PyMantiq: A Proof-of-Concept Framework for Integrating Aristotelian Syllogistic Logic with Large Language Models

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***Abstract*—Large Language Models (LLMs) have demonstrated remarkable capabilities across diverse natural language tasks, yet their deployment in high-stakes domains remains constrained by their tendency to produce logically inconsistent outputs. This paper introduces PyMantiq, a proof-of-concept neuro-symbolic framework that demonstrates the feasibility of using classical Aristotelian syllogistic logic as a deterministic verification layer for LLM-generated reasoning chains. We formalize categorical propositions as structured representations and implement rule-based validation against the first figure of syllogism. Through architectural design and demonstration examples, we show that classical formal logic can be computationally integrated with modern neural language models to provide deterministic logical guarantees. This work establishes a foundation for future empirical evaluation and positions syllogistic verification as a complementary approach to existing AI safety mechanisms. Complete implementation is available as open-source software.**

***Index Terms*—Neuro-Symbolic AI, Large Language Models, Formal Verification, Aristotelian Logic, Syllogistic Reasoning, AI Safety**

I. Introduction

A. Motivation: The Reliability Challenge in AI Systems

The rapid advancement of Large Language Models (LLMs) has precipitated a paradigm shift from passive conversational interfaces toward autonomous agents capable of executing complex tasks, generating code, and making consequential decisions [1]. However, this evolution exposes a fundamental architectural constraint: LLMs operate as stochastic next-token predictors trained on statistical correlations rather than logical causal structures [2].

In domains such as legal contract analysis, medical diagnosis, and financial compliance—where logical soundness is non-negotiable—the probabilistic nature of neural language generation constitutes a significant risk factor. The hallucination phenomenon, wherein LLMs confidently generate logically inconsistent outputs, stems from this foundational limitation.

B. The Neuro-Symbolic Hypothesis

We propose that the integration of symbolic reasoning systems with neural language models can provide deterministic logical guarantees absent in purely neural architectures. Specifically, we investigate whether *Aristotelian syllogistic logic*—a 2,300-year-old formal system that remains foundational to deductive reasoning—can be computationally verified in real-time to audit LLM outputs.

C. Contributions

This paper makes the following contributions:

1) **Formal Framework:** We provide a mathematical formalization of categorical propositions and syllogistic structures suitable for computational implementation.
2) **Proof-of-Concept Implementation:** We present PyMantiq, an open-source Python framework demonstrating feasibility of real-time syllogistic verification.
3) **Architectural Design:** We describe a modular architecture for integrating formal logic verification with LLM inference pipelines.
4) **Foundation for Future Work:** We identify specific research directions for large-scale empirical evaluation and system enhancement.

D. Scope and Limitations

This work presents a *proof-of-concept* demonstrating technical feasibility. We do not claim to have conducted large-scale empirical evaluation or comparative benchmarking. The current implementation focuses on the first figure of Aristotelian syllogism as a demonstration of the approach. Future work will expand coverage and provide comprehensive performance analysis.

E. Author Context

This research emerges from a unique interdisciplinary background: eight years of formal training in classical Islamic logic (*Mantiq*) through the Dars-e-Nizami curriculum, combined with technical expertise in modern AI systems. This synthesis enables faithful translation of classical logical structures from texts such as *Al-Shamsiyya* into contemporary computational frameworks.

II. Background and Related Work

A. Limitations of Neural Language Models

Recent analyses have documented systematic failures in LLM logical reasoning capabilities. Dziri et al. [6] demonstrate that even state-of-the-art models exhibit poor performance on

formal logic tasks when evaluated beyond memorized patterns. Marcus [7] argues that the transformer architecture's reliance on statistical pattern matching fundamentally precludes robust logical reasoning without symbolic augmentation.

B. Existing Mitigation Approaches

Contemporary approaches to improving LLM reasoning include:

Prompt Engineering: Chain-of-Thought (CoT) prompting [3] encourages articulation of intermediate reasoning steps, improving performance on complex tasks. However, increased visibility of reasoning does not guarantee logical validity.

