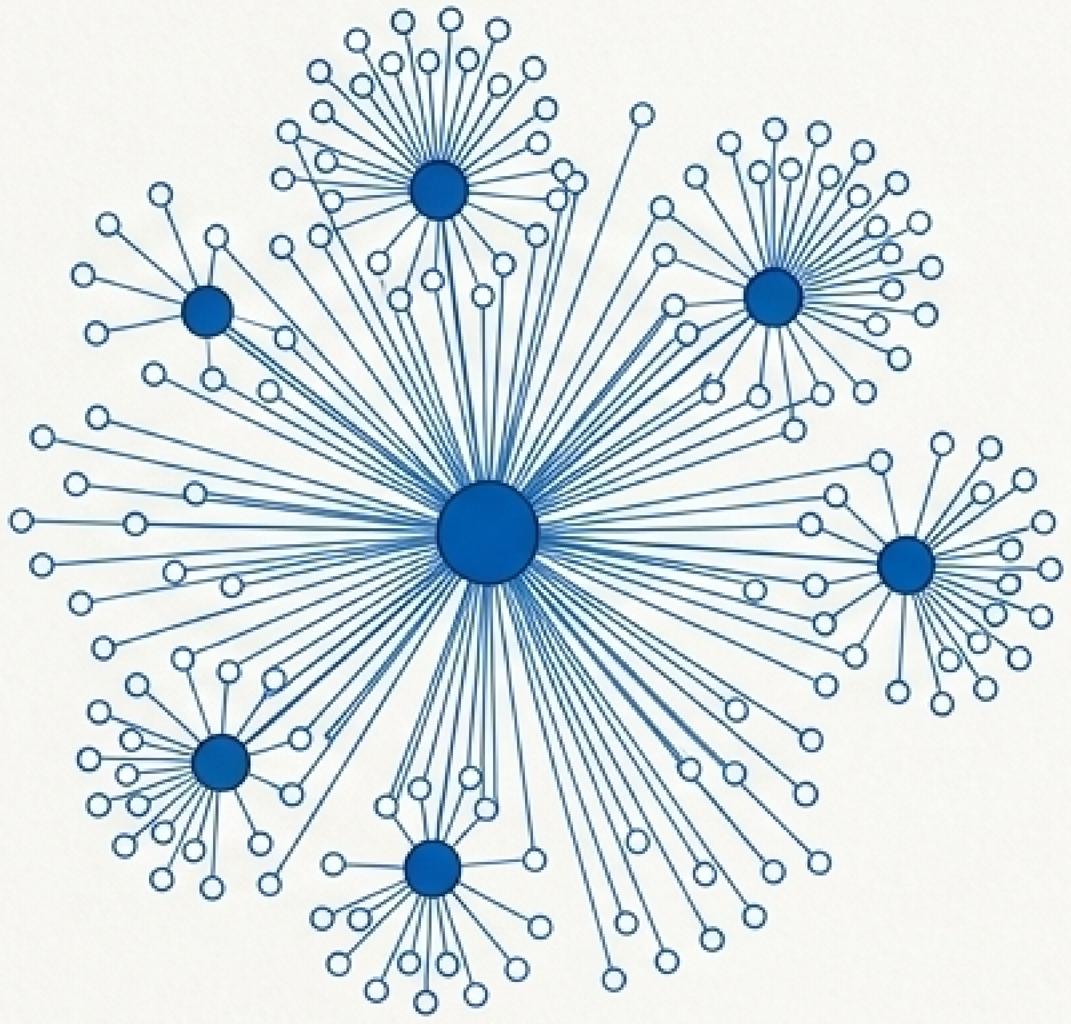
The conversation `geometric-mean-calculation` is a prime example of a **"hub-bridge,"** with both a high degree (61) and the highest **betweenness centrality**. In contrast, `compile-cuda-program-linux` is a **"pure bridge"** with a degree of only 2 but high betweenness, making it a vital but fragile link.

