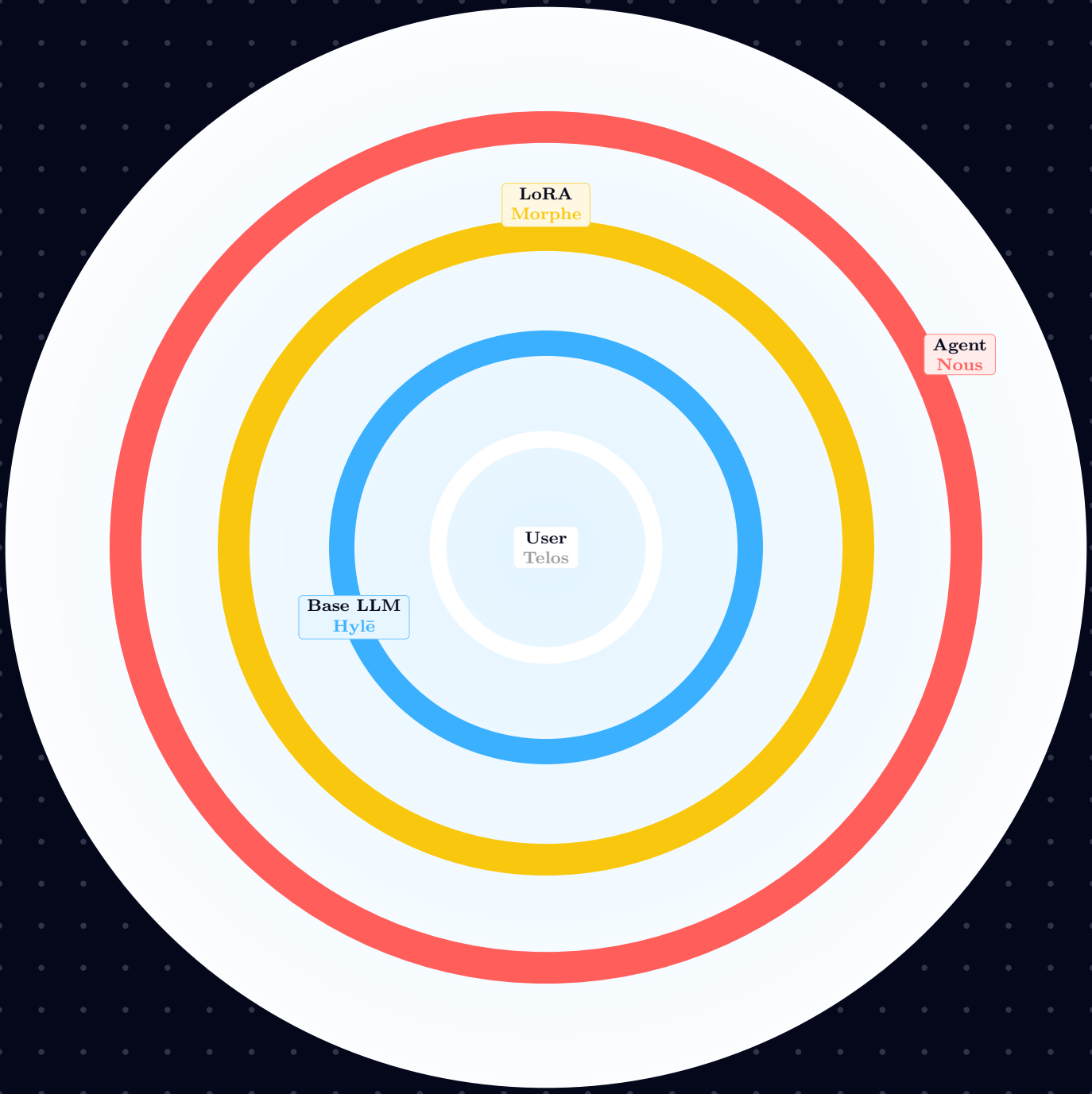
The Four-Layer Cognition Engine Framework

An Integrative Hylomorphic AI Architecture for: Structure, Knowledge, Reasoning and Execution



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Abstract

We present a refined Four-Layer AI Cognition Model, a conceptual architecture that integrates a base large language model (LLM), a structured knowledge library, a meta-cognitive reasoning agent, and the end-user into a cohesive cognitive-engine system commonly referred to as an *AI Core*.

