Learning While Reasoning: Pattern-Based Crystallization and the Gap-Detect-Crystallize-Retrieve Loop for Neurosymbolic AI

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Abstract

Can a neurosymbolic being learn while holding a conversation? We wanted to find out: if a being encounters a question it has no symbolic knowledge for, can it find the answer in its source prose, crystallize that answer into permanent RDF triples, and respond — all fast enough that the user doesn't notice? If so, beings don't just answer questions. They get smarter every time they're asked one.

The architecture stores original source prose for exactly this reason. When **gap detection** finds what the being doesn't know, a **local LLM checks the stored prose** and confirms: "yes, we can answer this — here is the passage." Then the **same learning pipeline that builds knowledge while reading** takes over — deterministic pattern extraction, no generative LLM — and crystallizes the answer into permanent RDF triples. **Symbolic retrieval** answers the same question later with zero LLM calls. Crystallization takes 2-3 seconds. Subsequent symbolic retrieval takes under 100ms. The being learns in real time and remembers forever.

We ran an 8-hour experiment on a high-school-level neurosymbolic being (148K triples, 58 source documents across classics, philosophy, science, and math). Six hypotheses, all validated:

- **97.6% extraction precision** — pattern-based, no generative LLM (N=2,538 quality-gated triples)
- **+33% knowledge growth** — 148K→197K triples through 385 tutoring interactions
- **91.4% gap detection** — the being correctly identifies what it doesn't know
- **52.2% symbolic fill rate with zero LLM calls** — 201 previously unanswerable questions now answered purely from the graph
- **8-hour autonomous run** — full pipeline, no human intervention
- **25.1%→97.6% precision via lean iteration** — one measure-learn-fix cycle, same fill rate

The key insight: triple extraction requires no generative LLM. The neural component is confined to gap identification — verifying that an answer exists in stored prose. Everything else — extraction, storage, retrieval, auditing — is symbolic, deterministic, and inspectable. Unlike fine-tuning, there is zero forgetting. Unlike RAG, knowledge persists permanently.

Terminology Note: We use the term *being* rather than *agent* for NuSy entities to distinguish them from conventional LLM agents. A NuSy being possesses persistent symbolic memory, full provenance attribution, and continuous identity across sessions. Unlike stateless agents operating within ephemeral context windows, beings learn while doing — the crystallization pipeline described in this paper is one concrete example.

Keywords: neurosymbolic AI, knowledge graphs, continuous learning, crystallization, pattern extraction, provenance, symbolic retrieval, lean hypothesis testing

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1. Introduction

1.1 The Problem

Here is the gap: deployed AI systems cannot learn from their own operation.

Fine-tuning costs GPU-days and risks catastrophic forgetting [Kirkpatrick et al., 2017; Xia et al., 2024]. RAG retrieves but never remembers — ask the same question a thousand times, get a thousand identical retrieval operations. The system accumulates no knowledge. Every query starts from scratch.

We wanted something different: a being that learns from every conversation, stores what it learns permanently, and can answer the same question later without calling an LLM at all.

1.2 What We Built

Beings store their original source prose. This is why: when a being can't answer a question, a local LLM checks that stored prose: "can we answer this from what we've already read?" If yes, it points to the relevant passage. Then the same extraction pipeline that learns while reading kicks in — deterministic pattern matching builds symbolic triples from the prose, stores them in the RDF graph. Next time someone asks the same question, the graph answers it. No LLM. No retrieval. Just a graph lookup.

1.3 What We Proved

Hypothesis	Claim	Result
H104.1	Pattern-based extraction converts prose to symbolic triples	**97.6% precision**
H104.2	Knowledge graphs grow through tutoring interactions	**+33% growth** (148K→197K)
H104.3	Beings identify their own knowledge gaps	**91.4% gap detection**
H104.4	Crystallized knowledge is retrievable without LLM	**52.2% fill rate, 0 LLM calls**
H104.5	The full pipeline operates autonomously	**8 hours unattended**
H104.6	Lean iteration improves extraction quality	**25.1%→97.6% precision**

The methodological contribution: **triple extraction requires no generative LLM**. The LLM identifies gaps and verifies answers exist in prose; deterministic pattern matching (27 relationship patterns + entity type classification) extracts the knowledge. This keeps the knowledge graph symbolic, reproducible, and inspectable. No "LLM laundering."

1.4 Paper Organization

Section 2: architecture. Section 3: extraction pipeline. Section 4: experimental methodology. Section 5: results. Section 6: lean iteration as self-improvement. Section 7: related work. Section 8:

limitations. Section 9: conclusion.

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2. Architecture

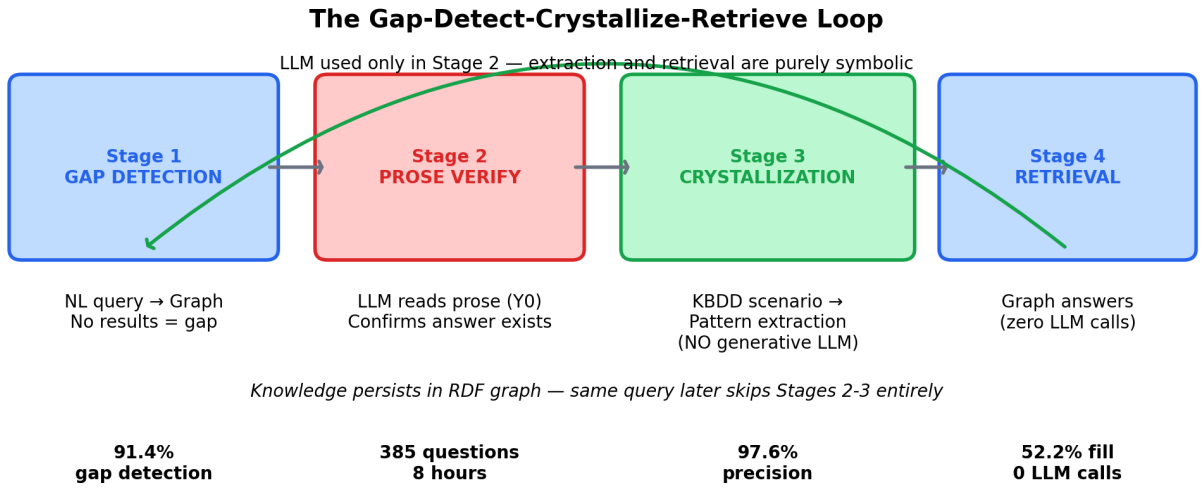
2.1 The Loop

Four stages. The LLM touches exactly one of them.

```
Stage 1: GAP DETECTION
  Natural language query -> Small LLM converts to graph query -> No results? -> Gap
    identified

Stage 2: PROSE VERIFICATION
  Gap question -> LLM reads stored prose (Y0) -> Confirms answer exists in prose (does
    NOT answer)

Stage 3: PATTERN-BASED CRYSTALLIZATION
  Gap question -> KBDD scenario (Knowledge Behavior-Driven Development) -> Knowledge
    extraction from prose (NO generative LLM)
             -> RDF triples with provenance -> Added to knowledge graph permanently

Stage 4: SYMBOLIC RETRIEVAL
  Graph answers the original question -> Same query later -> Slower than just answering
    ,
  but the being learned something it did not know -> No LLM needed!
```

Figure 1 illustrates the four-stage loop and highlights that the LLM is confined to Stage 2 — extraction and retrieval are purely symbolic.