Conversation	Betweenness Centrality	Degree	Bridge Type
geometric-mean-calculation	45467.51	61	**Evolutionary**
mcts-code-analysis-suggestions	36909.13	10	**Integrative**
loss-in-llm-training	35118.59	30	Evolutionary
compile-cuda-program-linux	9775.00	2	**Pure**

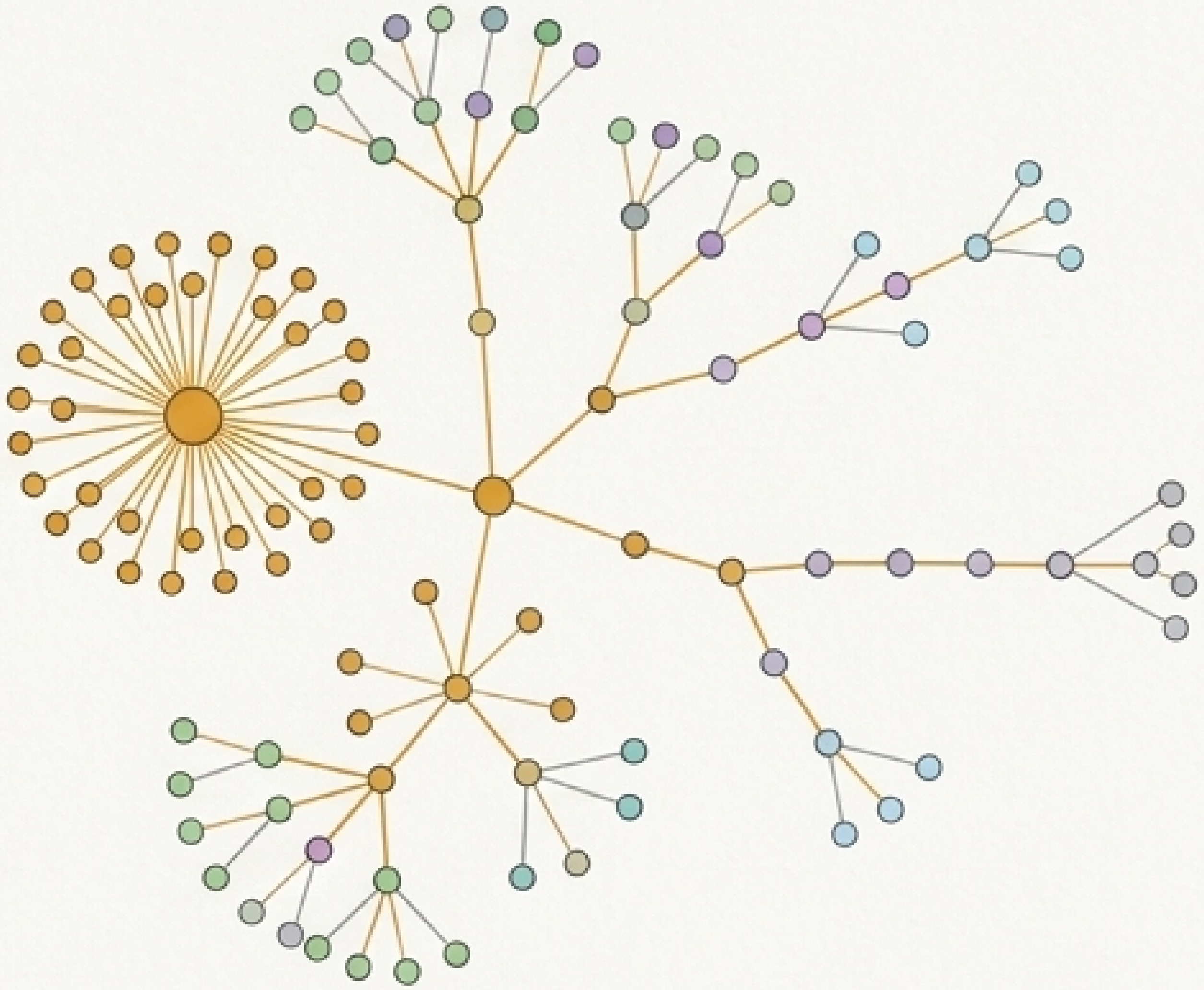
The network is a structural trace of thinking, revealing cognitive patterns distinct from traditional knowledge networks.

Unlike academic citation networks which build on established authorities (preferential attachment), our conversation network reflects real-time knowledge discovery. The presence of hub-less, tree-like communities shows that cognitive exploration often involves intense local investigation and cross-topic jumps, rather than cumulative authority building.

Just as an MRI reveals the physical structure of the brain, this 'Cognitive MRI' reveals the topological structure of thought.