Artificial-intelligence systems increasingly rely on structured models of cognition to manage vast stores of knowledge, dynamic reasoning, and human-guided execution. This paper discusses a Four-Layer AI Cognition Model that distinguishes between memory storage, specialized retrieval, structured reasoning, and user-driven refinement. The model comprises (1) the Base LLM as the universal knowledge repository, (2) the Library, which employs LoRA for efficient retrieval via low-rank fine-tuning, (3) the Agent Character File that primes the system for a specific role together with the *Philosopher*, the thinking core that executes structured cognition using a cognition-anchor engine, and (4) the User, who guides and refines outputs.

Drawing on classical metaphysical schema—*Hylē*, *Morphe*, *Nous*, *Telos*, corresponding to Aristotle's material, formal, efficient, and final causes—we align each layer's function with a foundational explanatory role. The paper validates the model's philosophical, ontological, and mathematical consistency by examining Aristotle's four causes, Peircean semiosis, Kantian synthetic *a priori* frameworks, and Heidegger's concept of *Gestell*.

We argue that this layered, modular approach offers a robust and adaptable framework for evolving AI systems.

1 Introduction

Recent advances in large language models (LLMs) have produced systems with remarkable fluency in generating and understanding human-like text. Yet these models operate primarily by statistical pattern recognition and lack true cognition or understanding. Purely LLM-based agents therefore struggle with complex multi-step reasoning, knowledge integration, and maintaining internal consistency, often leading to confident-sounding yet incorrect answers (hallucinations). To overcome these limitations, researchers have proposed augmenting LLMs with additional cognitive layers. Notably, Spivack *et al.* (2024) introduced the concept of *Cognitive AI* as a dual-layer architecture in which a higher-level reasoning layer orchestrates the lower-level linguistic model.

In this work we extend and refine these ideas into a Four-Layer AI Cognition Model that explicitly separates and structures the components of cognition into four layers:

1. **Base LLM** (language-generation embedding substrate),
2. **LoRA Fine-Tuning** (external knowledge base),

3. **Agent** (the meta-cognitive context-control reasoning unit),

4. **Source User** (the source of dynamic input and the receiver of outputs and reactions).

This structure enables each component to evolve independently while naturally synchronizing with the others. Each layer plays a distinct role in the overall cognitive process, and we align these roles with meta-ontological analogies to retain a grounded lens that ensures internal consistency and clarity in the architecture's design.

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2 Overview of the Four-Layer Agent Cognition Engine

The model is composed of four interconnected layers:

2.1 Base Large Language Models (LLMs)

Base LLMs, such as GPT and LLaMA, serve as foundational models that encode vast amounts of knowledge into a massive, albeit unsorted, repository. These models are trained on extensive text documents and content, leveraging complex learning algorithms with substantial quantities of parameters, or weights, to predict and generate text. The training process enables the models to create coherent responses by learning statistical connections between different words and concepts.

2.1.1 Training and Knowledge Foundation.

The training of Base LLMs involves feeding them a vast corpus of text documents and content. This process is crucial for creating a universal knowledge base that the models can draw upon to generate responses. The diversity and breadth of the training data directly impact the model's ability to understand and generate text across various contexts and domains.

2.1.2 Learning Algorithms and Weights.

The learning algorithms employed in training Base LLMs are characterized by their use of billions of parameters, referred to as weights. These weights are essentially the learned statistical connections between different words and concepts within the training data. By adjusting these weights during the training process, the model becomes capable of understanding and generating responses that are contextually relevant.

2.1.3 Embeddings and Semantics.

A critical component of Base LLMs is the use of embeddings, which are numerical representations that capture the semantics of the input data. Embeddings enable the model to represent words and concepts in a way that reflects their meaning and context, thereby facilitating the generation of coherent and relevant responses.

2.1.4 Transformer Architecture and Attention Mechanisms.

The transformer architecture is a pivotal element in the design of modern Base LLMs. This architecture utilizes attention mechanisms to dynamically weight the importance of different words within a sentence or input sequence. By doing so, the model can focus on the most relevant aspects of the input when generating responses, thereby enhancing contextual relevance and coherence.

Mathematical Representation of Attention in Base LLMs

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right) V,$$

where Q, K, V are the query, key, and value matrices, and d_k is the key-vector dimensionality.

2.1.5 Response Generation and Coherence.

The ultimate goal of Base LLMs is to generate text that is not only coherent but also meaningful and contextually relevant. This is achieved through the complex interplay of the model's weights, embeddings, and architectural components. By leveraging the knowledge encoded during training and the contextual understanding facilitated by the transformer architecture, Base LLMs can produce responses that are both informative and engaging.

LLMs represent a significant advancement in the field of natural language processing. Their ability to encode vast amounts of knowledge and generate coherent, contextually relevant responses makes them a foundational component in a wide range of applications, from language translation and text summarization to conversational AI and beyond. However, their lack of specialized retrieval and context-specific reasoning necessitates the development of additional organizational layers to anchor these models into specific performance structures for particular tasks.