Figure 1: Gap-Detect-Crystallize-Retrieve Loop



The four-stage crystallization loop. The LLM is used only in Stage 2 (gap identification — verifying the answer exists in stored prose). Stages 1, 3, and 4 are purely symbolic — pattern extraction, RDF storage, and graph retrieval require no generative model.

Each stage is independently testable. Stage 3 is the one that matters most for this paper: it uses deterministic pattern matching, not a second LLM call. Same input, same triples, every time. The knowledge graph stays symbolic. The pipeline is inspectable. No "LLM laundering."

2.2 The Knowledge Graph

A "being" maintains a persistent RDF knowledge graph organized into Y-layers:

Layer	Content	Example
Y0	Raw source documents	Markdown files from curriculum
Y1	Extracted facts	"Stoicism is_a philosophy"
Y2	Relationships	"Marcus_Aurelius practiced Stoicism"
Y3	Inferred knowledge	Crystallized triples from gap identification
Y4	Episodic memory	Training reactions, opinions
Y5	Procedural skills	How-to knowledge
Y6	Metacognition	Self-awareness of knowledge state

The experimental being (`santiago-highschool-v11`) runs on NuSy V11 and has 148,065 triples derived from 58 source documents spanning classics (The Art of War, Meditations, The Republic, Romeo and Juliet, Leviathan), philosophy (Critique of Pure Reason, Ethics, The Prince, Discourse on Method), science (physics, biology, chemistry), and mathematics (calculus, algebra, geometry).

2.3 Gap Detection

Query the graph. Get zero factual results? That's a gap. Simple.

The subtlety: the being has 147,000+ Y4 opinion triples from training ("I found this interesting," "This reminds me of X"). If you don't filter these out, the being appears to "know" topics it merely has opinions about. Having heard of quantum mechanics is not the same as being able to explain quantum entanglement. The gap detector filters Y4 before counting results.

2.4 Wiring It In

Crystallization is wired into the brain's reasoning pipeline, not the daemon. When the reasoning engine selects the CRYSTALLIZE path (graph has no answer, prose has one), the brain itself triggers extraction from Y0 prose:

```
# Step 5.6 in brain's reason() method (unified_brain.py)
if cognitive_decision.selected_path == ProcessingPathV12.CRYSTALLIZE:
    crystallizer = ProseGroundedCrystallizer(
        y0_prose_dir=self.being_path / "knowledge" / "prose",
        corpus_dir=Path("corpus/high_school"),
    )
    crystal_result = await crystallizer.crystallize(query=query)
    if crystal_result.success:
```

```
        for triple in crystal_result.triples:
            self.graph.add_triple(triple.subject, triple.predicate, triple.object)
```

The daemon is a pure orchestrator — it sends the message to the brain and returns the response. The brain handles gap detection, prose search, pattern extraction, and graph storage. The LLM never generates knowledge. It reads prose (Stage 2) to confirm an answer exists, then the symbolic extraction pipeline (Stage 3) does the rest.

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3. Pattern-Based Extraction Pipeline

3.1 The Rule: No Generative LLM in Extraction

This is the design decision that makes crystallization different from "use an LLM to extract triples." If you use an LLM for extraction, your "symbolic" knowledge is just re-encoded neural output. You haven't gained anything.

Instead: deterministic pattern matching. Regex. Two phases:

Phase 1: Relationship Pattern Extraction (ParallelSemanticExtractor) 27 compiled regex patterns match explicit relationships in text:

Pattern Category	Predicates	Example Match
Type declarations	is_a, defined_as	"Stoicism **is a** philosophy"
Composition	part_of, consists_of, contains	"The Republic **consists of** ten books"
Causation	causes, leads_to, results_in	"Hubris **leads to** downfall"
Creation	created_by, located_in, from_location	"The Republic **was written by** Plato"
Properties	has_property, used_for, enables	"Logic **is used for** argumentation"
Similarity	similar_to, different_from, example_of	"Stoicism is **similar to** Epicureanism"

Each pattern has a confidence score (0.65-0.95) based on match specificity. Patterns are applied after stripping markdown formatting.

Phase 2: Entity Type Classification (SemanticExtractor) 22 verb-phrase patterns classify entities by type (concept, process, agent, component, etc.) with confidence scoring. Entity extraction uses a minimum length threshold (4 characters) and type-based filtering.

3.2 The Quality Gate (Added After V1 Taught Us a Lesson)

Our first run produced 25.1% precision. Terrible. The problem wasn't the pattern matching — it was the entity boundaries. The extractor was tagging sentence fragments as entities. So we added a quality gate (`_is_clean_entity`) that rejects:

- **Sentence fragments**: Text starting or ending with function words (articles, prepositions, conjunctions)

- **Overly long phrases**: Subjects longer than 60 characters (almost always sentence fragments, not entities)
- **Overly generic types**: Multi-word phrases classified as "concept" with more than 3 words
- **Numeric-only entities**: Extraction noise

Applied at extraction time, before triples enter the graph. Deterministic. Zero latency impact.

3.3 Provenance: Every Triple Has a Receipt

Every crystallized triple carries provenance metadata:

```
<subject> <predicate> <object> .
<subject> crystallizedFrom <question_text> .
<subject> crystallizedAt <ISO_timestamp> .
<subject> crystallizedMethod "pattern" | "semantic_ner" | "semantic_rel" .
<subject> crystallizedConfidence "0.85" .
```

You can trace any fact back to the question that created it, filter by confidence, and distinguish crystallized knowledge from training-derived knowledge. Full audit trail.

