
LARGE CAUSAL MODELS FROM LARGE LANGUAGE MODELS*

A PREPRINT

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December 9, 2025

ABSTRACT

We introduce a new paradigm for building large causal models (LCMs) that exploits the enormous potential latent in today’s large language models (LLMs). We describe our ongoing experiments with an implemented system called DEMOCRITUS (Decentralized Extraction of Manifold Ontologies of Causal Relations Integrating Topos Universal Slices) aimed at building, organizing, and visualizing LCMs that span disparate domains extracted from carefully targeted textual queries to LLMs. DEMOCRITUS is methodologically distinct from traditional narrow domain and hypothesis centered causal inference that builds causal models from experiments that produce numerical data. A high-quality LLM (e.g. the 80-billion parameter Qwen3-Next-80B-A3B-Instruct²) is used to propose topics, generate causal questions, and extract plausible causal statements from a diverse range of domains. The technical challenge is then to take these isolated, fragmented, potentially ambiguous and possibly conflicting causal claims, and weave them into a coherent whole, converting them into relational causal triples and embedding them into a LCM. Addressing this technical challenge required inventing new categorical machine learning methods, which we can only briefly summarize in this paper, as it is focused more on the systems side of building DEMOCRITUS. We describe the implementation pipeline for DEMOCRITUS comprising of six modules, examine its computational cost profile to determine where the current bottlenecks in scaling the system to larger models. We describe the results of using DEMOCRITUS over a wide range of domains, spanning archaeology, biology, climate change, economics, medicine and technology. We discuss the limitations of the current DEMOCRITUS system, and outline directions for extending its capabilities.

Keywords Causal Discovery · Large Language Models · AI · Machine Learning

1 Introduction

“I would rather discover one true cause than gain the kingdom of Persia” – Democritus (460 – 370 B.C.)

We introduce a new paradigm for building large causal models (LCMs) that exploits the enormous potential latent in today’s large language models (LLMs) (Bommasani et al., 2022; DeepSeek-AI et al., 2025). Much of the decades-long effort in causal discovery (Imbens and Rubin, 2015; Pearl, 2009; Zanga and Stella, 2023) has focused on constructing causal knowledge from carefully controlled highly specialized topically narrow studies in particular domains that typically yields numerical data. DEMOCRITUS is a methodologically distinct enterprise: build LCMs spanning potentially hundreds of distinct domains and ranging over millions of very specific causal claims, by carefully combining the vast knowledge latent in LLMs, with state-of-the-art categorical causal (Mahadevan, 2025b; Fritz, 2020) and deep learning methods (Fong et al., 2019; Mahadevan, 2024; Gavranović et al., 2024). Our goal in this paper is to showcase the potential of DEMOCRITUS. To broaden the accessibility of this paper, we omit a detailed discussion of

* Draft under revision.

²Specifically, we used a highly optimized Apple MLX version of Qwen3-Next-80B-A3B-Instruct from Hugging Face in our experiments, downloadable from <https://huggingface.co/mlx-community/Qwen3-Next-80B-A3B-Instruct-6bit>

much of the categorical machinery used in building DEMOCRITUS. We use an implemented version of the Geometric Transformer (GT), proposed originally in (Mahadevan, 2024), combined with a generalized backpropagation method that works by “horn filling” gaps in simplicial sets (Mahadevan, 2023; May, 1992), and several technical enhancements of these methods will be described in forthcoming papers.

LLMs are increasingly capable of producing rich causal narratives: they can enumerate subtopics, pose causal questions, and articulate mechanistic explanations in domains ranging from macroeconomics to neuroscience. However, using an LLM alone leaves us with a *laundry list* of disconnected fragments. Democritus aims to turn these fragments into structured *large causal models*— which can be viewed categorically as slices of Topos Causal Models (TCMs) (Mahadevan, 2025b)— over which we can compute, visualize, and eventually reason. A *topos* is a type of category (MacLane and Ieke Moerdijk, 1994) that supports an internal intuitionistic logic. The use of such a logic was recently described in (Mahadevan, 2025b). DEMOCRITUS, as described here, is purely a topos builder, but not (yet) a topos reasoner. One of the key strengths of TCMs is that they are robust to individual variability: they provide the theoretical basis for “map-reduce” type decentralized approaches to causal discovery (Mahadevan, 2025a). This strength is fully utilized in DEMOCRITUS, which relies on combing through the vast nuggets of plausible causal statements generated by querying a modern state-of-the-art LLM to extract a coherent LCM.

At a high level:

- A strong LLM (e.g., Qwen3-Next-80B-A3B-Instruct) acts as a discovery engine for domain topics, causal questions, and statements.
- A Geometric Transformer (GT) layer runs over the resulting relational graph and produces a manifold of node embeddings.
- These manifolds are organized as slices of a larger topos, and can be queried, visualized, and selectively refined.

A naive implementation expands every topic to a fixed depth, asks the LLM for causal questions and statements at every node, and only then builds the manifold. This works, but the LLM cost dominates and the result is unfocused. In this paper, we first describe the basic six-module pipeline, and then motivate and sketch an *active* version of Democritus in which feedback from Geometric Transformers and downstream tasks guides where to explore next.

As a showcase of the potential of DEMOCRITUS to elaborate on causal claims in the published literature, we apply it to a recent study (Solanki et al., 2025) that provides an explanation of the collapse of the Indus Valley civilization, which flourished on the banks of the River Indus about 5000 years ago. Such studies, typical in the literature across the humanities, sciences, and technology, require combining many fields of expertise, and serves as showcase that illustrates the strengths and limitations of DEMOCRITUS. Figure 1 illustrates a local causal model learned by DEMOCRITUS, whereas Figure 2 shows the entire global LCM, projected onto 2D using the UMAP data visualization method (McInnes et al., 2018).

How did DEMOCRITUS end up with these local and global causal models? As a way to “prime the pump”, we begin by giving DEMOCRITUS a set of plausible topics from which to generate causal claims including:

- Indus Valley Civilization / Harappan civilization
- Harappa, Mohenjo-daro, Dholavira, Ghaggar-Hakra (Saraswati)
- Holocene monsoon / paleoclimate / 4.2 ka event
- Indus river discharge, river droughts, streamflow anomalies
- Lake/playa shrinkage, stalagmites/stalagmites in Indian caves, lake sediments
- Wheat/barley/cotton agriculture, irrigation, floodplain farming
- Riverine trade networks (Harappa–Mesopotamia–Egypt), maritime vs river trade
- Settlement dispersal / relocation vs violent collapse
- 4 long droughts, especially the 164-year drought with 13% rainfall drop

DEMOCRITUS could prompt an LLM, such as Qwen3-Next-80B-A3B-Instruct, with a prompt such as the following:

You are an expert in South Asian archaeology and paleoclimate. Given the topic ‘Indus Valley Civilization decline’, list 10 important subtopics that help explain its causes. Return only a numbered list, one per line.

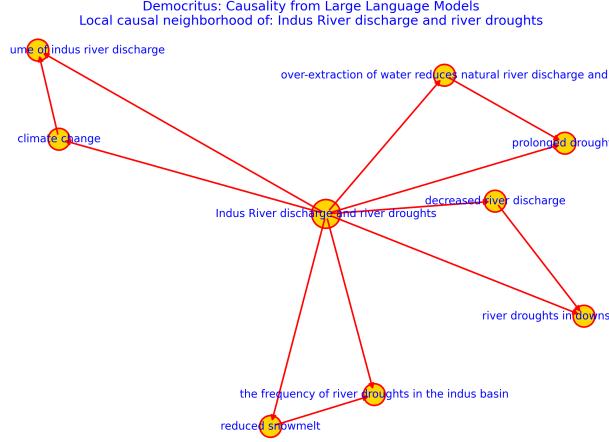


Figure 1: A local neighborhood causal model from a large LCM learned by DEMOCRITUS concerning the Indus river and droughts (Solanki et al., 2025), which was used to explain the collapse of the Indus Valley Civilization 5000 years ago. Crucially, such a model cannot be learned by a single prompt to an LLM, but instead is woven together by an assembly of carefully curated prompts.

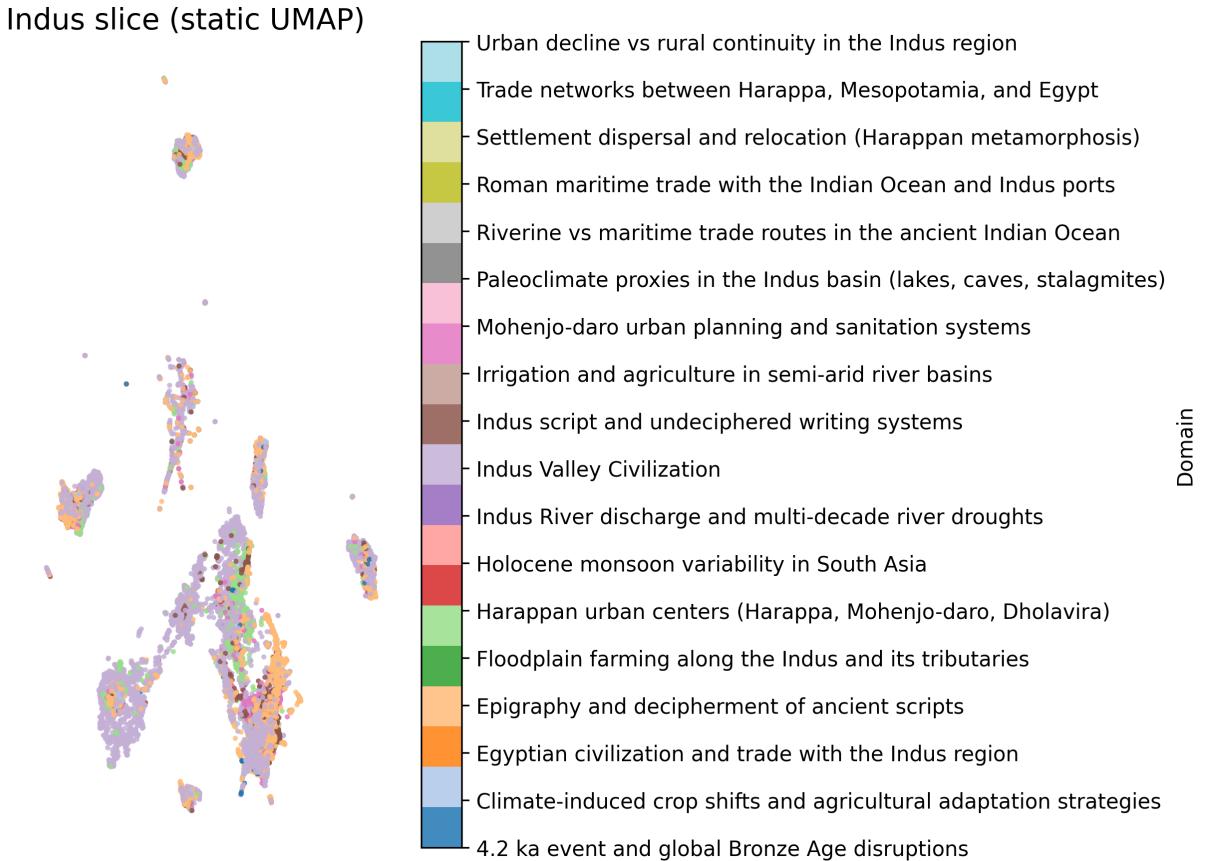


Figure 2: A global LCM underlying the collapse of the ancient Indus Valley civilization, shown as a 2D UMAP manifold of nodes colored by domain. Clusters correspond to Harappan urbanism and water systems, Indus script and epigraphy, climate and hydrology (Holocene monsoon variability, Indus river discharge and droughts), agriculture, and trade connections with Egypt and Rome, among others.