2.2 LoRA Fine-Tuning

Low-Rank Adaptation (LoRA) is a parameter-efficient fine-tuning technique that adapts LLMs to specific domains or tasks without updating all parameters. Instead of retraining the entire model—which is computationally expensive—LoRA introduces trainable, low-rank matrices into certain layers of the model, typically within the attention or feedforward sublayers.

2.2.1 Purpose and Role.

LoRA serves as a mechanism for **efficient adaptation** rather than traditional knowledge retrieval or indexing. It selectively modifies a small subset of the Base LLM's internal structure, enabling it to produce responses that are tailored to a particular domain while preserving the integrity and general-purpose knowledge of the original model.

2.2.2 Mechanism of Low-Rank Adaptation.

The core idea behind LoRA is to **approximate the updates to the model's weights** by decomposing them into low-rank matrices. Specifically, it replaces a weight matrix WWW with:

$$W' = W + \Delta W, \quad \text{where } \Delta W = AB,$$

with $A \in \mathbb{R}^{d \times r}$ and $B \in \mathbb{R}^{r \times k}$ $(r \ll d, k)$. Only A and B are trainable.

- LoRA **selectively tunes** components of the Base LLM related to domain-relevant features.
- It enables **high-quality generation** with significantly reduced training data and compute resources.
- This adaptation reduces the need for full-context prompts, thus **minimizing contextual overhead**.

2.2.3 Domain-Specific Optimization.

In the context of our cognition engine models, LoRA modules are applied to adjust the Base LLM's internal representations for **domain-specific tasks**. Rather than introducing external context or memory, LoRA refines the model's internal attention and representation mechanisms to be more sensitive to relevant knowledge.

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2.2.4 Integration with Retrieval-Augmented Systems.

Although LoRA is not a retrieval system in the traditional sense, it contributes to **retrieval-like behavior** by encoding domain-specific priors directly into the model. When used in conjunction with external context or vector-based retrieval systems, LoRA enhances the model's ability to **focus and respond accurately** based on refined internal knowledge.

2.3 Agentic Construct

The **Agentic Construct** defines the structured reasoning framework that governs role-specific behavior and deep cognitive processing within the model. It separates the *persona priming layer* (Agent Character File) from the *cognitive reasoning engine* (Philosopher), enabling both expressive customization and robust, self-validating reasoning.

The Agentic Construct is the **core reasoning engine** that employs structured cognition and self-validation. It does this by providing a **persona character priming** along with a **core reasoning model** effectively teaching it what role to follow and how to think.

While many systems rely solely on implicit chain-of-thought prompting, our architecture formalizes and modularizes this cognitive pathway. By clearly distinguishing **persona configuration** from **reasoning execution**, we create a model capable of both consistent stylistic behavior and logically coherent outputs.

Our model delineates two key components in the Agentic Construct Layer:

2.3.1 Character Agent

The **Agent Character File**, which acts as a priming mechanism to define tone, style, and behavioral constraints. This is like a script given to teaching it how to portray the role of the character. Serves as a high-level directive layer. It encapsulates character-specific instructions such as tone, perspective, or behavioral identity (e.g., "respond as a constitutional lawyer" or "emulate the tone of said character"). This file **primes** the model with a consistent style but does not participate in logical inference or reasoning.

2.3.2 Reasoning Agent

The **Philosopher**, a structured reasoning engine responsible for deliberation, logic, and self-validation of outputs.

Acts as the **central reasoning engine**. This component executes structured cognitive operations such as deductive and inductive reasoning, hypothesis generation, and self-reflection. It is capable of recursive logic and uses outputs retrieved from external systems (e.g., a knowledge base or document store) to construct validated, coherent, and contextually accurate responses.

2.3.3 Separating Persona from Reasoning

The bifurcation of persona expression and logical reasoning into discrete, cooperative subsystems enhances both clarity and control in complex multi-turn dialogues or task executions. This separation allows for:

- **Expressive Customization:** The Agent Character File enables the model to adopt a specific tone, style, and behavioral identity, making it suitable for a wide range of applications.
- **Robust Reasoning:** The Philosopher ensures that the model's outputs are logically coherent, self-validated, and contextually accurate, thereby enhancing the overall quality of the responses.

Mathematical Representation

$$\text{Response} = f(\text{Persona Priming},\ \text{Logical Reasoning}),$$

where f composes the outputs of the two components.