Citation Network (Preferential Attachment)

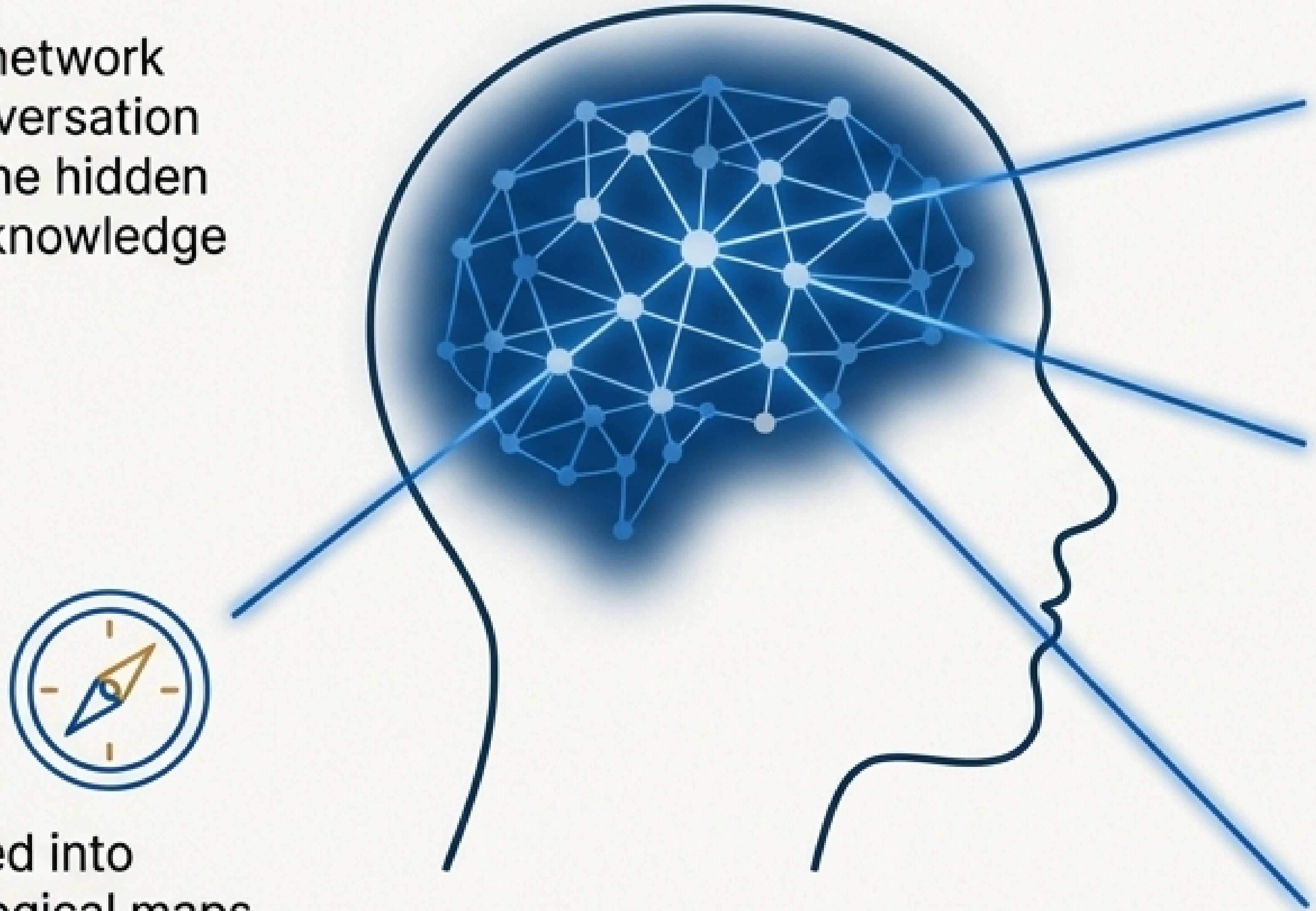


Cognitive Network (Real-time Exploration)

This ‘Cognitive MRI’ provides a new framework for understanding and enhancing AI-assisted knowledge work.

Summary:

By applying a user-weighted network analysis to a single user’s conversation archive, we have uncovered the hidden topological structure of their knowledge exploration.



Future

As AI becomes more integrated into human cognition, these topological maps will be essential for navigating and augmenting our own intellectual journeys.

Implications & Applications

This methodology can be used to improve knowledge retrieval systems.

surface creative connections by highlighting “pure bridges,” and understand how different cognitive styles influence exploration patterns.