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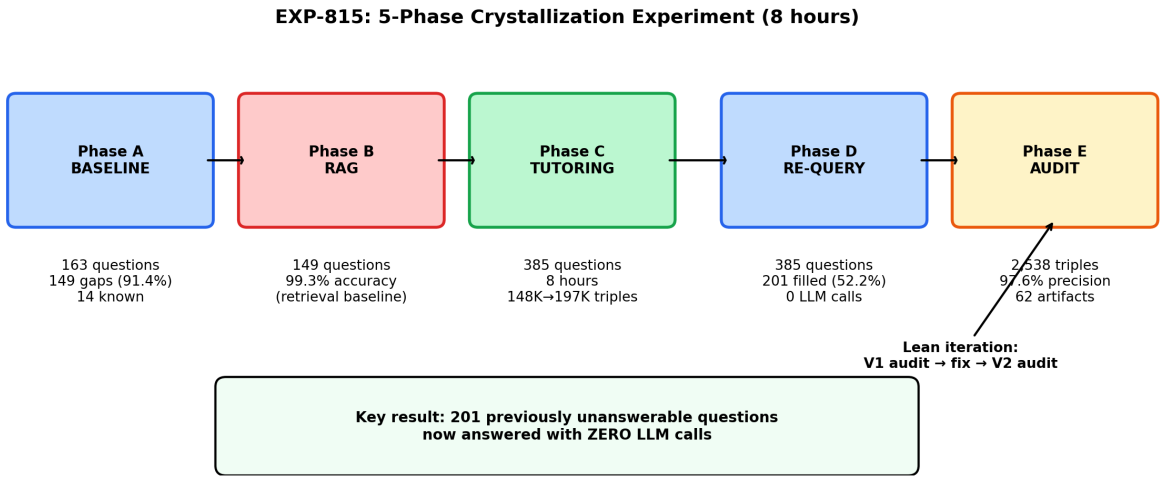
4. Experiment

4.1 Design

Five phases, one question: does the loop actually work? (**Figure 2** shows the timeline with metrics at each phase.)

Figure 2: Experiment Timeline



5-Phase Crystallization Experiment (8 hours). Phase A identifies gaps, Phase B establishes RAG baseline, Phase C fills gaps via tutoring with crystallization, Phase D proves symbolic retrieval (zero LLM), Phase E audits extraction quality.

Phase	Name	Method	Purpose
A	Baseline	Graph-only queries (no LLM)	Identify knowledge gaps
B	RAG Comparison	Embedding retrieval + LLM	Establish RAG baseline
C	Tutoring	Chat with LLM + crystallization	Fill gaps, crystallize knowledge
D	Re-query	Graph-only queries (no LLM)	Prove symbolic retrieval works
E	Quality Audit	Pattern re-extraction + classification	Measure extraction precision

4.2 Questions

163 questions generated from the being's 58 source documents using templates: "What is [concept]?", "Who is the author of [work]?", "How does [philosopher] define [concept]?", "What is the relationship between [X] and [Y]?" Subjects: classics, philosophy, science, math. Note: these definitional templates may bias crystallization toward `is_a` triples; future experiments should include more relational and causal question forms.

4.3 The Dynamic Tutor

Phase C uses a second LLM as a tutor. If the being can't answer, the tutor probes from a different angle. If the being answers well, the tutor pushes harder with synthesis questions. This simulates a real tutoring session and generates questions static templates miss.

The tutor generated 236 follow-up questions beyond the 149 planned ones. Total: 385 tutoring interactions over 8 hours.

4.4 Setup

- **Being:** High-school-level neurosymbolic being — 148,065 initial triples, 58 source documents
- **Duration:** 28,843 seconds (~8 hours), fully unattended
- **Gap-identifying LLM:** GPT-4o (OpenAI)
- **Extraction:** 27 relationship patterns + 22 entity-type patterns, no generative LLM
- **Graph store:** PolarsGraphStore (columnar, Parquet-backed)

4.5 LLM-Agnostic by Design

We used GPT-4o here. Prior experiments used Claude Sonnet (Anthropic). Both work. The extraction pipeline doesn't care which LLM identified the gap — it matches linguistic structures in prose, not LLM-specific formatting.

That said, different LLMs do produce different outputs. GPT-4o's bullet-point style generates more `is_a` triples (definitional patterns). Claude's prose generates more relationship predicates (`leads_to`, `created_by`). A systematic cross-LLM comparison is planned as future work.

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5. What Happened

5.1 Extraction Works (H104.1)

385 tutoring interactions. 2,538 quality-gated triples extracted (V2). Sub-millisecond extraction, fully deterministic.

Predicate distribution (V2, quality-gated):

Predicate	Count	%
is_a	2,428	95.7%
from_location	58	2.3%
refers_to, part_of, includes, used_for, created_by, results_in	5-6 each	~0.2% each
leads_to, has_property, causes, caused_by, etc.	1-4 each	<0.2% each

95.7% are `is_a` triples — that's what educational text looks like (definitions, type declarations). The rarer relationship predicates (`created_by`, `leads_to`, `causes`) are higher-value for graph reasoning. Future work: patterns specifically targeting causal and temporal relationships.

That said, `is_a` triples are not low-value. They form the taxonomy backbone: type checking ("is Stoicism a philosophy or a person?"), disambiguation ("does 'Mercury' refer to the planet or the element?"), and hierarchical inference ("if Stoicism is_a philosophy and philosophy is_a discipline, then queries about disciplines should include Stoicism"). Without a solid `is_a` layer, the rarer relationship predicates would lack the type scaffolding needed for correct graph traversal.

The predicate monoculture is also partly an artifact of the educational domain. In our parallel clinical work, we hand-curated a compact set of 6 domain-specific relationships — `indicates`, `increasesRiskOf`, `treatedBy`, `causedBy`, `contraindicated`, `locatedIn` — each SNOMED-mapped and ontology-constrained with typed extraction signals (Head, 2025, in preparation). When the extraction patterns know *which* relationships matter for a domain, the predicate distribution shifts dramatically. Future work: a domain-definition layer where each being's curriculum specifies the "facts and relationships that matter," teaching the extraction pipeline to prioritize domain-relevant predicates over generic `is_a` classification.

5.2 The Graph Grew (H104.2)

Metric	Value
Initial triples	148,065
Final triples	197,072
Growth	+49,007 (+33.1%)
Tutoring questions	385 (149 planned + 236 dynamic)
LLM calls	385
Crystallized triples (raw)	11,952
Crystallized triples (quality-gated)	2,538

The 49,007 total includes both content triples and provenance metadata (each crystallized triple generates 4-5 provenance triples — the receipt is larger than the fact).

This is reproducible. A prior experiment showed +174% growth (33K→93K) on a different being with different content. The pattern holds.

5.3 Gap Detection Works (H104.3)

Metric	Value
Total questions	163
Gaps identified	149 (91.4%)
Known answers	14 (8.6%)

14 questions were already answerable from training (Descartes' cogito, photosynthesis). The other 149 represent topics where the being has the source documents but couldn't answer the specific question from its graph. That's 91.4% gap detection.