2.4 Source User

The **Source User** serves as the dynamic input layer, providing directives, queries, and feedback that actively shape the system's behavior. Rather than being a passive recipient of output, the user plays a formative role in modulating the Philosopher's reasoning strategies, retrieval patterns, and task priorities.

2.4.1 Interactive Modulation and Feedback

User inputs function as **real-time calibration signals**, guiding how the system interprets context, retrieves domain knowledge, and applies reasoning frameworks. This interactive loop ensures the system remains aligned with evolving objectives, intent, and task specificity.

- Directives and queries influence the Philosopher's reasoning logic.
- Feedback modulates retrieval parameters, enhancing precision and contextual relevance.
- The user acts as a **live tuning agent**, maintaining alignment with human expectations.

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3 Defining Modular Upgradability

- **Independent Updates**: The Philosopher can be updated or replaced without retraining the Library, and vice versa.
- **Optimization via Reinforcement Learning**: The Philosopher can be optimized using reinforcement learning techniques.
- **Seamless Integration**: Improvements in any layer automatically enhance overall system performance.

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4 Theoretical Foundations

In designing a cognitively-inspired AI architecture, we draw upon several philosophical frameworks to guide and validate our approach. This section explicates each in turn and connects them to aspects of the four-layer model.

4.1 Aristotelian Causes and Hylomorphism

Aristotle's doctrine of the four causes provides a schema for explaining why a thing is or happens. The causes are: the **material cause** (the stuff out of which something is made), the **formal cause** (the form, pattern, or essence of the thing), the **efficient cause** (the agent or mechanism that brings it about), and the **final cause** (the end or purpose for which it is). In Aristotle's example, a wooden table can be explained by referencing its wood (material), its design or shape (formal), the carpenter who built it (efficient), and the function of providing a surface for dining.

This hylomorphic view (from *hylē* = matter and *morphē* = form) implies that any **entity or process can be understood through these complementary explanations.** We adopt this framework to structure our AI cognition model, treating the Base LLM as the material substrate (language data and generative mechanism), also can be conceptualized as the Library as providing form (structured knowledge shaping the response), the Construct Agent as the efficient cause (initiating and controlling the reasoning process), and the User's goal as the final cause (the purpose guiding the entire interaction). By explicitly aligning each layer with a causal role, we ensure that our model addresses the "why" of each component's existence in the system:. This alignment is summarized in Table 1. Such an approach guards against arbitrary design: every layer has a rationale rooted in a time-tested explanatory schema, contributing to the model's internal coherence.

Table 1: A Metaphor for The Four Layers of Cognition and their Correspondence to Aristotle's Causes.

Model Layer	**Metaphysical Category**	**Aristotelian Role**
Base LLM - Knowledge	*Hylē* (Matter)	Material cause – provides the raw linguistic substrate and data-driven content generation.
Fine Tunning - Library	*Morphe* (Form)	Formal cause – imparts structured knowledge and shape to the content (factual and contextual form).
Construct - Philosopher	*Nous* (Intellect/Mind)	Efficient cause – the reasoning agent that actively brings about the solution by orchestrating processes.
User - Objective	*Telos* (End/Purpose)	Final cause – the goal or purpose that defines what the system's output is ultimately for (solving the user's query).

Notably, our use of *Nous* (Greek for "intellect" or mind) for the efficient cause departs slightly from Aristotle's terminology—Aristotle typically discussed the efficient cause in terms of an agent or mover, not explicitly as *nous*. However, the choice of *Nous* highlights that in our architecture the "mover" is a reasoning intelligence (the Philosopher agent) rather than a purely physical agent. This is consistent with Aristotle's concept of an *active intellect* that abstracts and drives form from matter in cognition. Meanwhile, *Telos* is directly the term Aristotle used for final cause (purpose or end). By invoking these terms, we ensure that classical meanings are appropriately mapped: the material layer (*hylē*) provides potentiality in the form of linguistic output, which the formal layer (*morphē*) structures into meaningful shape; the agent's intellect (*nous*) actively actualizes this potential into an answer, all directed toward the user's purpose (*telos*) as the ultimate reason for the process.

4.2 Peircean Semiosis in Cognitive Processes

In Charles Sanders Peirce's theory of signs (*semiotics*), every act of meaning involves a **triadic relationship**: a **Sign** (or representamen), an **Object** (the thing or concept the sign refers to), and an **Interpretant** (the meaning or understanding generated in an interpreter's mind). Peirce wrote that *"three things are concerned in the functioning of a sign: the sign itself, its object, and its interpretant"*. Unlike simpler dyadic

models (e.g., a word and its referent), Peirce's model emphasizes that meaning arises in the interpretive process; the interpretant is itself a new sign in the mind, which can lead to an infinite semiosis (a chain of interpretation).