To seed the process of generating causal questions and statements, DEMOCRITUS can automatically generate causal questions, such as

- “What causes multi-decadal droughts in the Indus basin during the mid–late Holocene?”
- “How do changes in the tropical Pacific (El Niño/La Niña-like conditions) influence Indus monsoon rainfall?”
- “How does reduced monsoon rainfall propagate into river discharge, soil moisture, and crop viability?”
- “Why might repeated long droughts, rather than a single catastrophic event, drive gradual urban decline and dispersal?”

DEMOCRITUS then assembles the results of querying an LLM into “causal triples”, such as

- (tropical Pacific warming, reduces, monsoon rainfall)
- (reduced rainfall, decreases, Indus river discharge)
- (lower discharge, impedes, boat/barged river trade)
- (shrinkage of lakes/playas, reduces, local water storage)
- (multi-decade droughts, stress, agriculture and governance)
- (chronic water stress, leads to, relocation of Harappan settlements)

Our goal in doing this experiment is to explore how DEMOCRITUS can augment such published causal studies by filling in “potential holes” in the findings, by combining the breadth of expertise in an LLM with a deep manifold extraction computation aided by categorical machine learning methods, such as the Geometric Transformer. For example, the list of possible ways in which such a study can be elaborated include:

- Graph connectivity: The paper focuses on climate → hydrology → trade/agriculture → settlement decline. Democritus might link to other well-known 4.2 ka event stories (Akkadian, Egyptian Old Kingdom, Caral), and tie paleoclimate proxies (caves, lakes, stalactites) to similar records elsewhere.
- Alternative hypotheses / competing causes: DEMOCRITUS can enumerate other proposed drivers, including river avulsion and course changes, regional conflict, disease, trade shifts, internal social stratification. These additional possibilities might let researchers see how these hypotheses sit in the manifold: near or far from the climate/hydrology cluster, which might reveal missing links.
- Modern analogues: DEMOCRITUS can use the historical precedent of the Indus Valley collapse to explore potential modern impacts of climate change in the region. For example, it might suggest using the climate/hydrology structure in a modern South Asia slice (Ganges/Brahmaputra, current monsoon shifts), ask whether similar causal chains (multi-decade droughts, weak governance, river-dependent trade) appear today.
- Active deepening: DEMOCRITUS can be used as a research tool by scientists to actively explore deeper into the LCM for a particular study, by first constructing a shallow Harappan topos slice first, then let the user “click” on a region (e.g. “multi-century river droughts”), and have Democritus selectively deepen around that region: more subtopics, more Q&A, more triples.

1.1 Limitations of DEMOCRITUS

A key limitation of the current version of DEMOCRITUS is that the LCMs it proposes are not yet validated against numerical data or controlled experiments. In this paper we focus on the *hypothesis generation and organization* problem: extracting and geometrically structuring candidate causal edges from text. We do not attempt to estimate effect sizes or test these hypotheses using observational or interventional datasets. In a future v2 system, we plan to integrate DEMOCRITUS with quantitative causal inference tools, so that these edges can be assigned data-driven strengths and subjected to genuine causal validation.

Even in the absence of numerical datasets, scientists routinely seek causal explanations for events that cannot be experimentally replicated (e.g., the extinction of the dinosaurs, the collapse of the Indus Valley civilization). In such domains, evidence accumulates through the consilience of multiple partial traces: geological strata, inscriptions, settlement patterns, and so on. DEMOCRITUS v1 is designed for exactly this setting: it aggregates and geometrically organizes textual causal claims into a coherent hypothesis manifold, allowing researchers to see which mechanisms recur across sources and where contradictions or gaps remain. In future work, we aim to augment this textual aggregation with quantitative causal calculus when suitable datasets or simulations are available.

We emphasize that DEMOCRITUS does not attempt to replace formal causal inference or identification strategies. The LCMs it constructs are best viewed as structured *hypothesis spaces* and *narrative maps*: they make explicit what the LLM *implicitly* “knows” about causal structure given its training data, but they do not guarantee identifiability or causal correctness in the sense of Imbens and Rubin (2015); Pearl (2009). Rather, they provide:

- a way to explore how different mechanisms and variables are linked in the model’s knowledge,
- a source of candidate mechanisms and confounders for domain experts,
- a geometric substrate on which more formal causal discovery methods could operate.

In this sense, DEMOCRITUS is closer to a “legal discovery” or “literature review” tool than to a parametric structural model. It organizes and visualizes what an LLM already “knows” about a domain, and offers a starting point for human experts and traditional causal tools to dig deeper.

2 Related Work

DEMOCRITUS sits at the intersection of several research threads: causal relation extraction from text, causal knowledge base construction, large language models (LLMs) for causal discovery and reasoning, and causality-aware NLP more broadly. We briefly review each area and emphasize how DEMOCRITUS differs.

2.1 Causal relation extraction from text

There is a long line of work on identifying causal relations from natural language, ranging from early pattern and cue-phrase methods to modern neural models; see, for example, recent surveys on causal relation extraction and event causality in text (e.g. (Yang et al., 2022; He et al., 2025)). Classical systems often rely on handcrafted patterns and lexical cues such as “because” or “leads to”, while more recent approaches use supervised or semi-supervised neural architectures (including BERT variants) trained to classify whether a pair of spans in a sentence stands in a causal relation (Radinsky et al., 2012). These models typically operate at the level of individual sentences or local contexts and predict pairwise labels.

In contrast, DEMOCRITUS assumes that an LLM can already express causal relations in natural language, and uses the model as a generative source of causal statements. The focus is not on marginally improving pairwise classification accuracy, but on wiring thousands of such statements into large, multi-hop causal graphs that can be explored at different scales and embedded into manifolds.

2.2 Causal knowledge bases and graphs from corpora

Beyond pairwise extraction, several projects aim to construct causal knowledge bases or causal graphs from large corpora (Hassanzadeh et al., 2020). These systems mine causal tuples from text and aggregate them into graph-structured resources (“causal KBs”, causal mind-maps, etc.). Recent work has explored building such resources from specific domains (e.g. maintenance logs, scholarly articles) and evaluating them on downstream tasks.

DEMOCRITUS is similar in spirit, but differs in three ways. First, it heavily exploits LLMs rather than classic pattern-based or supervised models: Qwen3 is used to propose the variables, the causal questions, and the causal narratives themselves. Second, the output is not only a set of triples, but a navigable *LCM*: nodes are embedded via a Geometric Transformer and UMAP into 2D/3D spaces with interpretable local neighborhoods. Third, DEMOCRITUS is explicitly slice-based: causal graphs are organized as domain-specific slices (econ, bio, Indus Valley, ...) inside a larger topos-style architecture.

2.3 Large language models for causal discovery and reasoning

A rapidly growing literature investigates the use of LLMs for causal discovery, causal reasoning, and explanation. Some works treat LLMs as “meta-experts” that can propose causal directions or graph structures given textual descriptions of variables or data (Shen et al., 2023). Others use multi-agent LLM setups to discuss and refine candidate DAGs (Le et al., 2024), or probe LLMs’ internal representations for causal notions such as interventions and counterfactuals (Kosoy et al., 2023).

DEMOCRITUS occupies a complementary role. Rather than delegating causal discovery to the LLM directly, we ask the model to articulate causal *propositions* in natural language (topics, questions, statements), then treat these as noisy inputs to a separate causal representation pipeline. The relational graphs and manifolds that Democritus constructs can

be used by classical causal discovery algorithms or LLM-based reasoners, but the system itself is not a causal learner in the sense of recovering ground-truth DAGs from observational data.

2.4 Causality and NLP more broadly

More broadly, the intersection of causality and NLP has attracted significant attention, including work on causal effects of text, counterfactual data augmentation, and causal explanations for model predictions; see, e.g., recent CausalNLP reading lists and surveys (Jin et al., 2021). Democritus contributes a different perspective: rather than using causal ideas to *improve* NLP models, it uses NLP (in the form of LLMs) to construct explicit, structured causal artifacts that can be shared across domains and inspected by humans and other systems.

3 A Summary of How DEMOCRITUS Works

We begin by summarizing how DEMOCRITUS works and what it can produce, before getting into theoretical and implementation details. We show local causal models, which are simply neighborhoods near a causal variable, and manifold projections of LCMs learned in a number of domains.

3.1 A running example: influencer marketing

To illustrate what DEMOCRITUS builds, consider the neighborhood of an LCM shown in Figure 3. The focus node is the topic “*Building Long-Term Influencer Partnerships vs. One-Time Campaigns*”. Around this topic, DEMOCRITUS has constructed a small directed causal graph that includes variables such as “*long-term influencer partnerships*”, “*one-time campaigns*”, “*higher brand loyalty among followers by fostering consistent and relatable brand messaging*”, “*higher engagement rates than isolated promotional efforts due to deeper audience investment and repeated exposure*”, and “*the perceived authenticity of a brand compared to sustained collaborations*”. Arrows indicate causal directions (e.g. long-term partnerships *lead to* higher engagement and brand loyalty), and node size/colour reflects GT activations over this local graph.

Crucially, this structure is not the output of a single clever prompt to an LLM. No one-shot query of the form “*Explain the causal effects of long-term influencer partnerships versus one-time campaigns*” would return a navigable 2-hop graph with typed edges, shared variables, and a geometric notion of salience. The graph in Figure 3 arises from the entire DEMOCRITUS pipeline:

1. **Topic graph:** Qwen3-Next-80B-A3B-Instruct is first asked, in Module 1, to propose subtopics under marketing and influencer campaigns (e.g. long- term partnerships, one-time campaigns, brand authenticity, audience trust).
2. **Causal statements:** For each such topic, Modules 2–3 query Qwen3-Next-80B-A3B-Instruct for short statements of the form “*X causes Y*” or “*X leads to Y*” that describe causal relations in this niche.
3. **Triples and graph:** Module 4 extracts (subject, relation, object) triples from these sentences and wires them into a directed multi-relational graph whose nodes are phrases (e.g. “*long-term influencer partnerships*”, “*higher engagement rates*”).
4. **Local neighborhood and GT:** Finally, we take the 2-hop ego-graph around the focus node and run a Geometric Transformer layer over it, yielding the local causal neighborhood and activations visualised in Figure 3.

In this sense, DEMOCRITUS is not simply a prompting technique; it is a *structure-building* system. The LLM supplies fragments of causal knowledge, but the topic graph, triple extraction, and GT-based manifold together turn those fragments into a reusable object: a local causal model embedded in a larger economics topos slice. The rest of the paper generalizes this story from influencer marketing to other domains (macroeconomics, labor markets, biology, archaeology), and shows how DEMOCRITUS can selectively deepen such models in response to user tasks.

3.2 Building LCMs using the Geometric Transformer and Topos Causal Models

At the theoretical core of DEMOCRITUS lies two innovations: an implementation of the Geometric Transformer (GT) first theoretically conjectured in (Mahadevan, 2024) whose implementation details will be described in a forthcoming paper (Mahadevan, 2026). Second, a framework for causal data integration was used that builds on our previous work on a decentralized map-reduce framework for learning Topos Causal Models (Mahadevan, 2025a). We will describe each of these innovations in greater detail below, but briefly summarize the main ideas here and then show their results in a constructed LCM for several domains, ranging from biology to economics to Indus Valley archaeology.