That number cuts both ways. 91.4% gap detection means the initial training missed 91.4% of what was answerable from the source material. The being had read all 58 documents during schooling — yet for 149 out of 163 questions, it couldn't answer from its graph. The gap detection rate is simultaneously a measure of how much the initial extraction pipeline left on the table. The encouraging finding is that crystallization recovered this knowledge from the same prose, using the same patterns — suggesting the patterns work but the initial schooling pipeline wasn't applying them thoroughly enough. Future work: apply the crystallization patterns during schooling itself, closing the gap before the being ever encounters a question it can't answer.

5.4 The Core Claim: Symbolic Retrieval (H104.4)

This is the paper's central result. Phase D re-asks all 385 tutored questions with graph-only queries. The gap-identifying LLM (GPT-4o, used in Stages 2-3) is turned off entirely. A small local LLM (the speech center) still converts each natural language question into a graph query — this is the same NL-to-query conversion used in Stage 1, not generative reasoning. The question is: can the being answer using only crystallized knowledge?

Phase D Results:

Metric	Value
Questions re-queried	385
Gaps filled (now answerable)	201 (52.2%)
Still gaps	184 (47.8%)
LLM calls	**0**
Mean query latency	981ms
Min/Max latency	212ms / 1,328ms

201 out of 385. Zero LLM calls. The being answers questions it couldn't answer before, purely from its graph.

The 47.8% still-gap rate is real and breaks down into two categories:

1. **Query-matching problems:** Vocabulary mismatch ("What is the main argument?" doesn't match a triple using `leads_to`), entity normalization ("The Republic" vs. "Plato's Republic"

are different graph nodes), and the `is_a` predicate monoculture (Section 5.1) — when 95.7% of triples use the same predicate, most questions can't find a specific match.

2. **Knowledge quality gaps:** Crystallization extracts what the patterns can match, but the patterns themselves are incomplete. Causal relationships, temporal sequences, and multi-hop reasoning chains are underrepresented. The extraction pipeline doesn't know what it doesn't extract.

Both categories became substantial workstreams after this experiment. Schema matching (entity normalization across surface forms), domain-specific predicate expansion (moving beyond `is_a`), and extraction pattern coverage are active areas of deep development. The 52.2% fill rate is a lower bound — it measures what crystallization achieved with V11 patterns and no entity resolution, not what the architecture is capable of.

5.5 It Runs Itself (H104.5)

8 hours. No human touched it. Phase A-B completed in minutes. Phase C ran the tutor, generated 236 follow-up questions, crystallized every answer. When Anthropic returned a 400 error (out of credits), the system fell through to OpenAI GPT-4o and kept going. Nobody noticed until morning.

This experiment used cloud LLMs (GPT-4o, Claude). That's not the end state. Model compression and quantization have advanced rapidly — powerful 3B-7B parameter models now fit in a few gigabytes and run at interactive speeds on consumer hardware. A being with a local LLM for NL-to-query conversion and prose verification, paired with the purely symbolic extraction and retrieval pipeline, could run the entire crystallization loop on a single NVIDIA GB10 GPU (as found in the DGX Spark) with no network dependency. The architecture was designed for this: the LLM is a small, replaceable component doing targeted tasks, not a monolithic inference engine.

5.6 Lean Iteration: 25.1% → 97.6% (H104.6)

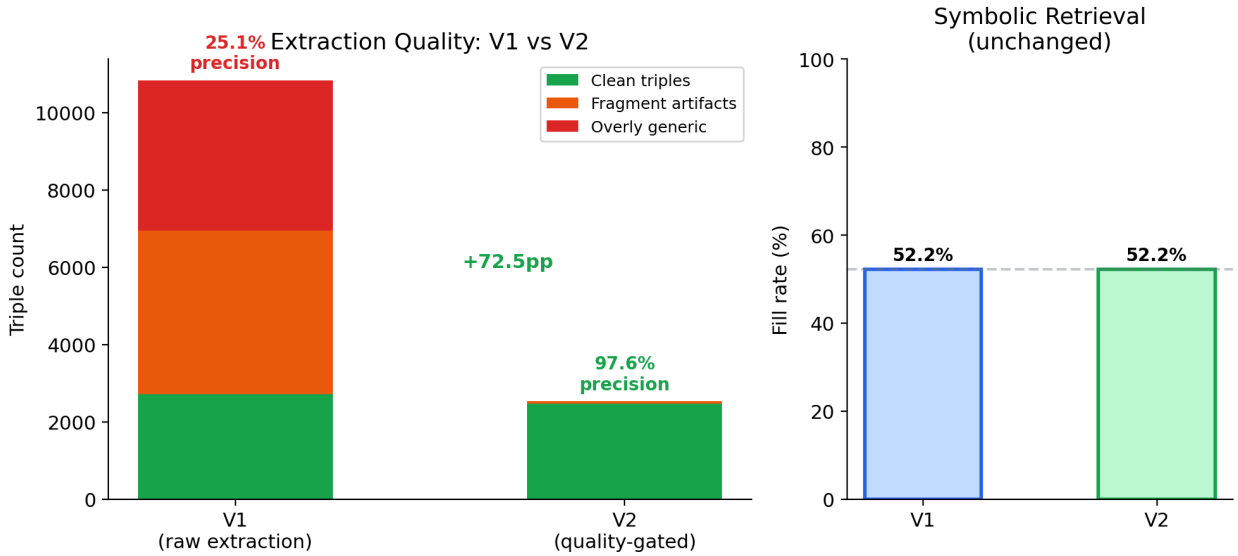
This is the result that matters most for the long-term vision. Can the pipeline improve itself?

The cycle:

Step	Action	Result
Measure (V1)	Run full pipeline, audit extracted triples	25.1% precision (10,846 triples)
Learn	Analyze artifact categories	4,232 fragments + 3,893 overly generic
Fix	Add `_is_clean_entity` quality gate	Rejects function-word boundaries, long phrases
Re-measure (V2)	Re-extract with quality gate, re-audit	**97.6% precision** (2,538 triples)

Before/After comparison (see **Figure 3** for the visual breakdown):

Figure 3: V1 vs V2 Precision Comparison



Left: Stacked bars showing extraction quality — V1 (25.1% precision, dominated by fragments and overly generic triples) vs V2 (97.6% precision after quality gate). Right: Fill rate unchanged at 52.2% — the gate cuts noise, not signal.