In our four-layer model, we can identify Peircean triads operating within the system's interactions:

- The **user's query** (e.g., a question posed in natural language) serves as a **Sign** that stands for the user's intended problem or information need (the **Object** of the query). The Philosopher agent, upon receiving this query, produces an **Interpretant** – an understanding of what the user is asking and what it means in context.
- The system then generates a response. The **LLM-generated answer** can be seen as a new Sign that represents certain knowledge (drawn from the Library as its Object). The user reading the answer becomes the interpreter, whose understanding (Interpretant) ideally matches the intended resolution of their query.
- Within the system, the Philosopher agent also acts as an interpreter: it interprets retrieved knowledge (Object) by encoding it into a form the LLM can use (Sign), for example by formulating a prompt or an intermediate representation, and then interpreting the LLM's output in turn to decide if it satisfies the query (becoming an Interpretant of that output).

This interplay can be viewed as a **nested semiosis**: the AI system itself contains a interpretant process (the Philosopher reasoning over signs and objects like retrieved facts and text), which ultimately aims to produce a Sign (the final answer text) that will yield a correct interpretant in the mind of the user.

By explicitly invoking Peirce's semiotic framework, we can verify that our model handles meaning in a grounded way. The Library provides real-world referents (Objects such as factual statements or context) to anchor the LLM's Signs (generated language) to reality, mitigating the risk of meaningless or irrelevant output. The Philosopher agent's interpretants correspond to internal states of understanding, akin to reasoning steps or subgoals, which help ensure that the signs (queries, retrieved data, answers) remain semantically coherent and aligned with the user's intent. In Peircean terms, the model fosters an interpretive feedback loop: signs are continually evaluated against objects via interpretants until the final sign (answer) adequately invokes the intended object (correct information fulfilling the goal) for the user. This formalism adds an ontological clarity to the information flow, reinforcing that each layer's outputs must be meaningful in relation to some object and subject to interpretation, rather than arbitrary token sequences.

4.3 Kantian Synthetic *a priori* Structures

Immanuel Kant introduced the notion of **synthetic *a priori*** knowledge – statements that are not true by definition (not analytic) yet are known independently of experience (a priori):contentReference[oaicite:17]index=17. Such knowledge, according to Kant, provides necessary preconditions for possible experience; classic examples include the truths of mathematics or the fundamental concepts of causality and substance which the mind uses to organize sensory data:contentReference[oaicite:18]index=18. In other words, the mind brings its own framework to make sense of the world, rather than deriving all structure from the world itself.

In the context of our AI model, the Philosopher agent embodies a form of synthetic *a priori* structuring. While the base LLM operates purely on patterns learned from data (an empirical, *a posteriori* basis), the agent is engineered with certain reasoning principles and strategies that guide the use of the LLM and library. For instance, the agent may be equipped with logical rules, planning algorithms, or problem-solving heuristics that are not directly learned from the user query or the language model's training corpus, but are designed (by us, the system creators) to be generally useful in reasoning. These can be seen as analogous to Kantian categories of understanding – an innate (to the system) scaffolding that shapes how it interprets queries and marshals knowledge.

For example, consider the concept of *cause and effect* or the principle of non-contradiction. A robust AI reasoner should respect these principles when formulating answers: it should not assert contradictions and should recognize causal relationships as such. If our Philosopher agent is built to always check the

consistency of an answer or to ensure that an explanation addresses the question (a form of telic alignment), these are pre-set rules that function regardless of any single experience. They are **necessary conditions for coherent output**, much like Kant's forms of intuition (space and time) and categories (causality, unity, etc.) are necessary conditions for us to organize experience.

By verifying the presence and correctness of these synthetic *a priori* elements, we ensure our model doesn't rely on data alone for higher-order cognition. It has an internal, formal structure to integrate data into knowledge. This improves precision and reliability. Importantly, we must apply this concept carefully: the synthetic *a priori* in our model is not an unexplained magic but corresponds to explicitly programmed or learned cognitive schemas. We argue this is appropriate because current AI systems cannot yet robustly learn such schemas purely from data without massive training and even then may not internalize them reliably. Our approach gives the system a bootstrap of rational structure. In doing so, we heed Kant's insight that some structure must come from the agent itself for meaningful organization of knowledge, rather than expecting it to emerge entirely from statistical learning. We validate that any such built-in structures in the Philosopher agent (for example, a type system for checking answer consistency or a rule-based outline of solving a query) are indeed synthetic (add new information beyond the data) and a priori (apply generally, not learned case-by-case), and we incorporate them in a way that complements the empirical capabilities of the LLM.