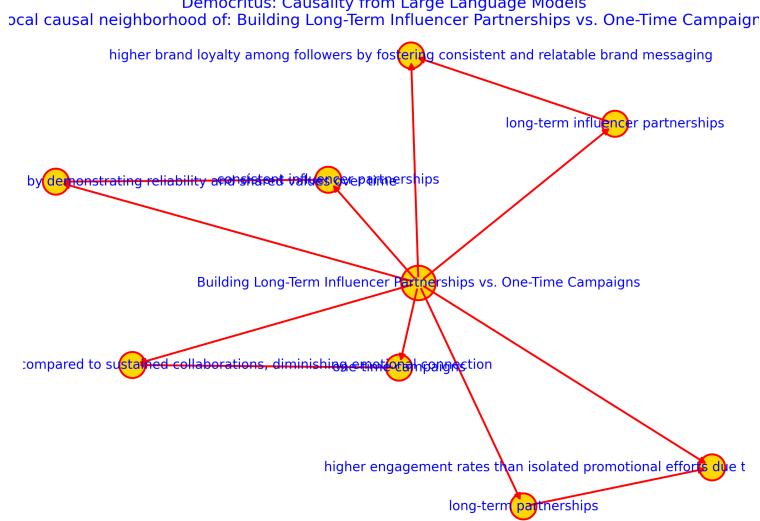


Figure 3: A neighborhood region of an LCM around the topic “*Building Long-Term Influencer Partnerships vs. One-Time Campaigns*”. Nodes are variables/phrases; red arrows indicate causal directions; node size/colour reflects GT activations. This structure arises from DEMOCRITUS’ multi-step pipeline (topic graph, causal statements, triple extraction, GT), not from a single prompt.

We ran DEMOCRITUS on 90,016 synthetic relational causal statements across 9 domains, from which a relational causal triples extracting module extracted 54,514 unique concepts and 57,390 typed relations. The Geometric Transformer with Diagrammatic Backpropagation (Mahadevan, 2026) then constructed a resulting multi-relational simplicial complex contains between 553 and 1,336 regime triangles per domain (approximately 9k 2-simplices in total). The 3D UMAP projection (Figure 4) reveals coherent domain clusters with smooth transition zones exhibiting stratified domain sheets and cross-domain membranes that classical knowledge graph embeddings fail to capture. Each sentence contains a linguistic relation (causes, influences, supports, prevents, is-a, part-of, etc.), and the model constructs a multi-relational simplicial complex. The causal statements generated across 60 topical areas (economics, AI, public health, climate, demographics, etc.). Each statement is of the form

$$X \text{ increases } Y, \quad X \text{ reduces } Y, \quad X \text{ leads to } Y,$$

and we extract causal triples to form a 1–simplicial causal graph. Semantic domains supply 2–simplices, producing a causal site.

3.3 LCMs: A Global View

Figure 4 shows the 3D UMAP embedding of the refined diagrammatic causal geometry. The manifold reveals several phenomena:

- **Macro-domain structure:** climate, inflation, vaccination, supply chains, mental health, and AI each form distinct regions.
- **Causal gradients:** e.g. a clear transition from energy-related factors → electricity demand → carbon emissions → climate impacts.
- **Cross-domain interactions:** e.g. “generative AI” lies at a hub connecting education, productivity, misinformation, and creativity domains.

3.4 Contrasting Domain and Relational LCMs

Figure 5 and Figure 6 contrast two types of LCMs learned by DEMOCRITUS: one projects the causal data into the domain space, and the other projects the data onto the specific type of causal relationship.

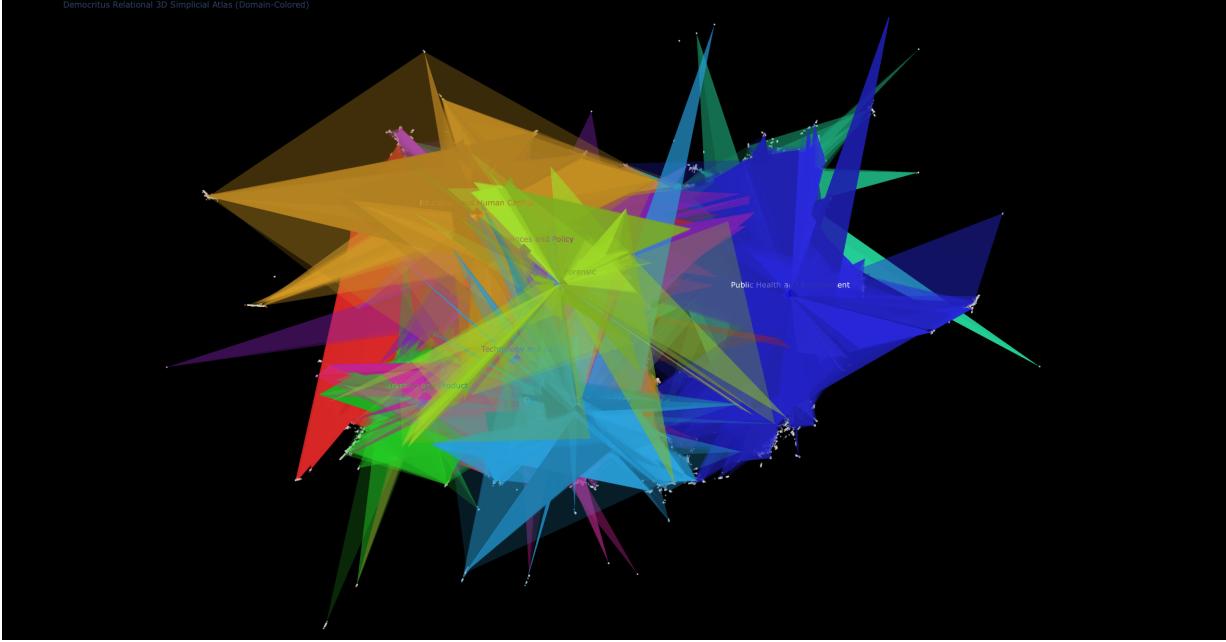


Figure 4: **Democritus LCM.** 3D UMAP projection of an LCM constructed from over 90,000 causal textual statements sampled from GPT models in over 10 domains. The structure exhibits clear domain clustering and smooth causal transition regions.

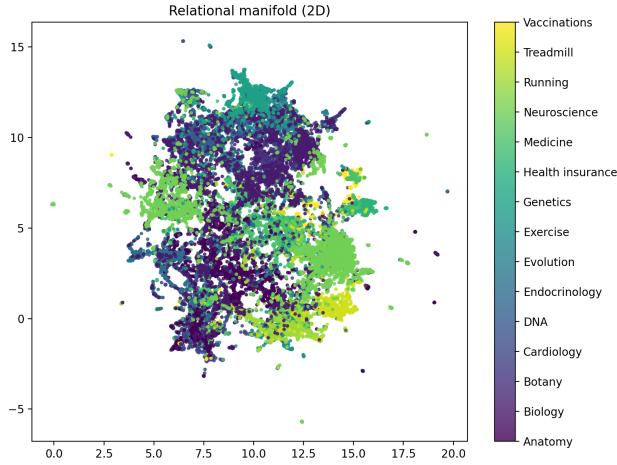


Figure 5: A 2D UMAP projection of an LCM for biology.

3.5 LCMs: A Local Projection on Neighborhoods

Figures 7–8 visualize 1-hop causal neighborhoods. These reveal that the learned LCM recovers interpretable causal structure:

- Electricity demand is linked to heating, cooling, EV charging, industrial activity, and insulation quality.
- Minimum wage connects to employment, consumer spending, inflation, and business closures.
- Daily online users reveal strong ties to content quality, load balancing, advertising spend, and recommendation algorithms.

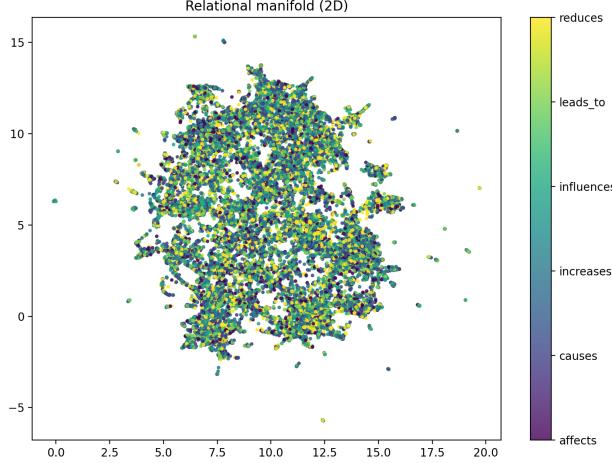


Figure 6: A relational LCM for a biology domain.

3.6 Causal Degree Structure

Figure 9 shows the degree distribution of the causal graph. The heavy-tailed structure suggests the existence of high-impact causal variables such as stress, inflation, vaccination, generative AI, and exercise — all of which emerge as central causal hubs in the manifold.

3.7 Interpretation

These experiments show that the learned LCMs produce a coherent system of causal beliefs from raw textual statements. The learned LCM demonstrates:

- global causal coherence,
- domain separation,
- cross-domain bridges,
- interpretable local neighborhoods,
- and causal hubs that resemble domain expertise.

4 System overview

Figure 10 shows the overall Democritus pipeline for a single domain slice (e.g. economics or biology). The modules are:

1. **Topic graph (Module 1).** Build a topic hierarchy via LLM-driven breadth-first expansion.
2. **Causal questions (Module 2).** For each topic, generate causal questions.
3. **Causal statements (Module 3).** For each topic, generate causal statements or explanations.
4. **Relational triples (Module 4).** Extract subject–relation–object triples from questions and statements.
5. **Relational manifold (Module 5).** Embed the relational graph with a Geometric Transformer, and compute a low-dimensional manifold (2D/3D) for visualization.
6. **Topos slice and unification (Module 6).** Store the resulting slice, optionally unify multiple slices, and make them available to downstream intuitionistic causal reasoners using Judo calculus (Mahadevan, 2025b).

In the current implementation, each LCM is built independently for a given domain (e.g. economics, biology), and the Geometric Transformer operates at the level of each slice. Figure 10 gives a high-level overview of the DEMOCRITUS pipeline. We briefly describe each module, illustrating with the economics (econ) and biology (bio) slices constructed in our current implementation.

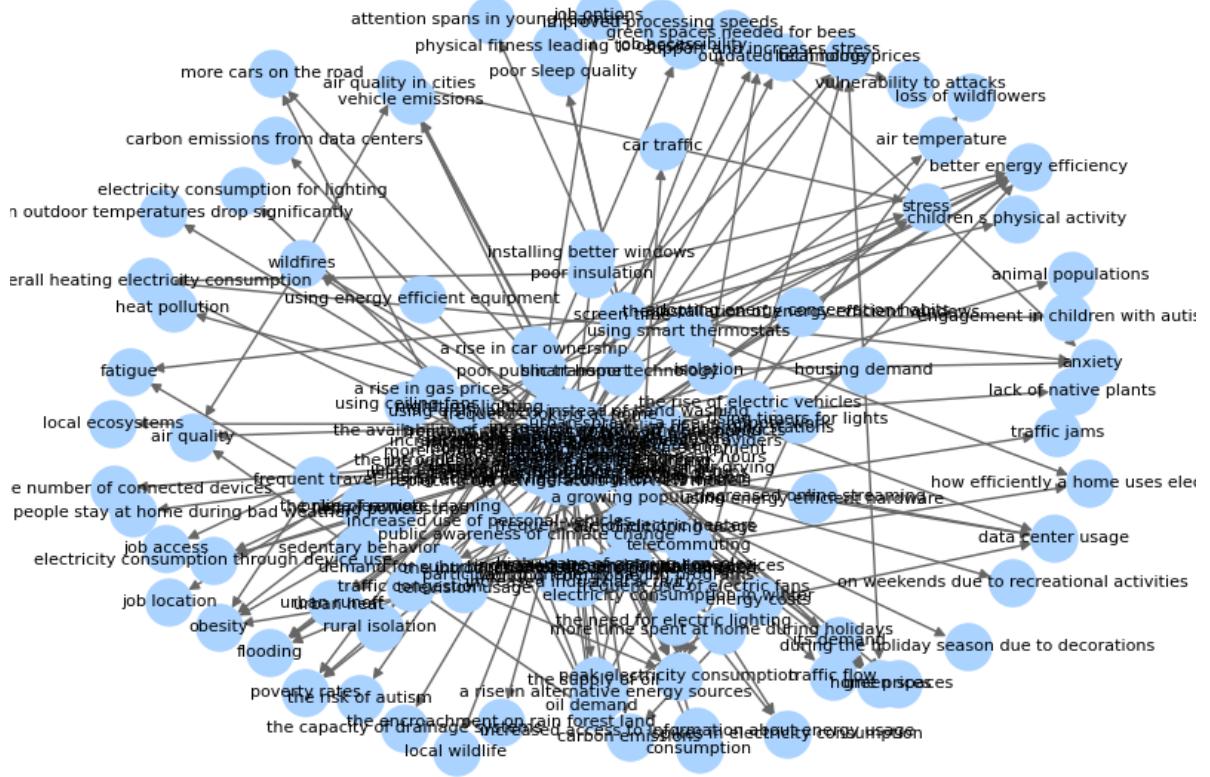


Figure 7: Electricity demand causal neighborhood. Democritus recovers the natural causal cluster of heating/cooling, EV charging, industrial activity, insulation, and demand-side behavior.