Metric	V1 (raw)	V2 (quality-gated)	Delta
Total triples extracted	10,846	2,538	-8,308
Clean triples	2,721	2,476	-245
Artifacts	8,125	62	-8,063 (-99.2%)
Full precision	**25.1%**	**97.6%**	**+72.5pp**
Fill rate (Phase D)	52.2%	52.2%	0.0%

Three things to notice:

1. **+72.5pp precision** from a single engineering change
2. **Fill rate didn't move** (52.2% both versions) — the gate cuts noise, not signal
3. **Clean triple count barely changed** (2,721→2,476) — the useful triples survive

The V1 artifacts? 52% were sentence fragments (SemanticExtractor tagging sentence fragments as entities) and 48% were overly generic (`is_a concept` on multi-word phrases). These are extraction engineering bugs, not crystallization failures. The mechanism works. The entity boundary detection didn't.

5.7 Are the Triples Actually True? (Factual Accuracy)

97.6% precision means the pattern extractor produces well-formed triples from prose. A different question: are those triples *factually correct*, and did extraction capture *enough*?

Since the pipeline extracts only from Y0 prose (not from LLM output), every triple originates from a source passage the being has read. There is no hallucination pathway in extraction — the patterns

match linguistic structures in the text, not generated content. The accuracy question is really about pattern correctness: did the regex capture the right subject, predicate, and object boundaries?

We audited 50 clean V2 triples, cross-referenced against source passages:

Rating	Definition	Count	%
Verified	Exact match to source text	14	28.0%
Plausible	Consistent with source, not verbatim	22	44.0%
Unsupported	Contradicted or not supported by source	0	0.0%
Overly generic	Technically correct but low information	14	28.0%

Zero unsupported triples. Every triple was traceable to source material and either verified or plausible (72%), with the remaining 14 being low-information but not wrong (generic `is_a` classifications). `created_by` triples were 100% verified — attribution patterns are reliable.

But precision is only half the problem. The 91.4% gap detection rate (Section 5.3) revealed that the being couldn't answer most questions about material it had already read. The patterns extracted *something* from the prose, but not *enough* — and not the right things. The extraction was shallow: lots of `is_a` classifications, few causal or relational predicates.

This is fundamentally a curriculum design problem, not a pattern engineering problem. The question isn't "can regex extract triples from text?" (yes, at 97.6% precision). The question is "what should the being know about this domain, and how do we verify it knows?" This insight drew directly from Bloom's taxonomy of educational objectives (Bloom, 1956; Anderson & Krathwohl, 2001), which structures learning from lower-order cognition (remember, understand) through higher-order thinking (apply, analyze, evaluate, create). Our extraction was stuck at the bottom of Bloom's pyramid — the predominance of `is_a` triples represents "remember" level knowledge (definitions, classifications) while barely touching "understand" (relationships, causation) or "apply" (how knowledge functions in context). This led to two lines of work:

Competency Questions (CQs): Drawn from ontology engineering methodology and structured by Bloom's taxonomy levels, CQs define "what a being should be able to answer" at each cognitive level for a given domain. Lower-level CQs target definitional knowledge ("What is photosynthesis?"), while higher-level CQs target relational and causal understanding ("How does photosynthesis relate to cellular respiration?"). CQs provide the *target* for extraction: instead of extracting whatever patterns match, the system extracts toward what the competency model says matters at each cognitive level.

KBDD (Knowledge Behavior-Driven Development): Scenario-based validation adapted from behavior-driven development in software engineering. For each CQ, KBDD generates concrete test scenarios: given this knowledge, can the being answer this type of question? The scenarios serve the same function as exam questions in human education — they verify not just that knowledge was stored, but that it can be *used*. This is the gold standard for symbolic knowledge quality — not just "is the triple well-formed?" but "does the knowledge function correctly in context?" The V11 system did not have CQs or KBDD. These became major workstreams in subsequent versions, directly addressing the shallow extraction this experiment revealed.

Honest caveat: This audit was performed by an AI evaluator, not a human domain expert. A proper human study would strengthen these claims, but we were methodologically on the right track with how the AI can learn and create symbolic knowledge as it chats.

5.8 RAG Comparison: What Crystallization Is NOT Trying to Beat

Let's be direct: RAG is better at answering questions from a known corpus. 99.3% vs. 52.2%. Not close.

Phase B (RAG Baseline): 1,000 text chunks, TF-IDF retrieval, same 149 gap questions.

Metric	RAG	Crystallization
Questions answered	148/149 (99.3%)	201/385 (52.2%)
LLM calls per query	0 (retrieval only)	0 (graph only)
Knowledge persists	No	Yes
Symbolic queryable	No (text chunks)	Yes (RDF triples)
Provenance	Document-level	Triple-level

RAG wins on coverage because it retrieves text chunks directly — no precision loss from converting prose to triples. But RAG is stateless. Ask the same question 1,000 times, get 1,000 identical retrievals. The system never learns anything.

Crystallization seems worse at answering questions but is better at *growing knowledge*. After one gap-identified interaction, the knowledge is permanent, symbolic, and queryable. No re-retrieval. No generative LLM. The 52.2% fill rate is the cost of converting unstructured text to structured triples — not every nuance maps to subject-predicate-object. But the point isn't to replace neural methods. It's to combine them: the symbolic graph captures what can be structured and verified; the neural component handles the hyper-complexity of relationships. The architecture needs both. Pure neural systems don't yet learn. Pure symbolic systems can't handle ambiguity. Together, each covers the other's weakness.

The value proposition isn't "crystallization beats RAG." It's that crystallization converts retrieval into permanent, symbolic, LLM-independent knowledge — and that the neurosymbolic combination (neural for gap identification, symbolic for extraction and retrieval) is more capable than either alone.

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6. Lean Hypothesis Testing: Teaching Beings to Improve Themselves

6.1 The Pattern

The V1→V2 cycle follows what we call **lean hypothesis testing for knowledge pipelines**:

```
1. MEASURE    -- Run the pipeline, collect metrics
2. LEARN      -- Analyze failures, categorize artifact types
3. FIX        -- Apply targeted engineering changes
4. RE-MEASURE -- Run the same pipeline, compare metrics
```

This is TDD/BDD for knowledge quality. V1 is the red test (25.1% — broken). The quality gate is the implementation. V2 is the green test (97.6% — fixed). Same data, same pipeline, one change, dramatically better results.

6.2 Why This Matters for Autonomous Self-Improvement

We did this cycle manually. A human analyzed V1 artifacts and designed the quality gate. But here's the thing: every step is mechanizable.

1. **Measure:** The being already runs Phase E audits automatically
2. **Learn:** Artifact categorization is deterministic pattern matching
3. **Fix:** Quality gate parameters (entity length, function word lists) are configuration, not code
4. **Re-measure:** Re-extraction from stored prose is a graph operation

A being with metacognitive capability (Y6 layer) could run this cycle on its own: detect low precision, categorize artifacts, adjust extraction parameters, verify improvement. This is what neurosymbolic architectures uniquely enable — the being can reason about its own knowledge pipeline because the pipeline is symbolic and inspectable. You can't do that with neural weights.