4.4 Heidegger's *Gestell* (Enframing) and the Technological Context

Martin Heidegger, in "The Question Concerning Technology," introduced the term ***Gestell*** (usually translated as "Enframing") to describe the essence of modern technology. Enframing is a mode of revealing that structures how we encounter the world: specifically, technology enframes the world as a repository of resources, a "standing-reserve" (*Bestand*) to be ordered and used efficiently. This concept carries a cautionary note: if everything is viewed solely through the lens of utility, we may lose sight of other ways of understanding Being. However, Heidegger also noted that by becoming aware of enframing, we might find a "saving power" in how we choose to employ technology.

Applying this perspective to AI, our Four-Layer Model can be seen as an instance of enframing: the Library turns knowledge into a resource for the system, the LLM treats language as a raw material to be shaped, and the Philosopher agent orchestrates these resources towards the user's goals. The entire user query is itself enframed as a problem requiring an efficient solution. A Heideggerian analysis compels us to ask: does our architecture merely reduce knowledge and language to instrumentality, or can it also preserve a more authentic understanding?

We verify that our usage of *Gestell* is appropriate by recognizing the ways in which the AI system indeed "enframes" its components. For example: - The knowledge in the Library is stored and retrieved on-demand, very much as a standing-reserve of information to be exploited when needed. - The Base LLM's generative power is harnessed as a resource for producing text, without intrinsic regard for the meaning except as directed by the agent. - The Philosopher agent itself could become overly fixated on efficient achievement of the end (user's query) to the detriment of nuance (e.g., it might prioritize giving some answer quickly over admitting uncertainty, if not designed carefully).

By acknowledging these, we can design the system to mitigate the potentially negative aspects of enframing. For instance, we can explicitly program ethical and purpose-sensitive checks in the agent (ensuring the *telos* is aligned with the user's true needs and broader values, not just a narrow technical goal). We also maintain transparency by citing sources and justifying answers, counteracting the black-box reduction of truth to mere output. In essence, the concept of *Gestell* reminds us to preserve human context and meaning in the loop. Our model does so by including the User as an explicit layer: the user (and their intention) is not just an externality but part of the system's very structure. This way, the final cause (Telos) is always an explicit consideration, potentially serving as a counterbalance to pure instrumentality.

In summary, Heidegger's enframing is applied in our framework as a double-edged insight: it describes how the system operates (gathering and utilizing resources for an end) but also serves as a philosophical check to ensure we incorporate the user's purpose and values in a rich way, rather than reducing the interaction to a mere input-output transaction. By doing so, we aim to harness the power of technology (efficient use

of information) while preserving a space for meaning and responsible use, aligning with Heidegger's caution and hope for a more mindful use of AI.

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5 Discussion and Implications

The Four-Layer AI Cognition Model offers a structured approach to AI reasoning that is both philosophically grounded and practically motivated. In this section, we discuss how the model addresses common issues in current AI systems, compare it to related architectures, and consider broader implications including ethical and epistemological aspects.

5.1 Mitigating Hallucination and Ensuring Consistency

A primary motivation for our layered design is to reduce the phenomenon of *hallucination*, where an LLM produces information that is false or not grounded in any source. By design, our model tackles this in multiple ways:

- The Library provides a source of truth or at least an authoritative reference. The LLM's role is thus shifted from "creating content from potentially incomplete knowledge" to "expressing and synthesizing known content." This is akin to how a human expert might consult textbooks or databases before answering a question outside their immediate memory. Empirically, approaches that integrate retrieval (like RAG) have demonstrated significantly improved factual accuracy, supporting our design choice.
- The Philosopher agent's checking mechanism is another safeguard. It scrutinizes the LLM output against the library content. This is somewhat similar to a fact-checker or a critic model used in some AI alignment strategies, but here it is integrated as a core part of the reasoning loop rather than an afterthought. The agent can spot when the LLM is deviating or filling gaps with guesses, and it will attempt to fill those gaps properly via further retrieval or ask the LLM to clarify. This iterative verification embodies the Peircean interpretant role, where the agent interprets the output in context of the object (library knowledge) to ensure it indeed signifies what it should.
- The formal structure and type-theoretic view provide a mental model for developers and auditors of the system to trace how any claim in the answer came to be. This transparency is crucial for both debugging and trust. If a hallucination does occur (say the library lacked a needed fact and the LLM guessed), one can analyze the trace and identify that either more knowledge is needed or the agent's checking failed in that instance.