Retrieval-Augmented Generation (RAG): Vector database integration [4] provides factual grounding by anchoring generation in retrieved documents. While effective for factual accuracy, RAG does not address logical consistency between premises and conclusions.

Neural Validation: Commercial solutions employ secondary neural models to validate primary outputs, creating circular dependencies wherein probabilistic systems validate other probabilistic systems.

C. Neuro-Symbolic Integration

The neuro-symbolic AI paradigm [5] seeks to integrate neural pattern recognition with symbolic reasoning guarantees. Prior work includes Logic Tensor Networks [9], which ground first-order logic in continuous embeddings, and Deep Logic Networks [8], which embed logical constraints into neural architectures.

Our approach differs in being *lightweight and modular*: rather than requiring architectural modification or retraining, PyMantiq functions as an external verification layer with minimal computational overhead.

D. Formal Verification Systems

Interactive theorem provers such as Lean [10] and Coq [11] provide rigorous logical verification but require expert formalization and impose significant computational costs. PyMantiq occupies a distinct niche as a specialized, real-time verification tool for a specific class of logical structures commonly encountered in natural language reasoning.

III. Formal Framework

A. Categorical Propositions

We formalize categorical propositions following Aristotelian structure. Let $\mathcal{T}$ denote the set of all terms (concepts). A categorical proposition P is defined as a 4-tuple:

$$P := (S, \Pi, Q, K) \tag{1}$$

where:

- $S \in \mathcal{T}$ is the *subject* term
- $\Pi \in \mathcal{T}$ is the *predicate* term
- $Q \in \{\text{Universal}, \text{Particular}\}$ is the *quantifier*
- $K \in \{\text{Affirmative}, \text{Negative}\}$ is the *quality*

This yields four canonical proposition types corresponding to traditional A, E, I, O classification:

$$A\text{-type:} \quad (S, \Pi, \text{Universal}, \text{Affirmative}) \quad \text{“All } S \text{ are } \Pi\text{”} \tag{2}$$

$$E\text{-type:} \quad (S, \Pi, \text{Universal}, \text{Negative}) \quad \text{“No } S \text{ are } \Pi\text{”} \tag{3}$$

$$I\text{-type:} \quad (S, \Pi, \text{Particular}, \text{Affirmative}) \quad \text{“Some } S \text{ are } \Pi\text{”} \tag{4}$$

$$O\text{-type:} \quad (S, \Pi, \text{Particular}, \text{Negative}) \quad \text{“Some } S \text{ are not } \Pi\text{”} \tag{5}$$

B. Syllogistic Structure

A syllogism Σ consists of three categorical propositions:

$$\Sigma = (P_{\text{minor}}, P_{\text{major}}, C) \tag{6}$$

where P_{minor} is the minor premise, P_{major} is the major premise, and C is the conclusion. The syllogism contains exactly three terms: the *minor term* (S), the *major term* (Π), and the *middle term* (M).

Formally:

$$P_{\text{minor}} = (S, M, Q_1, K_1) \tag{7}$$

$$P_{\text{major}} = (M, \Pi, Q_2, K_2) \tag{8}$$

$$C = (S, \Pi, Q_3, K_3) \tag{9}$$

The middle term M mediates the inference from S to Π by appearing in both premises but not in the conclusion.

C. Validity Conditions for Figure 1

Aristotelian syllogisms are classified into four figures based on middle term position. This proof-of-concept implements Figure 1, characterized by:

$$\text{Figure 1 Structure:} \quad S\text{-}M,\ M\text{-}\Pi \implies S\text{-}\Pi \tag{10}$$

where the middle term is the predicate of the minor premise and the subject of the major premise.