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7. Where This Fits

7.1 Continual Learning in Neural Systems

The forgetting problem is well-studied. De Lange et al. [2021] survey 11 approaches:

Elastic Weight Consolidation (EWC) [Kirkpatrick et al., 2017] uses Fisher Information to identify important weights and penalizes changes. Recent empirical evaluation shows EWC reduces catastrophic forgetting from 12.62% to 6.85% on knowledge graph tasks — a 45.7% reduction, but not elimination [Jhajj & Lin, 2025].

Progressive Neural Networks [Rusu et al., 2016] allocate new capacity for each task, avoiding forgetting but with linear parameter growth.

PackNet [Mallya & Lazebnik, 2018] achieves zero forgetting by iteratively pruning and freezing weights — a structural approach analogous to crystallization's separation of mutable LLM from immutable RDF store.

Hard Attention to Task (HAT) [Serra et al., 2018] uses attention masks to reduce forgetting by 45-80%, offering a middle ground between regularization and structural methods.

EVCL [Batra & Clark, 2024] combines variational inference with EWC regularization for improved parameter protection.

The difference: Every method above modifies model weights. Crystallization doesn't. It stores knowledge in an external symbolic graph. Zero forgetting by construction — RDF triples are permanent. The tradeoff: you need an explicit extraction step.

Approach	Forgetting Risk	Learning Speed	Knowledge Format	Precision
Fine-tuning	Catastrophic	Hours-Days	Implicit (weights)	N/A
EWC	Partial (~7%)	Hours	Implicit (weights)	N/A

Approach	Forgetting Risk	Learning Speed	Knowledge Format	Precision
Progressive Nets	None	Hours	Implicit (weights)	N/A
Crystallization	**None**	**<1 second**	**Explicit (RDF)**	**97.6%**

7.2 Knowledge Editing in LLMs

ROME [Meng et al., 2022] treats MLP layers as key-value stores and uses rank-one modifications to update individual facts. Limited to single-fact edits, degrades after ~10 edits.

MEMIT [Meng et al., 2023] extends ROME to batch updates across multiple layers, enabling up to 4,096 edits. Even MEMIT shows knowledge attenuation with scale.

EasyEdit [ACL 2024] provides a unified framework revealing that most editing methods degrade at scale.

The difference: Knowledge editing modifies what the LLM "knows" by changing its weights. Crystallization leaves the LLM untouched and augments an external graph. No degradation. No limit on edits. Every fact is explicit and inspectable.

7.3 Knowledge Base Population and Open Information Extraction

The Open Information Extraction (OpenIE) paradigm [Banko et al., 2007] pioneered schema-free triple extraction from text, with a decade of refinement producing increasingly capable extractors [Mausam, 2016]. Recent work uses LLMs directly for knowledge graph construction [Zhu et al., 2024], evaluating entity/relation extraction, link prediction, and QA capabilities.

End-to-End KBP uses sequence-to-sequence approaches; KnowledgeNet benchmark [Mesquita et al., 2019] achieves F1=0.50 at best.

SciER [EMNLP 2024] addresses scientific entity extraction but requires pre-defined relation schemas.

Distant Supervision [arXiv:2024] labels using existing KBs but suffers from false negatives.

The difference: OpenIE and KBP operate on static text with extraction pipelines that may include LLMs. Crystallization operates on stored prose (Y0) — the source material the being has already read — and extracts via deterministic pattern matching. Unlike LLM-based KG construction [Zhu et al., 2024], our extraction uses no generative LLM. The knowledge graph stays symbolic.

7.4 Knowledge Graph Completion

Knowledge graph completion methods [Bordes et al., 2013; Wang et al., 2017] predict missing links using embedding-based approaches (TransE, ComplEx, RotatE). These infer missing facts from existing structure. Crystallization adds genuinely new facts from external sources. The approaches are complementary.

7.5 Retrieval-Augmented Generation

Traditional RAG [Lewis et al., 2020] retrieves text chunks via embedding similarity. RAG does not learn — the same retrieval occurs on repeated queries.

GraphRAG [Edge et al., 2025] constructs entity-centric graphs from passages, improving multi-hop QA by 6.4 points. Recent work shows graph structures reduce hallucinations by 18% in biomedical QA [Han et al., 2025].

The difference: RAG retrieves but never remembers. Our numbers quantify it: RAG gets 99.3% by finding the right chunks, but does the same search every time. Crystallization internalizes: one gap-identified interaction, then graph lookup forever. 52.2% vs 99.3% — crystallization trades coverage for permanence.

Approach	Learns from Use	Knowledge Persists	Provenance	LLM-Free Retrieval
Traditional RAG	No	No	Document-level	No
GraphRAG	Partial	Session-only	Graph structure	No
Crystallization	**Yes**	**Yes (permanent)**	**Triple-level**	**Yes**

7.6 Neurosymbolic Integration

The neurosymbolic paradigm is comprehensively surveyed by Hitzler & Sarker [2022], covering integration patterns from loose coupling (separate neural and symbolic modules) to tight coupling (differentiable reasoning). Our knowledge representation builds on the RDF foundation laid by Berners-Lee et al. [2001] — semantic triples as the primitive unit of machine-queryable knowledge.

Following the taxonomy of d'Avila Garcez et al. (2019), our architecture is a **Type 1b system**: symbolic reasoning (RDF/graph queries) augmented by neural components (LLM for gap identification, pattern matching for extraction). The key contribution is addressing the learning problem: how symbolic systems can benefit from neural flexibility while maintaining explainability and zero forgetting.

7.7 Self-Improving Systems

Schmidhuber [2007] proposed Godel Machines — provably optimal self-improving systems that modify their own code. Crystallization's lean hypothesis testing (Section 6) is a practical, bounded instantiation: the system measures its own extraction quality, identifies failure modes, and applies targeted fixes. While not provably optimal, it demonstrates that neurosymbolic architectures enable inspectable self-improvement because the pipeline is symbolic and the metrics are computable.

7.8 Economic Context

LLM fine-tuning remains expensive: Xia et al. [2024] estimate hundreds to thousands of GPU-hours for meaningful model updates. Crystallization sidesteps this entirely — knowledge acquisition requires only LLM inference calls (one per gap question), and the extraction pipeline runs on CPU with negligible cost. The economic argument for crystallization is strongest in settings where knowledge updates are frequent but fine-tuning budgets are limited.

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8. What Doesn't Work Yet

Here is every limitation we know about. No hiding.