4.1 Module 1: Topic graph

Given a set of root topics (e.g. Macroeconomics, Microeconomics, Game Theory, Finance, Trade, Marketing, Stock Market, Investing, Cryptocurrency, Bonds, Monetary Policy, Banking, Fiscal Policy, Inflation, Unemployment), we perform a breadth-first search (BFS) expansion using Qwen3-Next-80B-A3B-Instruct-6bit. At each node the LLM is prompted to list a small number of subtopics; these become children in the topic graph.

A typical run with depth limit 5 and maximum 7000 topics in the domain of economics yields a rich hierarchy including subtrees for monetary policy, game theory, cryptocurrency/DeFi, bond markets, agricultural subsidies, and so on. An analogous bio run with roots such as Neuroscience, Genetics, Evolution, Botany, Cardiology yields a similarly rich hierarchy.

The output of this module is:

- a JSONL topic graph (`topic_graph_econ.jsonl`, `topic_graph_bio.jsonl`),
 - a tabular topic list with depths (`topic_list_econ.txt`, `topic_list_bio.txt`).

4.2 Modules 2 and 3: Causal questions and statements

For each topic in the graph, we prompt Qwen3 to generate:

- causal questions (Module 2), e.g. “*What causes a rise in the price of gold?*”, “*What leads to a leftward shift in the demand curve?*”

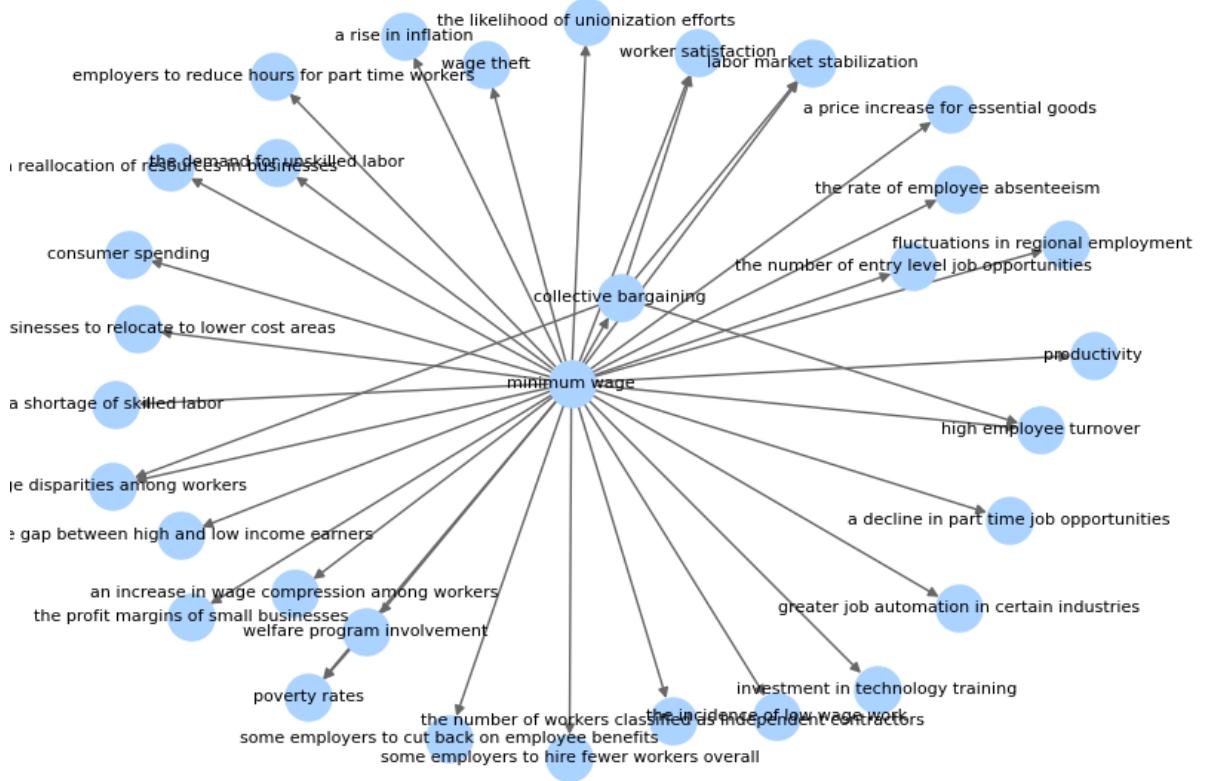


Figure 8: **Minimum wage causal neighborhood.** A coherent causal cluster emerges: employment dynamics, consumer spending, inflationary pressure, and labor productivity.

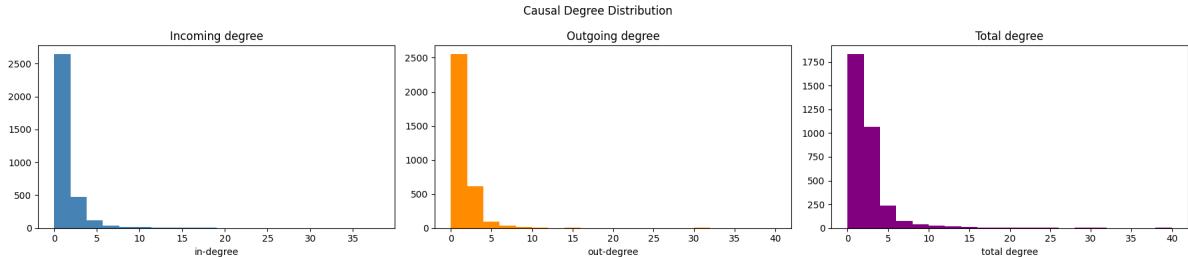


Figure 9: **Causal degree distribution.** The causal graph exhibits a heavy-tailed distribution with recognizable real-world “high-impact drivers” emerging as hubs.

- causal statements or explanations (Module 3), e.g. “*Increased demand for gold as a safe-haven asset during economic uncertainty causes its price to rise.*”

These are stored as JSONL files (`causal_questions.jsonl`, `causal_statements.jsonl`) with fields for topic, path, question, and an array of statements. For example, an econ entry might read:

```
{"topic": "Macroeconomics", "path": ["Macroeconomics"], "question": "What causes a rise in the price of gold?", "statements": ["Increased demand for gold as a safe-haven asset during economic uncertainty causes its price to rise.", "A decline in the value of the U.S. dollar leads to higher gold prices due to its inverse correlation.", ...]}
```

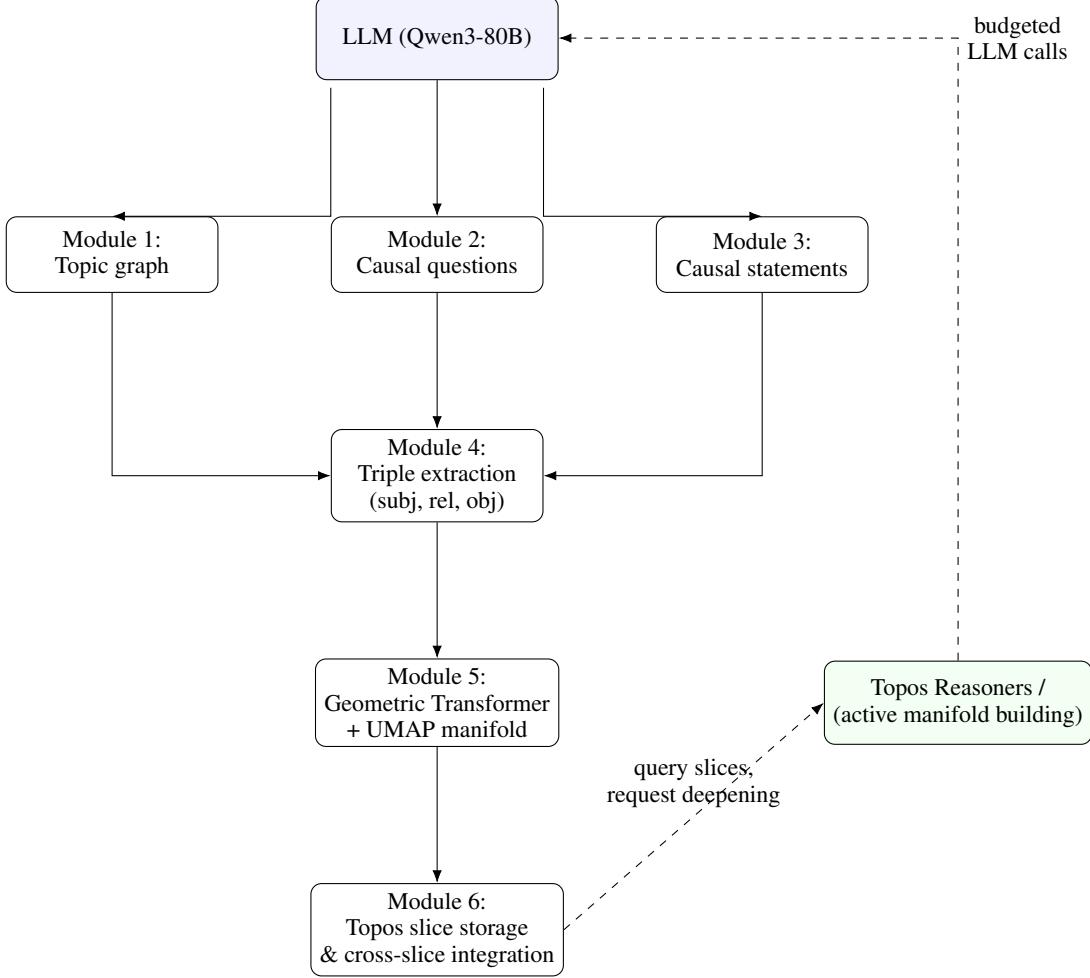


Figure 10: High-level DEMOCRITUS pipeline. Modules 1–3 use the LLM to propose topics, causal questions, and statements. Module 4 extracts triples and builds a relational graph. Module 5 applies a Geometric Transformer and UMAP to obtain a LCM. Module 6 stores domain-specific slices and supports cross-slice integration. A topos reasoner (e.g., Judo calculus (Mahadevan, 2025b)) can be used to actively query slices and request further LLM calls in selected regions.