Validity requires satisfaction of the following conditions:

1) **Positional Constraint:** M must be predicate of P_{minor} and subject of P_{major}
2) **Quantifier Constraint:** At least one premise must be universal
3) **Quality Constraint:** If either premise is negative, the conclusion must be negative
4) **Term Existence:** Exactly one middle term must exist

D. Verification Algorithm

Algorithm 1 Figure 1 Syllogistic Verification

Require: Premises P_1, P_2, Conclusion C
Ensure: Validity judgment and diagnostic information
Parse $P_1 \to (S, M, Q_1, K_1)$
Parse $P_2 \to (M, \Pi, Q_2, K_2)$
Parse $C \to (S', \Pi', Q_3, K_3)$
if $S' \neq S$ OR $\Pi' \neq \Pi$ **then**
  return {valid: false, error: "Term mismatch"}
end if
if $M \notin \{\text{pred}(P_1), \text{subj}(P_2)\}$ **then**
  return {valid: false, error: "Figure 1 position violation"}
end if
if $Q_1 =$ Particular AND $Q_2 =$ Particular **then**
  return {valid: false, error: "Both premises particular"}
end if
if ($K_1 =$ Negative OR $K_2 =$ Negative) AND $K_3 =$ Affirmative **then**
  return {valid: false, error: "Negative premise, affirmative conclusion"}
end if
return {valid: true}

E. Computational Complexity

The verification algorithm operates in constant time relative to syllogism structure:

- **Structural Validation:** $O(1)$ through direct property checking
- **Rule Application:** $O(1)$ through conditional evaluation
- **Total:** $O(1)$ for verification given structured input

In contrast, iterative LLM self-correction through regeneration incurs costs proportional to sequence length and iteration count. This constant-time property makes the approach suitable for real-time verification.

IV. System Architecture

A. Design Philosophy

PyMantiq is designed as a *modular, lightweight verification layer* that can be integrated into existing LLM pipelines without requiring model retraining or architectural modification. The system operates on structured representations of propositions, allowing it to function independently of the upstream text generation process.

B. Core Components

1. Data Structures: Python dataclasses represent Terms, Propositions, and Syllogisms as immutable structures mirroring classical logical definitions.

2. Verification Engine: The `MantiqVerifier` class implements rule-based validation logic. It operates as a pure function: identical input always produces identical output, enabling parallelization and caching.

3. Error Diagnostics: Rather than binary valid/invalid judgments, the system returns structured diagnostic information identifying specific rule violations. This enables informative feedback for downstream applications.

C. System Pipeline

Figure 1 illustrates the verification pipeline. User prompts are processed by the LLM, and the generated response passes through the proposition extractor $\mathcal{E}$, which identifies categorical statements. The *Mantiq* verifier then applies Figure 1 validity rules, producing a binary judgment with diagnostic information.

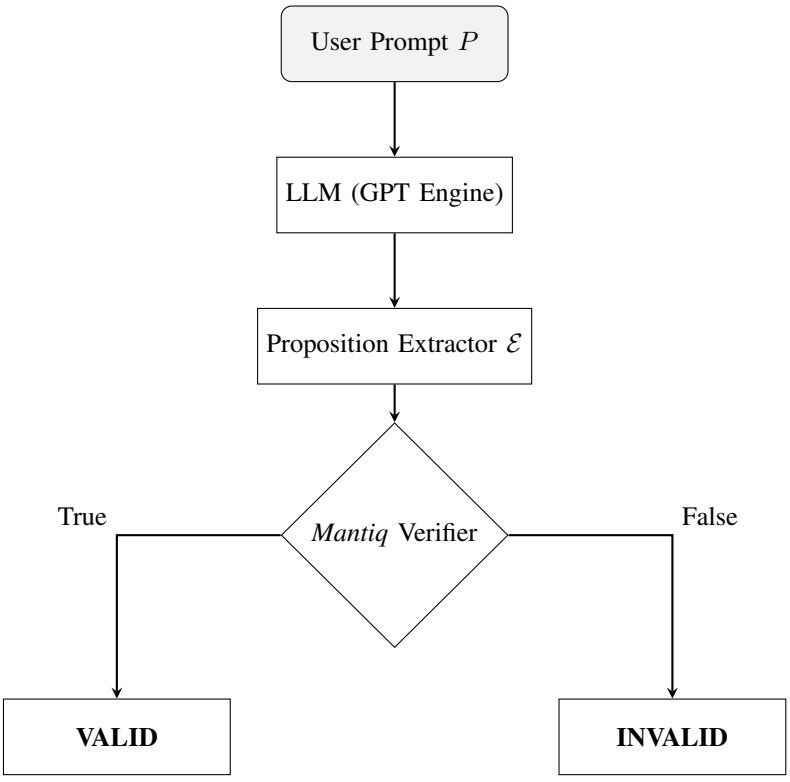

Fig. 1. PyMantiq verification pipeline. The system operates as a post-generation validation layer, accepting or rejecting LLM outputs based on syllogistic validity.