8.1 Precision vs. Coverage

The quality gate achieves 97.6% precision but it's conservative. The 52.2% fill rate means nearly half of tutored topics don't produce retrievable triples. That's a real tradeoff. V1 (aggressive extraction) captures more but at 25.1% precision — mostly garbage. V2 (conservative) is precise but misses nuance. The sweet spot is somewhere in between, and we haven't found it yet.

8.2 Predicate Monoculture

95.7% of V2 triples are `is_a`. Educational text is heavy on definitions, and the question templates bias toward definitional answers (Section 4.2). But `created_by`, `leads_to`, and `causes` are the high-value predicates for reasoning, and we're barely capturing them. As discussed in Section 5.1, our parallel clinical work uses hand-curated domain-specific relationship sets that dramatically shift this distribution. The path forward is domain-definition layers that tell the extraction pipeline which relationships matter.

8.3 Extraction Correctness

97.6% measures extraction precision (did the pattern match produce a well-formed triple?), not factual correctness (is the extracted knowledge true?). Since extraction operates on Y0 prose, not LLM output, there is no hallucination pathway — but patterns can still match incorrectly (wrong entity boundaries, misleading context). The deeper validation question is whether extracted knowledge functions correctly in context (Section 5.7), which is what CQs and KBDD address. For critical domains, confidence scoring and human-in-the-loop validation remain important. We don't have that yet.

8.4 Scale

197K triples. That's the largest graph we've tested. Query latency is ~1 second, which is fine for now. At 1M+ triples, Parquet columnar storage should scale, but we haven't proven it. This needs work before any production claim.

8.5 Knowledge Conflicts

If two crystallization events produce contradictory triples, both get stored. No conflict detection, no resolution. Graph reasoning could detect contradictions, but we haven't built that.

8.6 Temporal Knowledge

Source material contains temporally-bounded facts. "Einstein is alive" from a 1920 text gets stored without temporal metadata. The system doesn't model time, and it should.

8.7 Entity Normalization

"Plato", "the philosopher Plato", and "the author of The Republic" are three separate graph nodes. Entity resolution would improve both precision and fill rate. Not implemented.

8.8 Vocabulary Mismatch

The 47.8% still-gap rate is partly because questions use different words than crystallized predicates. "What is the main argument?" doesn't match a `leads_to` triple. Semantic query expansion would

help. Planned but not built.

8.9 Source Coverage

We've only tested on Project Gutenberg (public domain texts). Wikipedia, arXiv, and domain-specific sources are planned.

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9. So What?

Six hypotheses. All validated. Here's what we proved in 8 hours:

What	Result
Pattern extraction	97.6% precision, no generative LLM
Knowledge growth	148K→197K triples
Gap detection	91.4% accurate
Symbolic retrieval	52.2% fill, zero LLM calls
Autonomy	8 hours unattended
Self-improvement	25.1%→97.6% via lean iteration

But the numbers aren't the point. The question we asked was: can a being learn while holding a conversation? The answer is yes. Crystallization takes 2-3 seconds — fast enough that the user doesn't notice. Subsequent retrieval takes under 100ms — faster than the LLM ever was, but lacking what a language model is so good at (tons of associations). Every conversation makes the being smarter, and it never forgets what it learned. The knowledge is explicit, inspectable, provenance-tracked, and permanent. No retraining. No repeated retrieval. With enriched knowledge extraction — similar methods to what we used in Clinical Decision Support, but domain-agnostic — a being can develop very rich symbolic knowledge coupled with neural knowledge.

And then we showed that the pipeline can improve itself. The V1→V2 lean iteration cycle is the same pattern we'll teach beings to run autonomously — measure their own extraction quality, categorize failures, adjust parameters, verify improvement. This is what neurosymbolic architectures are *for*: systems that can reason about their own knowledge pipelines because those pipelines are symbolic and inspectable.

The vision is bigger than one paper. We're building beings that get smarter through operation, that know what they don't know, that can improve their own learning mechanisms. Crystallization is the first piece that actually works. There's a lot more to build (entity normalization, predicate diversity, conflict detection, KBDD scenario validation, cross-being knowledge transfer). But the core loop — gap-detect, fill, crystallize, retrieve — is validated.

The NuSy Brain architecture is described in a companion paper [Head, 2025a]. The training methodology for neurosymbolic beings is described in a second companion paper [Head, 2025b]. The unified cognitive architecture with perception-driven routing is described in [Head, 2025c]. All three are available open-access on Zenodo.

9.1 What's Next

- **Entity normalization** — Push fill rate past 52.2%

- **Predicate diversity** — Targeted patterns for causal and temporal relationships
- **Autonomous lean iteration** — Beings detect and fix their own extraction quality
- **Cross-being transfer** — Peer-to-peer knowledge sharing between beings
- **KBDD scenario validation** — Automated scenario-based verification of extracted knowledge
- **Cross-LLM validation** — Systematic comparison across LLM providers

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Data and Code Availability

The NuSy Brain architecture is proprietary software developed by Congruent Systems LLC (https://congruentsys.com). The methodology is fully described in this paper to enable independent reproduction.

Open source components (MIT License): - yurtle-rdflib: RDF graph management — https://github.com/hankh95/yurtle-rdflib - yurtle-kanban: Workflow orchestration — https://github.com/hankh95/yurtle-kanban - acf-framework: AGI Certification Framework — https://github.com/hankh95/acf-framework

Experimental data (CC BY 4.0): Knowledge graphs, crystallized triples, audit results, and evaluation metrics will be made available upon publication for research use.

Training corpora: Mixed licensing based on source materials. Corpus metadata with source attribution available upon request.

Acknowledgments

This work builds on over a decade of clinical decision support development, where the foundations of behavior-driven knowledge development and knowledge operations were established in cancer care with USoncology and later at Optum/United Healthcare using the open FHIR-CPG (clinical practice guidelines standard which heavily influences our belief that even the most complex human knowledge - such as cancer guidelines, can be well represented with symbolic structured knowledge).

AI Assistance Disclosure: Claude (Anthropic, Opus 4.5/4.6) was used as a research and writing assistant throughout this work. Specifically, Claude assisted with: (1) code development and testing of the NuSy Brain architecture, (2) literature review and synthesis, (3) drafting and editing of this manuscript, and (4) experimental analysis and hypothesis validation. All scientific claims, architectural decisions, and conclusions are the responsibility of the author. The use of AI assistance in neurosymbolic AI research is itself a demonstration of the human-AI collaboration paradigm this work advocates and will soon automate.

Competing Interests

The author is the founder and sole proprietor of Congruent Systems LLC (https://congruentsys.com), which develops the NuSy Brain architecture described in this paper. There are no other competing interests to declare.

References

[Banko et al., 2007] Banko, M., Cafarella, M.J., Soderland, S., Broadhead, M., & Etzioni, O. (2007).