4.3 Module 4: Relational triples

From questions and statements we extract relational triples of the form (subj, rel, obj), e.g.

“demand for gold”, causes, “price of gold rises”.

These triples define a directed multi-relational graph over phrases or variables with relation types such as `causes`, `increases`, `influences`, `leads_to`, `reduces`. In practice we obtain hundreds to thousands of triples even for small runs (e.g. depth 2, 100 topics), and many more for larger runs.

4.4 Module 5: Refining the LCM via the Geometric Transformer

We then embed the relational graph using a Geometric Transformer (Mahadevan, 2024). Nodes carry initial text-based embeddings from sentence encoders or LLM-derived vectors; GT passes messages along edges (1-simplices) and optionally across higher-order motifs (e.g. triangles as 2-simplices), and produces refined node embeddings. A low-dimensional manifold is obtained via UMAP. Even small runs show dense, semantically coherent clusters; larger runs (e.g. 7000 topics at depth 5) yield richer, thicker models.

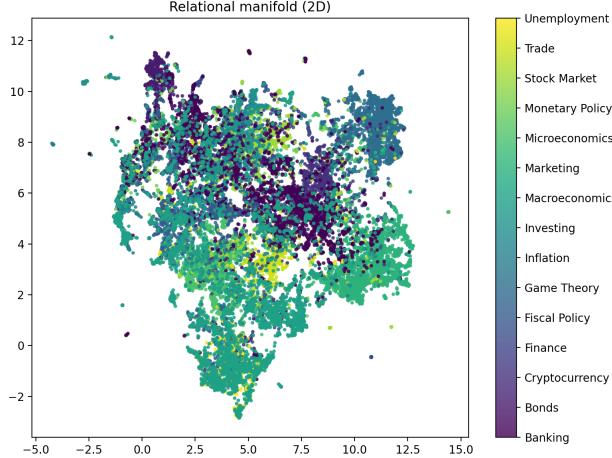


Figure 11: The global LCM for an economics domain over $\sim 35,000$ variables.

4.5 Module 6: Topos slices and unification

Each domain (econ, bio, etc.) yields a slice: a relational graph with structured embeddings, visualizations, and metadata. These slices are stored as persistent objects, and can be unified or queried jointly. Controllers built around topos reasoners, such as Judo Calculus (Mahadevan, 2025b), can treat these slices as structured external memory, asking to deepen specific regions or relate patterns across domains.

Figure 11 shows the result of running all the six modules on an economics domain using the Qwen3-Next-80B-A3B-Instruct LLM, where the resulting manifold is over almost $\sim 35,000$ variables.

5 A Walk Through of the DEMOCRITUS Pipeline

We highlight a single path through this pipeline, starting from the topic **Macroeconomics** and ending in a local causal neighborhood around gold prices in the global manifold.

1. Topic expansion (Module 1)

Given an initial list of root topics, DEMOCRITUS asks Qwen3-Next-80B-A3B-Instruct to propose subtopics for each parent. For example, for the root topic **Macroeconomics** we issue a prompt of the form:

Prompt (topic expansion).

```
You are an expert economics textbook author.  
Given the topic "Macroeconomics", list 10 important subtopics.  
Return only a numbered list of subtopics, one per line.
```

Qwen3-Next-80B-A3B-Instruct responds with subtopics such as:

1. Gross Domestic Product (GDP) and its measurement
2. Inflation and price indices
3. Unemployment types and rates
4. Fiscal policy and government spending
5. Monetary policy and central banking
6. Aggregate demand and aggregate supply
7. Business cycles and economic fluctuations
8. International trade and balance of payments
9. Exchange rates and foreign exchange markets
10. Long-run economic growth and productivity

Each line becomes a child node in the topic graph, with a depth counter (0 for roots, 1 for their children, etc.). Similar prompts expand subtopics under **Microeconomics**, **Game Theory**, **Finance**, and so on, yielding a directed acyclic graph of several thousand topics at depths up to 5.

2. Causal questions and statements (Modules 2 and 3)

For each topic in the graph, DEMOCRITUS next asks Qwen3-Next-80B-A3B-Instruct to generate causal questions and statements. For example, for the topic **Macroeconomics** we might ask:

Prompt (causal questions).

You are an expert in macroeconomics.

Topic: "Macroeconomics".

Write 3 causal questions a student might ask about this topic.

Each question should start with "What causes" or "What leads to".

Prompt (causal statements).

For the topic "Macroeconomics", write 3 short statements of the form "X causes Y" or "X leads to Y" that describe causal relationships in this topic.

The model might respond with a question such as:

"What causes a rise in the price of gold?"

and statements such as:

"Increased demand for gold as a safe-haven asset during economic uncertainty causes its price to rise."

"A decline in the value of the U.S. dollar leads to higher gold prices due to its inverse correlation."

"Geopolitical instability influences investor behavior, resulting in greater gold accumulation and higher prices."

Similar prompts are issued for hundreds or thousands of topics (e.g. Inflation, Unemployment, Fiscal Policy, Cryptocurrency, Systemic risk identification and monitoring frameworks, etc.), producing a large collection of causal sentences.

3. Triples and causal graphs (Module 4)

From the questions and statements, DEMOCRITUS extracts relational triples of the form (subject, relation, object). For the gold example above, this yields entries such as:

(“demand for gold as a safe-haven asset”, causes, “price of gold rises”),
 (‘decline in the value of the U.S. dollar’, leads_to, “higher gold prices”),
 (“geopolitical instability”, influences, “gold accumulation and prices”).

Collecting triples across all topics yields a directed multi-relational graph whose nodes are phrases/variables and whose edges carry relation types such as **causes**, **increases**, **influences**, **leads_to**, **reduces**. Even a small run at depth 2 with 100 topics produces several hundred such nodes and edges; a larger run at depth 5 with 7000 topics yields tens of thousands.

4. Manifold embedding and local views (Module 5)

To organize this graph, DEMOCRITUS applies a Geometric Transformer layer over the triples. Nodes are initialized with text-based embeddings; GT passes messages along edges and across higher-order motifs (e.g. triangles of variables), producing refined node embeddings. Applying UMAP to these embeddings yields a 2D/3D visualization.

6 Causal graph construction and manifold refinement

In this section we briefly describe how DEMOCRITUS turns LLM-derived triples into a refined LCM. Our goal is to explain the process we actually use in the system, without developing the full theoretical machinery, which can be found in our earlier publications (Mahadevan, 2024).

6.1 Relational causal graph construction

After Modules 1–3 have generated causal questions and statements for a given slice (e.g., economics, biology, Indus Valley), Module 4 extracts typed triples of the form (head, relation, tail) along with a domain label, following the standard OpenIE-style parsing. We then build a variable-level relational graph:

- Each distinct head or tail string becomes a variable node $v \in V$ (e.g. “chronic stress”, “cardiovascular risk”).
- For each triple (h, r, t) we add a directed edge $h \rightarrow t$ of relation type r and domain label d (e.g. biology, economics).
- This yields a multi-relational directed graph $G = (V, E, \text{rel}, \text{dom})$ which aggregates causal statements across all topics in the slice.

Edge multiplicities and domain labels encode how often and in which subdomains a given mechanism is asserted. The result is a large, sparse, heavy-tailed causal graph (Section 10.1) with a few high-degree variables (hubs) and many low-degree fringe nodes.

6.2 Higher-order message passing

To refine and denoise the raw relational graph, we apply a small higher-order message-passing network before running UMAP. In our current implementation, DEMOCRITUS uses a lightweight two-layer architecture with both edge-level and triangle-level aggregation:

- Each variable node v starts with an initial embedding $\mathbf{h}_v^{(0)}$ obtained from a sentence encoder applied to the variable string (we use a standard transformer-based encoder).
- At each message-passing layer $\ell+1$, we update $\mathbf{h}_v^{(\ell+1)}$ by aggregating messages from its neighbours u along edges $u \rightarrow v$, weighted by learned embeddings of the relation type and domain label. This is a standard edge-based message-passing step.
- In addition, we detect simple higher-order motifs (triangles) where $(u \rightarrow v)$ and $(v \rightarrow w)$ share the same domain; these define 2-simplices (u, v, w) in the graph. We aggregate messages over such triangles and add them as an extra term to the update, so variables that participate in many coherent motifs are nudged towards each other in the embedding space.

This results in a refined embedding \mathbf{h}_v for each variable that smooths over local inconsistencies and takes higher-order structure into account (e.g. chains and triangles of causal influence), without requiring any labeled supervision. Conceptually, this is a simple instantiation of higher-order geometric message passing over a causal graph; more sophisticated versions are possible, but we find this lightweight architecture sufficient for the slices considered here.

6.3 Manifold embedding and visualization

Finally, we run UMAP on the refined embeddings $\{\mathbf{h}_v\}_{v \in V}$ to obtain two- and three-dimensional coordinates for each variable. The resulting low-dimensional manifold exhibits coherent clusters corresponding to subdomains and mechanisms (e.g. stress and cardiometabolic risk, Indus monsoon and river discharge). In Section 10 we examine the degree distributions, Laplacian spectra, and stability of these graphs and manifolds, and show that the resulting structures are sparse, heavy-tailed, and robust to modest noise and repeated runs.

7 Comparative Experiments

We report on some preliminary baseline experiments that show the effect of using the Geometric Transformer in constructing LCMs, as opposed to a naive use of UMAP to directly construct embeddings.

7.1 Baseline Experiment 1: Modules 1 through 4 only

Suppose we just use UMAP to construct manifold embeddings of the relational triples extracted from Modules 1 through 4. Does that reveal the same structure? Figure 12 shows that without the Geometric Transformer, the UMAP-generated embeddings are a like a “giant hairball” with no discernible structure. This experiment used the economics domain, with almost 35,000 causal variables extracted from a run on Qwen3-80B. Clearly, comparing the plot produced earlier in Figure 11, we can see that UMAP alone is unable to discover the deep structure of the global economics LCM, even

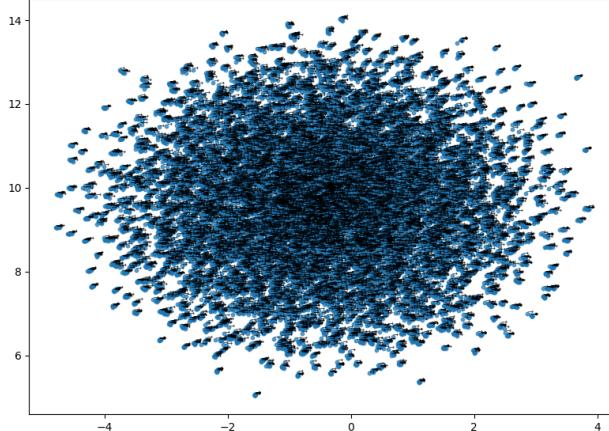


Figure 12: The unstructured LCM that results from running UMAP on causal triples over $\sim 35,000$ variables, without using the Geometric Transformer.

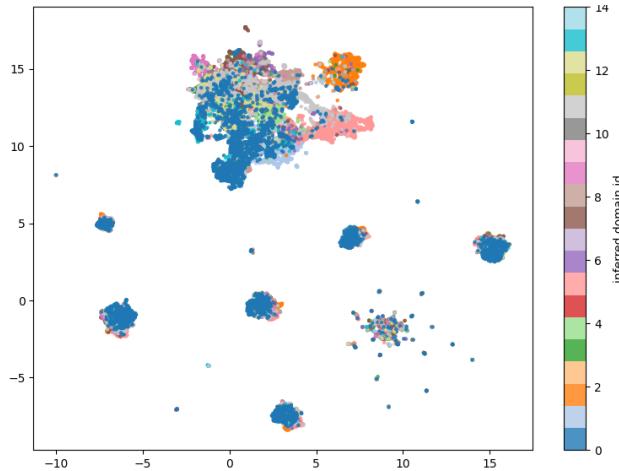


Figure 13: The LCM structure discovered by Modules 1 through 5, including the Geometric Transformer refinement.

given the same exact relational triples embedded in a high-dimensional space using a Sentence Transformer encoder like BERT.