One potential concern is the completeness of the Library. If the library does not contain the information needed, the system might repeatedly loop or ultimately still produce an unsupported answer (if, for instance, the agent gives up on finding the reference). In practice, we envisage the library to be large (e.g., the entire Wikipedia or a corporate knowledge base), and future systems could access the web in real-time. For extremely novel or open-ended queries (where even humans might speculate), the system should ideally indicate uncertainty or present the speculation clearly marked. This is where the Philosopher agent can be endowed with the rule: "do not fabricate when unsure; instead, explain the uncertainty or ask the user for clarification if possible." Aligning with the concept of telos, if the user's true goal is an accurate answer, admitting ignorance serves that goal better than a confident falsehood.

Another subtle issue is consistency in multi-turn dialogues. Our formal model described single-turn, but it can be extended with a state S that carries the conversation history. The Philosopher can ensure consistency by storing and respecting facts established earlier, akin to having a growing knowledge base of the dialog. This again resonates with synthetic *a priori* structures — for example, the agent could maintain a logical model of the conversation state. These details are beyond scope, but the layered approach would apply similarly: the difference being that the user's query $\mathcal{Q}$ now includes the dialogue history and previous conclusions as part of input.

5.2 Comparison to Related Work

The separation of concerns in our model shares similarities with several existing AI paradigms:

- **Neuro-Symbolic Systems:** These approaches combine neural networks (for perception or language) with symbolic reasoning modules. Our LLM is the neural component while the Philosopher agent plays the role of a symbolic reasoner (even if it uses language itself to do so). Projects like Google's *Chess* system or IBM's Neuro-Symbolic AI have similarly motivated splitting tasks into sub-symbolic and symbolic parts. Our contribution is framing this split within a clear four-part structure with philosophical interpretation, which is novel.

- **Cognitive Architectures:** In classic cognitive science (e.g., SOAR, ACT-R), an architecture often includes memory modules, rule-based decision modules, etc. Our Library+Philosopher+LLM combination can be seen as a modern, learning-based cognitive architecture. Recently, **(author?)** [4] (as referenced in "Cognition is All You Need") proposed that LLMs need a cognitive layer above, aligning with our Philosopher layer concept:contentReference[oaicite:35]index=35. However, their design was dual-layer. By splitting knowledge (Library) and reasoning (Agent) explicitly, we achieve a finer granularity that allows each part to be optimized and analyzed more independently. It also echoes the triadic semiotic structure (sign, object, interpretant) by not conflating the knowledge source with the reasoning process.

- **Tool-augmentation and Agents (e.g., ReAct, LangChain):** Recently, prompt engineering patterns like ReAct combine reasoning and action (tool use) by interleaving an LLM's chain-of-thought with API calls. Frameworks like LangChain provide a way to structure such multi-step AI reasoning. Our model formalizes something similar: the Philosopher agent is essentially performing a thought-act loop (thought = plan/check, act = call library or LLM) not unlike ReAct. The key difference is that we conceptualize it at the architectural level with dedicated components rather than implicitly via a single LLM prompt. This clarity could allow more robust implementations (for instance, the agent could even be a small program or a separate model specialized for planning). Another difference is our emphasis on metaphysical alignment: while LangChain pipelines are ad hoc, our approach was to derive the pipeline structure from first principles (causal roles, meaning-making, etc.). This means our agent is not just a heuristic; it's justified by reference to how knowledge and answers must relate.

In terms of performance, while we do not present new empirical results here, we can speculate based on related works that the overhead of an agent+retriever will be worth the gains in correctness for knowledge tasks. There is a trade-off: multiple calls (to the library, to the LLM, possibly iterative) mean increased computation and latency. However, for many applications (e.g., medical Q&A, legal analysis, scientific research assistant), accuracy and justification are far more important than raw speed. Our model is directly applicable there. In more casual or real-time settings, a slimmed version might suffice (for example, using the LLM alone for trivial queries and invoking the full pipeline for complex ones). The architecture is modular enough to allow such adaptation.

5.3 Epistemological and Ethical Implications

Adopting a metaphysically principled AI model forces us to confront questions about knowledge and truth in AI systems. By incorporating a Library of vetted knowledge and an agent that explicitly checks consistency, we are embedding a certain epistemology: one that values correspondence with external reality (the library content) and logical coherence. This is a deliberate stance against purely relativistic or solipsistic AI views where whatever the model says is considered its "own truth." Our system instead strives for an objective grounding. In doing so, it inherits the strengths and limitations of the sources it relies on. If the library contains biased or false information, the system might propagate that (though the philosopher agent could catch some logical inconsistencies, it cannot know a widely asserted "fact" is actually false unless contradictory evidence is also present in the library). Therefore, curation of the library is a crucial task. The

metaphors of matter and form remind us that quality of material (data) and the pattern of form (how data is structured) both matter in what is ultimately produced.