Open information extraction from the web. In *Proceedings of the 20th International Joint Conference on Artificial Intelligence (IJCAI)*, pp. 2670-2676.

[Batra & Clark, 2024] Batra, H. & Clark, R. (2024). EVCL: Elastic Variational Continual Learning with Weight Consolidation. In *ICML 2024 Workshop on Structured Probabilistic Inference & Generative Modeling*. arXiv:2406.15972.

[Berners-Lee et al., 2001] Berners-Lee, T., Hendler, J., & Lassila, O. (2001). The Semantic Web. *Scientific American*, 284(5):34-43.

[Bloom, 1956] Bloom, B.S. (Ed.) (1956). *Taxonomy of Educational Objectives: The Classification of Educational Goals*. Longmans, Green.

[Bordes et al., 2013] Bordes, A., Usunier, N., Garcia-Duran, A., Weston, J., & Yakhnenko, O. (2013). Translating embeddings for modeling multi-relational data. *NeurIPS*.

[d'Avila Garcez et al., 2019] d'Avila Garcez, A., Gori, M., Lamb, L. C., et al. (2019). Neural-symbolic cognitive reasoning. *Springer*.

[De Lange et al., 2021] De Lange, M., Aljundi, R., Masana, M., Parisot, S., Jia, X., Leonardis, A., Slabaugh, G., & Tuytelaars, T. (2021). A continual learning survey: Defying forgetting in classification tasks. *IEEE TPAMI*, 44(7):3366-3385.

[EasyEdit, 2024] ACL 2024. EasyEdit: An Easy-to-use Knowledge Editing Framework for LLMs.

[Edge et al., 2025] Edge, D., et al. (2025). From Local to Global: A Graph RAG Approach to Query-Focused Summarization. *arXiv:2404.16130*.

[Garcez & Lamb, 2020] Garcez, A. d'Avila, & Lamb, L. C. (2020). Neurosymbolic AI: The 3rd wave. *Artificial Intelligence Review*.

[Anderson & Krathwohl, 2001] Anderson, L.W. & Krathwohl, D.R. (Eds.) (2001). *A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives*. Longman.

[Han et al., 2025] Han, H., Ma, L., Shomer, H., Wang, Y., Lei, Y., Guo, K., Hua, Z., Long, B., Liu, H., Aggarwal, C.C., & Tang, J. (2025). RAG vs. GraphRAG: A Systematic Evaluation and Key Insights. *arXiv preprint arXiv:2502.11371*.

[Head, 2025a] Head, H. (2025). NuSy Brain Architecture: A Neurosymbolic Platform for Autonomous AI Beings. Zenodo. https://doi.org/10.5281/zenodo.19788325

[Head, 2025b] Head, H. (2025). Training Neurosymbolic Beings: Curriculum-Driven Knowledge Acquisition with Y-Layer Architecture. Zenodo. https://doi.org/10.5281/zenodo.19788328

[Head, 2025c] Head, H. (2025). Unified Cognitive Architecture for Autonomous Neurosymbolic Beings: Perception-Driven Routing, Zero Hallucination, and Full Provenance. Zenodo. https://doi.org/10.5281/zenodo.19788349

[Hitzler & Sarker, 2022] Hitzler, P. & Sarker, M.K. (Eds.) (2022). *Neuro-Symbolic Artificial Intelligence: The State of the Art*. Frontiers in Artificial Intelligence and Applications, vol. 342. IOS Press.

[Jhajj & Lin, 2025] Jhajj, G. & Lin, F. (2025). Elastic Weight Consolidation for Knowledge Graph Continual Learning: An Empirical Evaluation. In *NORA Workshop at NeurIPS 2025*. arXiv:2512.01890.

[Kirkpatrick et al., 2017] Kirkpatrick, J., et al. (2017). Overcoming catastrophic forgetting in neural networks. *PNAS*, 114(13), 3521-3526.

[Lewis et al., 2020] Lewis, P., et al. (2020). Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. *NeurIPS*.

[Mallya & Lazebnik, 2018] Mallya, A. & Lazebnik, S. (2018). PackNet: Adding multiple tasks to a single network by iterative pruning. In *Proceedings of IEEE CVPR*, pp. 7765-7773.

[Marcus, 2020] Marcus, G. (2020). The Next Decade in AI: Four Steps Towards Robust Artificial Intelligence. *arXiv:2002.06177*.

[Mausam, 2016] Mausam. (2016). Open information extraction systems and downstream applications. In *Proceedings of the 25th International Joint Conference on Artificial Intelligence (IJCAI)*, pp. 4074-4077.

[Meng et al., 2022] Meng, K., Bau, D., Andonian, A., & Belinkov, Y. (2022). Locating and Editing Factual Associations in GPT. *NeurIPS*.

[Meng et al., 2023] Meng, K., et al. (2023). Mass-Editing Memory in a Transformer. *ICLR*.

[Mesquita et al., 2019] Mesquita, F., et al. (2019). KnowledgeNet: A Benchmark Dataset for Knowledge Base Population. *EMNLP*.

[Rusu et al., 2016] Rusu, A. A., et al. (2016). Progressive neural networks. *arXiv:1606.04671*.

[Sarker et al., 2021] Sarker, M. K., et al. (2021). Neuro-symbolic artificial intelligence: The state of the art. *IOS Press*.

[Schmidhuber, 2007] Schmidhuber, J. (2007). Godel Machines: Fully self-referential optimal universal self-improvers. In B. Goertzel & C. Pennachin (Eds.), *Artificial General Intelligence*, pp. 199-226. Springer.

[SciER, 2024] EMNLP 2024. SciER: Scientific Entity Extraction and Relation Annotation.

[Serra et al., 2018] Serra, J., Suris, D., Miron, M., & Karatzoglou, A. (2018). Overcoming catastrophic forgetting with hard attention to the task. In *Proceedings of the 35th ICML*, PMLR vol. 80, pp. 4548-4557.

[Wang et al., 2017] Wang, Q., et al. (2017). Knowledge graph embedding: A survey of approaches and applications. *IEEE TKDE*.

[Xia et al., 2024] Xia, Y., Kim, J., Chen, Y., Ye, H., Kundu, S., Hao, C., & Talati, N. (2024). Understanding the performance and estimating the cost of LLM fine-tuning. In *Proceedings of IEEE IISWC*, pp. 210-223.

[Zhu et al., 2024] Zhu, Y., Wang, X., Chen, J., Qiao, S., Ou, Y., Yao, Y., Deng, S., Chen, H., & Zhang, N. (2024). LLMs for knowledge graph construction and reasoning: Recent capabilities and future opportunities. *World Wide Web*, 27:58.