7.2 Baseline Experiment 2: Adding the Geometric Transformer only

Now, we extend the previous baseline experiment of running Modules 1 through 4 only and producing the UMAP embedding shown in Figure 12 by adding the Geometric Transformer in Module 5. Figure 13 shows the results, again over the economics domain of $\sim 35,000$ variables. Now, we see the effect of the Geometric Transformer, where the structural aspects of the economics LCM snap into sharp relief. There are clearly discernible structures across the various subfields of economics.

7.3 Baseline Experiment 3: Adding the Causal Refinement Step

To complete the baseline experiments, we now show the effect of the causal refinement step, where we now begin to introduce actual causal experimental on the manifold structure shown in Figure 13. The result is shown in Figure 14. Now we begin to see edges form between major hubs in the economics manifold. These edges correspond to real causal effects, such as:

government spending \rightarrow an increase in aggregate demand by injecting more money into the economy
inflation \rightarrow the purchasing power of consumers by raising the prices of goods and services
unemployment \rightarrow overall economic growth by lowering household income and consumer spending

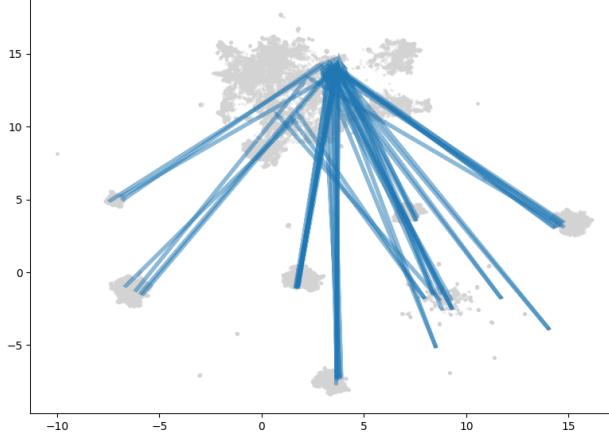


Figure 14: This figure shows the effect of the causal refinement layer, which brings in causal inference to refine the $\sim 35,000$ economics LCM.

increased competition \rightarrow the profitability of small firms by compressing profit margins
 game theory \rightarrow players to adopt strategic behaviors in competitive environments
 the presence of nash equilibrium \rightarrow how rational agents make decisions over time
 uncertainty in payoffs \rightarrow the risk of suboptimal outcomes in non-cooperative games
 increased government debt \rightarrow long-term economic growth by crowding out private investment,

A key limitation of the current version of DEMOCRITUS is that the plausible causal relationships it proposes are not yet validated against numerical data or controlled experiments. In this paper we focus on the *hypothesis generation and organization* problem: extracting and geometrically structuring candidate causal edges from text. We do not attempt to estimate effect sizes or test these hypotheses using observational or interventional datasets. Accordingly, in Figure 14 all edges are drawn with a default weight of 1.0, purely for visualization. In a future v2 system, we plan to integrate DEMOCRITUS with quantitative causal inference tools, so that these edges can be assigned data-driven strengths and subjected to genuine causal validation.

Even in the absence of numerical datasets, scientists routinely seek causal explanations for events that cannot be experimentally replicated (e.g., the extinction of the dinosaurs, the collapse of the Indus Valley civilization). In such domains, evidence accumulates through the consilience of multiple partial traces: geological strata, inscriptions, settlement patterns, and so on. DEMOCRITUS v1 is designed for exactly this setting: it aggregates and geometrically organizes textual causal claims into a coherent hypothesis manifold, allowing researchers to see which mechanisms recur across sources and where contradictions or gaps remain. In future work, we aim to augment this textual aggregation with quantitative causal calculus when suitable datasets or simulations are available.

8 DEMOCRITUS: A Causal Observatory Learned from Language

We can view DEMOCRITUS as a large-scale “Causal Observatory” that constructs LCMs directly from natural-language causal statements.

From Causal Text to a Simplicial Causal Complex. Starting with thousands of statements of the form

$$\text{“}X \text{ increases } Y\text{”,} \quad \text{“}A \text{ reduces } B\text{”,} \quad \text{“}C \text{ causes } D\text{”,}$$

we extract causal triples ($X \rightarrow Y$) and cluster them into coarse *domains* (e.g. climate, economics, public health). These domains induce 2-simplices whose vertices are variables and whose edges are causal relations, producing a causal simplicial set.

LCM Learning Using the Diagrammatic Backpropagation Geometric Transformer, we propagate causal information across the simplicial complex, enforcing compatibility between overlapping causal regimes. The resulting embeddings are passed to UMAP to obtain a two- or three-dimensional LCM (Fig. 4). This manifold reveals:

- **Coherent macro-domains** (e.g. “climate change causes...”, “inflation causes...”, “vaccination reduces...”).

- **Cross-domain causal bridges** representing multi-factor interactions.
- **Topological neighborhoods of causal influence:** variables that lie near one another tend to share similar causal roles across multiple regimes.

9 Cost structure and limitations of naive BFS

DEMOCRITUS uses a high-quality LLM (Qwen3-Next-80B-A3B-Instruct-6bit) in Modules 1–3. Geometric Transformers and UMAP (Module 5) are comparatively cheap. Table 1 shows timing profiles for a small econ run (depth 2, 100 topics) and a larger run (depth 5, 1000 topics; illustrative numbers).

| Module | Econ (100 topics, depth 2) | Econ (1000 topics, depth 5) |
|-------------------------|----------------------------|-----------------------------|
| 1: Topic graph | 13.5 s | ~750 s |
| 2: Causal questions | 104.3 s | ~730 s |
| 3: Causal statements | 139.6 s | ~1400 s |
| 4: Triples | 0.1 s | ~1 s |
| 5: Manifold (GT + UMAP) | 7.5 s | ~4 s |
| Total | 264.9 s | ~2900 s (~48 min) |

Table 1: Illustrative timing profile for DEMOCRITUS econ slices. LLM calls in Modules 1–3 dominate; GT and UMAP are cheap. Larger runs (e.g. 7000 topics) can take many hours if we naively expand all nodes to depth 5.

At small scales (100 topics) a full run completes in minutes. At larger scales (e.g. 7000 topics, depth 5), Modules 1–3 alone can consume many hours of wall-clock on a single Mac Studio. Empirically, the cost is approximately linear in the number of topics and the number of topics for which we generate questions and statements.

Moreover, naive BFS treats all branches equally. As a sample output from the econ run shows, Qwen3-Next-80B-A3B-Instruct-6bit happily expands topics such as:

- *Military infrastructure and base maintenance,*
- *Cybersecurity and information warfare funding,*
- *Administrative costs and efficiency in public insurance programs,*
- *Environmental incentive programs for sustainable farming practices,*
- *Systemic risk identification and monitoring frameworks,*
- *Stress testing methodologies for financial institutions and systems,*

all with similar depth and breadth, even if a particular user or task never touches those regions.

This suggests that:

1. LLM calls are the true bottleneck; GT+UMAP cost is negligible.
2. We should not expand all nodes to the same depth with the same query budget.
3. Structural feedback—from the topic graph, causal triples, and GT embeddings—should guide where to spend additional LLM time.

These observations motivate *active manifold building*, which we outline next.

10 Manifold structure and robustness

So far we have focused on how DEMOCRITUS constructs LCMs from LLM outputs and how these manifolds can be used for exploration and visualization. In this section we discuss more quantitative methods to analyze the resulting structures, which we are currently exploring.

1. How stable are the relational graphs and manifolds across repeated runs of the pipeline with the same configuration?
2. How does the quality of the manifold change as we vary the capacity of the teacher model (e.g. 8B, 30B, 80B, 235B)?

3. How sensitive are the graphs and manifolds to occasional false or conflicting causal statements?
4. What spectral properties do the relational graphs exhibit, and how do these relate to the manifold geometry?

10.1 Example: spectral and scale-free structure in the bio slice

To make the discussion above concrete, we analyze the relational graph and Laplacian spectrum for the 7k-topic biology slice constructed with Qwen3-Next-80B. The resulting relational graph has $|V| = 36,720$ variables and $|E| = 21,621$ directed edges. After symmetrizing, the average (undirected) degree is approximately 1.18, while the maximum degree is 127. This confirms that the DEMOCRITUS graphs are sparse—edge count scales approximately linearly with node count—and exhibit a strongly skewed, heavy-tailed degree distribution: a small number of variables act as hubs with degree in the hundreds, while the majority of nodes have degree close to one.

The symmetrized bio graph decomposes into many connected components, corresponding to subdomains such as genetics, botany, cardiology, neuroscience, and so on. The largest connected component (LCC) contains 153 nodes and 159 edges, with average degree ≈ 2.08 and maximum degree 97. Thus even within this core island the hub–fringe structure is pronounced: a single high-degree variable connects to well over half of the component, while most nodes have degree near two.

We examine the connectivity of this LCC via the spectrum of the normalized Laplacian $\mathcal{L} = I - D^{-1/2}AD^{-1/2}$. Using a sparse eigensolver on \mathcal{L} , the first five eigenvalues are

$$\lambda_1 \approx 0, \quad \lambda_2 \approx 0.056, \quad \lambda_3 \approx 0.080, \quad \lambda_4 \approx 0.138, \quad \lambda_5 \approx 0.293.$$

The zero eigenvalue reflects connectivity of the component, while the positive Fiedler value $\lambda_2 \approx 0.056$ indicates a cohesive but nontrivial community structure: the graph is neither tree-like nor fully entangled, but instead exhibits meaningful bottlenecks and clusters. We observe similar sparse, heavy-tailed, and multi-component structure in the economics and Indus slices (not shown), with a small set of high-degree hubs and many low-degree fringe nodes.

From the standpoint of robustness, this scale-free, hub–fringe geometry is important. Widely supported mechanisms (hubs) are structurally central and connected to many topics; injecting or removing a small number of edges at the periphery has little effect on their degree or on the low-frequency spectrum of \mathcal{L} . Conversely, isolated or idiosyncratic claims tend naturally to occupy low-degree, peripheral nodes, which are structurally marginal in the graph and in the induced manifold.

10.2 Stability across repeated runs

We plan to study the stability under repeated runs with the same teacher model and configuration. We fix a slice (here: [*Indus/exercise slice*]) and run Modules 1–5 of the pipeline R times with identical prompts and hyperparameters but different random seeds. This yields R relational graphs $G^{(r)} = (V^{(r)}, E^{(r)})$ and manifold embeddings $E^{(r)} \in \mathbb{R}^{N_r \times d}$.

On the shared node set $V_{\cap} = \bigcap_r V^{(r)}$ we compute:

- **Pairwise distance correlation:** for each pair of runs (r, s) we compute the correlation between the upper-triangular entries of the pairwise distance matrices of $E^{(r)}$ and $E^{(s)}$.
- **k -NN neighborhood overlap:** for each node we compute the Jaccard overlap between its k -nearest neighbors across runs and average over nodes.
- **Graph–manifold consistency:** for each run we compute the correlation between shortest-path distances in $G^{(r)}$ and Euclidean distances in $E^{(r)}$ on V_{\cap} .

We aim to report on these stability metrics in a subsequent paper. Our expectation from preliminary analysis is that the variance across runs is small, indicating that the relational graph and manifold geometry are largely stable under the stochastic sampling of Modules 1–3.