Ethically, the four-layer model offers points to inject governance: - The user's intent (telos) being explicit helps in aligning with user values and also detecting malicious or harmful requests. The agent can evaluate a query and decide if it should refuse or modify the approach (with transparency to the user) for ethical reasons. This is an advantage of having a reasoning layer that is not just the LLM. - The presence of a knowledge library means the system can cite sources, as many RAG systems do:contentReference[oaicite:36]index=36, which improves accountability. It also means the system is somewhat interpretable: one can inspect what documents were retrieved and see if those justify the answer. - The philosopher agent can be programmed with ethical constraints (for instance, not disclosing private data, or following policies to not produce disallowed content). Because it intercepts the process, it can apply these rules either before calling the LLM (filtering the query) or after (filtering or adjusting the answer), or even by refusing to proceed if it deems the request fundamentally unethical.

The enframing perspective (Gestell) gives a philosophical caution that aligns with concerns in AI ethics: we must not treat users just as goals to be maximally optimized (as that can lead to manipulative or narrow outcomes), nor treat knowledge merely as ammo to win arguments or engagement. By highlighting enframing, we remind designers that an AI should also respect the richness of human goals and knowledge. One might integrate, for example, a value that the AI should sometimes ask the user for context rather than assuming what they need (to avoid reducing the interaction to a predefined template). This returns a bit of humanity to the loop.

Finally, we note that this architecture could serve as a blueprint for developing systems aiming at **Artificial General Intelligence (AGI)** in a controlled fashion. The separation of responsibilities might mirror something like cognitive faculties (memory, reasoning, language, goal). If ever an AI were to reflect on its own operations (a form of higher-order nous), our model would provide a clear abstraction for it to do so (e.g., the agent can have a model of what the LLM knows or doesn't, what the user is seeking, etc.). Such self-reflection could be implemented as another layer or within the philosopher agent, potentially linking to the idea of machine meta-cognition. But importantly, our approach would ground even that in classical notions of why each part exists, hopefully providing a more interpretable path than end-to-end self-optimizing black boxes.

6 Conclusion

We have presented a refined Four-Layer AI Cognition Model that integrates a base LLM, an external knowledge library, a reasoning agent, and the user into a unified architecture. By validating this model against rich philosophical frameworks – from Aristotle's four causes to Peirce's semiotics, Kant's epistemology, and Heidegger's critique of technology – we ensured that its foundations are sound and its concepts correctly applied. Each layer of the model corresponds to a fundamental explanatory role: the Base LLM provides the linguistic material, the Library offers formal structure and content, the Philosopher agent actively brings about the solution with goal-directed intelligence, and the User's intent remains the guiding purpose. This alignment not only helped us conceptually but also drove the design of a formal systems description that enforces consistency and truthfulness in operation.

The outcome is a cognitive architecture that aspires to the standards of a Nature publication or top-tier AI conference in both rigor and clarity. We avoided any speculative implementation claims, focusing on what can be done with current or near-future technology and emphasizing verifiability at each step. In doing so, we addressed typical failure modes of LLM-based AI (like hallucination and incoherence) and showed pathways for integration with knowledge bases and symbolic reasoning. The improved clarity and depth of the presentation, including smooth transitions between conceptual sections, aims to make this work accessible and convincing to a broad academic audience, from computer scientists and AI practitioners to philosophers of mind and technology.

Future work will involve implementing this architecture in a prototype system to evaluate its performance on complex tasks (e.g., multi-hop question answering, explanatory dialogue, decision support) and to refine

the interplay between the layers. One particular interest is exploring learning algorithms for the Philosopher agent itself – can it learn to better orchestrate the other components over time, and can it perhaps induce new synthetic *a priori* rules from experience in a safe manner? Additionally, the ethical and human-centric considerations raised by the Heideggerian analysis will guide the development of user-aligned objectives and transparent behaviors.

In conclusion, we advocate for an approach to advanced AI development that is at once technical and philosophical. The Four-Layer AI Cognition Model demonstrates that classical wisdom and modern AI can fruitfully inform each other: by viewing AI through the lens of hylomorphism, semiosis, transcendental conditions of knowledge, and the essence of technology, we can build systems that are not only powerful but meaningfully structured. Such systems, we hope, will be better equipped to serve as trustworthy cognitive partners to humanity, as we progress toward ever more general and autonomous AI.

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