10.3 Scaling with teacher model size

We plan to also explore how manifold quality varies with the capacity of the teacher LLM. We fix a small slice configuration (*e.g.* 3 roots, depth 2, ~ 400 topics) and run the pipeline with teacher models of different sizes:

Qwen3-8B, Qwen3-30B, Qwen3-80B, Qwen3-235B.

For each teacher we obtain a relational graph and manifold embedding. On the intersection of topics that appear across models we compute the same geometry-level metrics as above (pairwise distance correlation, k -NN overlap, graph–manifold consistency), as well as basic graph statistics (node/edge count, average degree, number of components). We have qualitatively observed that larger teachers (80B and above) produce denser, more cohesive graphs (higher average degree, fewer components) and manifolds with more stable local neighbourhoods, while smaller teachers (8B) exhibit more isolated nodes and noisier geometry.

10.4 Robustness to noisy and conflicting claims

To probe robustness to occasional false or conflicting statements, we plan to construct a clean slice and a “polluted” version. In the clean condition we will run DEMOCRITUS on a small LCM and obtain a relational graph G_{clean} and manifold. In the polluted condition we inject a small set of explicitly incorrect or reversed causal statements (e.g. “exercising less improves cardiorespiratory fitness”) into the causal statement files before triple extraction, producing G_{noisy} .

We plan to compare:

- **Node degree and centrality:** degree distributions and centrality ranks for nodes/edges involved in injected false claims vs. the high-degree “hub” nodes.
- **Manifold position:** location of false-claim nodes in the UMAP embedding (distance to the core clusters).
- **Spectral stability:** changes in the Laplacian spectrum (in particular the algebraic connectivity λ_2) between G_{clean} and G_{noisy} .

We hope to find that injected incorrect statements attach to the low-degree fringe of the graph and have little effect on the degree and centrality of hub nodes. In the manifold, false-claim nodes appear as peripheral points rather than reshaping core clusters. The Laplacian spectrum, including λ_2 , should remain essentially unchanged under modest noise levels. Together, these observations may suggest that DEMOCRITUS acts as a structural aggregator: isolated false claims become marginal, while consensus mechanisms (hubs) dominate the relational structure.

10.5 Spectral and scale-free structure

Finally, we plan to examine the spectral properties and degree distributions of DEMOCRITUS graphs. For each large slice (econ, bio, Indus) we symmetrize the relational graph, compute the normalized Laplacian $\mathcal{L} = \bar{I} - D^{-1/2}AD^{-1/2}$, and extract its low-frequency eigenvalues and eigenvectors. We also compute in- and out-degree distributions. In this experiment, we hope to find that:

- Edge count scales approximately linearly with node count, so graphs are sparse.
- Degree distributions are strongly skewed/heavy-tailed: a few high-degree hubs and many low-degree fringe nodes.
- The second smallest eigenvalue λ_2 of \mathcal{L} (algebraic connectivity) is positive and moderately large, indicating cohesive graphs without severe bottlenecks.

Hubs correspond to widely supported mechanisms (e.g. “physical activity reduces cardiovascular risk”, “Indus River discharge and multi-decade droughts”) that appear in many topics and occupy central positions in the manifold. Combined with the noise experiment above, this scale-free, hub–fringe structure helps explain DEMOCRITUS’ robustness: injected noise affects low-degree fringe nodes and has little influence on the connectivity or geometry induced by the hubs.

11 Active manifold building

Another direction we are planning to explore is instead of treating DEMOCRITUS as a one-shot BFS-to-depth- D pipeline, we can view it as an *active explorer* of a LCM, analogous to:

- Legal discovery: lawyers do not read every case; they prioritize branches of doctrine that matter to a given case.
- Chess search: engines use iterative deepening and selective extensions instead of searching every line to the same depth.

- Active learning: we choose where to sample next based on current uncertainty or expected utility.

We consider each topic/node t in the topic graph as having:

- a depth $\text{depth}(t)$,
- structural properties (degree, centrality),
- textual activity (how many questions/statements mention t),
- an optional GT embedding in the current manifold.

We define a simple utility score $U(t)$ for *expanding* t :

$$U(t) = w_1 e^{-\alpha \text{depth}(t)} + w_2 \deg(t) + w_3 \text{triple_count}(t) + w_4 U_{\text{novel}}(t),$$

where $U_{\text{novel}}(t)$ is a GT-derived novelty term, e.g. inverse local density in embedding space. The weights (w_i) and depth decay α control how aggressively we prioritize shallow vs deep nodes.

Given a limited LLM budget B (number of Qwen3-Next-80B-A3B-Instruct-6bit calls we are willing to spend in a wave), an active Democritus loop can proceed as:

1. Initialize with a shallow topic graph (depth $\leq d_0$) and a small set of questions/statements for depth 0–1 topics.
2. Build an initial manifold via GT on the available triples.
3. Compute $U(t)$ for all frontier topics t at depths d_0, \dots, d_{\max} .
4. Select a batch of topics $\mathcal{B} \subseteq \{t\}$ with highest $U(t)$ (or sample proportionally to U), constrained by budget B .
5. For each $t \in \mathcal{B}$, allocate LLM calls:
 - Module 1: generate additional subtopics (children of t),
 - Module 2: generate causal questions for t ,
 - Module 3: generate causal statements for t ,
 according to a depth-aware policy (e.g. full Q&A for depth ≤ 2 , reduced Q&A for deeper nodes).
6. Update triples and rebuild or incrementally update the GT manifold.
7. Recompute $U(t)$ and repeat.

In this view, Qwen3-Next-80B-A3B-Instruct-6bit is an expensive but powerful research assistant: we only call it when $U(t)$ justifies the cost. GT serves as both a *geometric organizer* of causal structure and a *critic* that provides signals such as embedding novelty or local density.

11.1 Task-conditioned refinement

User tasks can further condition $U(t)$. For example, if a user asks an econ policy question about inflation under different monetary regimes, Democritus can:

- map the query to a set of seed topics (Inflation, Monetary Policy, Expectations),
- increase $U(t)$ for nodes in the vicinity of these seeds,
- spend budget deepening those regions via Qwen,
- present local GT neighborhoods and global manifold views back to the user.

For a question about exercise and metabolic health, the system would instead increase $U(t)$ around exercise/endocrine/metabolic clusters in the bio slice. We view this as the DEMOCRITUS analog of RLHF and task-conditioned search: rather than building a single, universal manifold, we maintain shallow priors and refine specific regions on demand.

12 Geometric Transformers and prior work

Democritus uses Geometric Transformers (GTs) to embed relational graphs into manifolds. GTs extend standard message-passing neural networks and Graph Transformers by allowing messages to flow not only along edges (1-simplices), but also across higher-order motifs (e.g. triangles as 2-simplices). Diagrammatic Backpropagation (GT+DB)

is our term for performing backpropagation through these richer computation diagrams. In a forthcoming paper (Mahadevan, 2026), we compare GT on larger synthetic and benchmark datasets to PyG baselines (GNNs, Graph Transformers). For example, in a ProGraph triangle detection task, we train on synthetic triangle/no-triangle graphs and evaluate on a ProGraph slice where the label is whether a graph contains a triangle. Table 2 summarizes the results.

| Model | ProGraph has_triangle accuracy |
|---|--------------------------------|
| Graph Transformer (edges only) | 0.5487 |
| Geometric Transformer (edges + triangles) | 1.0000 |

Table 2: Accuracy on a ProGraph slice where the task is to detect the presence of a triangle. All models are trained on a synthetic triangle/no-triangle dataset and evaluated on ProGraph graphs. GT with an explicit triangle channel generalises cleanly; an edge-only Graph Transformer does not.

These results mirror the toy triangle vs path example: when higher-order structure matters, GT’s explicit 2-simplicial channel provides an advantage. Democritus leverages this capability to organise and visualize LCMs once triples are available; the detailed architecture and algorithms of GT+DB are presented in a separate paper.

13 DEMOCRITUS Web Interface

We have constructed an interactive web-based demo that combines:

1. a birds-eye 3D view of a slice’s manifold, and
2. a local causal graph + GT activation view for a single topic and its statements.

This combination may prove useful both for explaining DEMOCRITUS to potential users and for teaching. For a full-scale economics LCM, we ran DEMOCRITUS with Qwen3-Next-80B-A3B-Instruct-6bit as the LLM, a depth limit of 5, and a cap of 7000 topics. The resulting econ slice contains 7004 topics in the topic graph and tens of thousands of causal triples. The end-to-end pipeline completed in 58124.4 seconds (approximately 16.1 hours) on a single Mac Studio. Table 3 shows the per-module timing breakdown. Modules 1–3, which rely on the LLM for topic expansion, causal questions, and causal statements, account for virtually all of the wall-clock time: 13700.4 s for topic graph construction, 31005.8 s for causal questions, and 13368.6 s for causal statements. In contrast, triple extraction (Module 4) and GT+UMAP manifold construction (Module 5) together take less than a minute (4.7 s and 44.8 s respectively). In other words, more than 99.9% of the compute budget is spent in LLM calls, and the cost of pushing the resulting relational graph through a Geometric Transformer layer and low-dimensional embedding is negligible by comparison.

| Module | Econ slice (7004 topics, depth 5) time [s] |
|----------------------------------|--|
| 1: Topic graph (Qwen3) | 13700.4 |
| 2: Causal questions (Qwen3) | 31005.8 |
| 3: Causal statements (Qwen3) | 13368.6 |
| 4: Relational triples | 4.7 |
| 5: Relational manifold (GT+UMAP) | 44.8 |
| 5.1: Write topos slice | 0.1 |
| Total | 58124.4 |

Table 3: Timing breakdown for the full economics DEMOCRITUS slice (Qwen3-Next-80B-A3B-Instruct-6bit, depth limit 5, 7004 topics) on a single Mac Studio. LLM-based Modules 1–3 dominate the cost; triple extraction and GT-based manifold construction are effectively free in comparison.

14 Limitations and Scope

DEMOCRITUS is an exploratory system to extract a coherent body of causal knowledge from textual queries to state of the art LLMs, and it is not intended to serve as a complete solution to causal inference. We briefly discuss its main limitations and the intended scope of its outputs.

Reliance on LLM knowledge and biases. The slices that DEMOCRITUS builds reflect whatever causal beliefs and associations are implicit in the underlying LLM. If the model has never seen certain mechanisms, or if it has absorbed biased or incorrect narratives, the resulting graphs and manifolds will mirror those gaps and biases. DEMOCRITUS does not correct or debias the LLM; it organizes and visualizes what the model already implicitly “knows”.

No identifiability guarantees. The structures produced by DEMOCRITUS should be viewed as structured *hypothesis spaces* and *narrative maps*, not as identified causal models in the strict sense described in (Imbens and Rubin, 2015; Pearl, 2009). We do not claim that the edges correspond to true causal effects or that confounding and selection bias have been resolved. Rather, the slices offer candidate mechanisms and variables that can inspire further analysis and formal modeling.

Hallucinations and factual correctness. Like any LLM-based system, DEMOCRITUS is vulnerable to hallucinations: some extracted triples will be factually false or overconfident. The Geometric Transformer may still organize these cleanly, giving them an appearance of coherence. Human oversight and external validation are therefore essential, especially in high-stakes domains.

Domain shifts and coverage gaps. In domains that are under-documented in text or far from the LLM’s training distribution, Democritus may miss crucial mechanisms or over-emphasize idiosyncratic anecdotes. Some slices (e.g. Indus Valley archaeology) are inherently speculative; they should be treated as computational stories to be compared against expert knowledge, not as authoritative accounts.

Computational cost and active exploration. Our timing results show that LLM calls dominate the cost of building a slice (Modules 1–3), whereas triple extraction and GT-based manifold construction are inexpensive. Naively expanding every branch of the topic graph to a fixed depth is therefore not sustainable at very large scales. This motivates the active manifold building strategies discussed in Section 11, where we allocate LLM budget to topics that are likely to yield high utility for a given slice or user task.

14.1 Beyond DAGs: towards dynamical and mechanistic models

The slices we present in this paper are, by design, relatively simple: they treat causal structure as a directed graph over variables and mechanisms, with edges extracted from statements of the form “X causes Y” or “X leads to Y”. This DAG-like view is already useful for exploration and hypothesis generation, but it is only a first step. Many of the domains we care about are fundamentally dynamical and mechanistic.

The Indus Valley case study (Solanki et al., 2025), which we used as inspiration, is not just a list of causal arrows; it combines paleoclimate archives, climate model simulations, hydrological models of Indus River discharge, and archaeological evidence about settlement patterns. In principle, one could write down a system of differential equations or a coupled climate–hydrology–agriculture model that simulates monsoon variability, river discharge, drought episodes, crop yields, and population responses over centuries. Such a model is far richer than any static DAG.

Modern LLMs open up the possibility of helping to construct and document these more sophisticated causal models. In a future version of DEMOCRITUS, we envision the slices not only as DAG-like narrative maps, but also as front-ends to mechanistic simulators: LLMs could propose variables, equations, and boundary conditions; human experts and classical numerical solvers would define and calibrate the dynamical system; and Geometric Transformers could embed the resulting state spaces and trajectories into manifolds for comparison across scenarios and domains.

In this sense, the DAG-style slices in the present paper should be understood as a minimal substrate on which more complex causal machinery can be built. Our focus here is on showing that LLMs and GTs can already produce useful structured causal maps across econ, biology, and archaeology. Extending DEMOCRITUS to assist with simulation-based causal models—differential equations, agent-based models, or structural dynamical systems—is an important direction for future work.

15 Discussion and future work

Democritus, as presented here, is deliberately modular: LLM choice, triple extraction, GT architecture, and manifold visualization can all be upgraded independently. The key lessons from our initial experiments are:

- High-quality LLMs (e.g. Qwen3-Next-80B-A3B-Instruct-6bit) are essential for building useful slices; lower-quality models produce sparse, noisy manifolds.

- LLM calls dominate the cost; GT and UMAP are negligible by comparison.
- Naive BFS to depth D wastes LLM budget on branches that may not be relevant to downstream tasks.
- Active manifold building—using structural and GT-based feedback to decide where to spend LLM calls—is both necessary and promising.

Future work includes:

- formalizing utility functions $U(t)$ and budget policies,
- integrating task-conditioned controllers that steer DEMOCRITUS based on user goals using the intuitionistic internal logic of a Topos Causal Model (Mahadevan, 2025b)
- extending GT to richer simplicial patterns (beyond triangles) and evaluating on additional benchmarks,
- and scaling DEMOCRITUS to many slices across domains (econ, bio, law, climate) with nightly or continuous updates.

15.1 Towards DEMOCRITUS-ODE: dynamical causal models

In this paper, we have treated causal structure primarily as a directed, mostly acyclic graph over variables and mechanisms extracted from language. This DAG-like perspective is already useful for exploration and hypothesis generation, but many of the domains we care about are fundamentally dynamical. For example, the Indus Valley case study in our archaeology slice involves climate model simulations, hydrological models of Indus River discharge, and multi-decadal drought episodes, which are naturally described by systems of differential equations, state-space models, or agent-based simulators.

A natural next step is to extend DEMOCRITUS beyond static graphs and toward *dynamical causal models*. In a “DEMOCRITUS-ODE” variant, one could imagine using LLMs not only to propose variables and qualitative relations, but also to suggest candidate ordinary differential equations, coupling terms, and boundary conditions for simplified dynamical systems. Human experts and classical numerical solvers would remain essential for specifying, calibrating, and validating such models, but Democritus could serve as a front-end that connects narrative causal knowledge to mechanistic simulators.

We leave this direction for future work. Our focus here is on showing that LLMs and Geometric Transformers can already produce rich, structured causal maps across economics, biology, and archaeology. These slices provide a minimal substrate on which more sophisticated dynamical causal machinery—including ODE-based models, agent-based simulations, and structural state-space systems—can be built in future versions of DEMOCRITUS.

16 Acknowledgments

This research was funded by Adobe Corporation. The simulation experiments described in this paper were carried out on a pair of Mac Studio computers, each equipped with 512 GB of RAM and an 8TB disk drive. The use of Qwen3-Next-80B-A3B-Instruct-6bit and other LLMs is intended purely as an academic research demonstration.

A Sample Topics from DEMOCRITUS Slices

To give a flavor of the content in each slice, we include brief samplings of topics discovered in the econ, bio, and Indus (Harappan) runs. These are drawn from the topic graphs produced in Module 1 and represent only a small subset of the thousands of nodes in each slice.

A.1 Economics slice (econ)

Examples of topics at depths 0–2 in the econ slice include:

- Macroeconomics
- Microeconomics
- Game Theory
- Finance
- Trade

- Marketing
- Stock Market
- Investing
- Cryptocurrency
- Bonds
- Monetary Policy
- Banking
- Fiscal Policy
- Inflation
- Unemployment

And some representative depth-1 / depth-2 subtopics:

- Gross Domestic Product (GDP) and its measurement
- Inflation and price indices
- Unemployment types and rates
- Fiscal policy and government spending
- Monetary policy and central banking
- Aggregate demand and aggregate supply
- Business cycles and economic fluctuations
- International trade and balance of payments
- Exchange rates and foreign exchange markets
- Long-run economic growth and productivity
- Callable vs. non-callable bonds
- Systemic risk identification and monitoring frameworks
- Stress testing methodologies for financial institutions
- Building long-term influencer partnerships vs. one-time campaigns

A.2 Biology slice (bio)

Examples of root topics in the bio slice include:

- Neuroscience
- Genetics
- Evolution
- Botany
- Cardiology
- Endocrinology
- Immunology
- Oncology
- Exercise physiology
- Metabolic disorders

And some representative depth-1 / depth-2 subtopics:

- Chronic stress and cardiovascular risk
- Hypertension and stroke
- Atherosclerosis and myocardial infarction

- Insulin resistance and type 2 diabetes
- Obesity and metabolic syndrome
- Sleep deprivation and cognitive decline
- Physical activity and metabolic health
- Neurodegenerative diseases (e.g., Alzheimer's, Parkinson's)
- Genetic variants influencing lipid metabolism
- Exercise-induced changes in insulin sensitivity

A.3 Indus / Harappan slice (Indus Valley)

For the Indus (Harappan) slice, we seed the slice with roots from archaeology, paleoclimate, and ancient trade. Examples of depth-0 topics include:

- Indus Valley Civilization
- Harappan urban centers (Harappa, Mohenjo-daro, Dholavira)
- Mohenjo-daro urban planning and sanitation systems
- Indus script and undeciphered writing systems
- Epigraphy and decipherment of ancient scripts
- Holocene monsoon variability in South Asia
- 4.2 ka event and global Bronze Age disruptions
- Climate-induced crop shifts and agricultural adaptation strategies
- Irrigation and agriculture in semi-arid river basins
- Floodplain farming along the Indus and its tributaries

Sampling a few of the depth-1 / depth-2 topics (from the longer run):

- Urban planning and city layout
- Urban planning and grid-like street layouts
- Standardized brick sizes and construction techniques
- Advanced drainage and sanitation systems
- Drainage systems with covered sewers and manholes
- Water supply through wells and reservoirs
- City-wide flood mitigation and raised platform foundations
- Harappan script and undeciphered inscriptions
- Structure and syntax of Indus symbols
- Possible linguistic affiliations (Dravidian, Austroasiatic, or isolate)
- Paleographic analysis of ancient inscriptions
- Bilingual and trilingual inscriptions as decipherment keys
- Trade networks and economic systems
- Interregional trade network disruptions due to climate-induced instability
- Agricultural practices and crop cultivation
- Decline and abandonment of Indus Valley cities

These lists are not exhaustive, but they illustrate the breadth and granularity of topics that Democritus can organise within each slice.

B Prompt Templates

For reproducibility, we summarise the main prompt templates used in Democritus. In all cases we use Qwen3-Next-80B-A3B-Instruct-6bit from the MLX community repository.³

³Model available from <https://huggingface.co/mlx-community/Qwen3-Next-80B-A3B-Instruct-6bit>.

B.1 Topic expansion

A typical topic expansion prompt (Module 1) is:

```
You are an expert in {domain}.
Given the topic "{TOPIC}", list 10 important subtopics
that help explain its causes, consequences, or mechanisms.
Return ONLY a numbered list of subtopics, one per line,
with no explanations.
```

The domain phrase is set to, for example, “macroeconomics and financial markets” (econ slice), “neuroscience and medicine” (bio slice), or “South Asian archaeology and paleoclimate” (Indus slice).

B.2 Causal questions

For causal questions (Module 2) we use prompts of the form:

```
You are an expert in {domain}.
Topic: "{TOPIC}".
Write 3 causal questions a student might ask about this topic.
Each question should start with "What causes" or "What leads to".
Return only the questions, one per line.
```

B.3 Causal statements

For causal statements (Module 3) we use:

```
You are an expert in {domain}.
Topic: "{TOPIC}".
Write 3 short statements of the form "X causes Y" or
"X leads to Y" that describe causal relationships in this topic.
Each statement should focus on a single mechanism.
Return only the statements, one per line.
```

These templates are instantiated for every topic in the topic graph at depth up to a configured limit.

C Implementation Details

C.1 Geometric Transformer configuration

Unless otherwise specified, the Geometric Transformer layer in Democritus uses hidden dimension $d = 128$, depth 2, a single relation embedding for 1-simplices (edges), and a single relation embedding for 2-simplices (triangles). Node features are initialised using Sentence-BERT embeddings of the subject/object phrases concatenated with simple structural features (degree, domain ID). We detect triangles as length-3 cycles in the directed graph and treat them as undirected 2-simplices for message passing.

C.2 UMAP hyperparameters

For UMAP we use cosine distance and the following parameters: `n_neighbors = 30`, `min_dist = 0.1`, `n_components = 2` or `3` (for 2D/3D visualisations respectively). We find that the qualitative manifold structure is robust to modest changes in these settings.

C.3 Slice configurations

For the econ slice we use 15 root topics (macroeconomics, microeconomics, game theory, . . .), depth limit 5, and a cap of 7000 topics. For the bio slice we use roots such as neuroscience, genetics, cardiology, endocrinology, and exercise physiology with similar depth and topic caps. For the Indus (Harappan) slice we use roots including Indus Valley Civilization, Holocene monsoon variability in South Asia, Indus River discharge and river droughts, trade networks with Mesopotamia and Egypt, and Indus script and epigraphy, with a depth limit of 3 in our current experiments.

C.4 Hardware and runtime

All experiments are run on Apple Silicon Macs using the MLX framework. The econ 7k slice uses Qwen3-Next-80B-A3B-Instruct-6bit quantised for MLX and completes in approximately 16.1 hours on a Mac Studio (see Table 3). The bio slice has similar timing. Triple extraction and GT+UMAP manifold construction take less than a minute per slice.

D Additional Manifolds and Local Models

Due to space limitations, we include additional manifold plots and local causal neighborhoods for the econ, bio, and Indus slices in the supplementary material. These include:

- relation-coloured manifolds (causes, increases, influences, leads_to, reduces, affects),
- local GT neighborhoods for topics such as callable vs non-callable bonds, gender-based underemployment in STEM and healthcare, long-term unemployment and skill atrophy,
- and Harappan examples such as Indus River discharge and river droughts, and overexploitation of natural resources and environmental degradation.

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