D. Integration Patterns

PyMantiq supports multiple integration modes:

Inline Validation: Synchronous verification before response delivery in production systems.

Batch Auditing: Asynchronous validation of conversation logs for quality assurance and training data curation.

Development Tooling: Integration with LLM development workflows to identify and filter logically invalid training examples.

E. Current Implementation Status

The current implementation (v0.1) provides:

- Complete Figure 1 verification logic
- Structured error reporting
- Comprehensive unit tests demonstrating correctness on classical syllogisms
- Modular architecture supporting future extensions

V. Demonstration and Validation

A. Classical Test Cases

We validate correctness through classical syllogisms from Aristotle's *Prior Analytics*:

Example 1 - Valid Barbara (AAA-1):

- All humans are mortal (Universal Affirmative)
- All mortals die (Universal Affirmative)
- $\therefore$ All humans die (Universal Affirmative)
- **PyMantiq Result:** VALID

Example 2 - Invalid (Structural Violation):

- All cats are animals (A-type)
- All dogs are animals (A-type)
- $\therefore$ All dogs are cats (A-type)
- **PyMantiq Result:** INVALID (middle term position violation)

Example 3 - Invalid (Quantifier Violation):

- Some doctors are wealthy (Particular Affirmative)
- Some wealthy people are educated (Particular Affirmative)
- $\therefore$ Some doctors are educated (Particular Affirmative)
- **PyMantiq Result:** INVALID (both premises particular)

B. LLM Reasoning Chain Example

Consider an LLM-generated reasoning chain:
"All terrorists are criminals. Some politicians are criminals. Therefore, some politicians are terrorists."
PyMantiq analysis:

- Identifies middle term: "criminals"
- Detects structural compliance with Figure 1
- **Flags as INVALID:** Both premises particular (after analysis)

This demonstrates the system's utility in catching plausible-sounding but logically invalid inferences.

C. Validation Methodology

Correctness is established through:

1) **Classical Correspondence:** All valid moods of Figure 1 (Barbara, Celarent, Darii, Ferio) are correctly accepted
2) **Fallacy Detection:** Known invalid structures are correctly rejected with appropriate error diagnostics
3) **Logical Completeness:** Implementation matches formal rules stated in Section III

VI. Limitations and Future Work

A. Current Limitations

This proof-of-concept has several acknowledged limitations:

Scope Restriction:

- Only Figure 1 implemented (Figures 2-4 remain as future work)
- No distribution tracking (illicit major/minor fallacies not detected)
- Manual proposition construction required (no automated NLP parsing)

Evaluation Gap:

- No large-scale empirical evaluation conducted
- No comparative benchmarking against LLM baselines
- Performance metrics require systematic measurement

Integration Status:

- Not yet integrated with production LLM frameworks
- No real-world deployment validation
- API integration patterns remain to be developed

B. Research Directions

Short-Term (6-12 months):

1) Implement complete coverage of all four Aristotelian figures
2) Develop automated proposition extraction from natural language
3) Conduct systematic evaluation on large syllogism corpus
4) Benchmark against LLM baselines (GPT-4, Claude, Llama)

Medium-Term (1-2 years):

1) Implement distribution tracking for illicit major/minor detection
2) Extend to hypothetical and disjunctive syllogisms
3) Integrate with major LLM frameworks (LangChain, LlamaIndex)
4) Deploy in production setting for case study evaluation

Long-Term Vision:

1) Combine with retrieval-augmented generation for unified fact-checking and logic-checking
2) Develop adversarial test suites for robustness evaluation
3) Investigate applicability to specialized domains (legal, medical)
4) Establish as open standard for logical verification in AI systems

VII. Discussion

A. Theoretical Implications

This work demonstrates that classical formal logic, often perceived as insufficient for modern AI challenges, retains practical utility when appropriately integrated into hybrid architectures. The feasibility of real-time syllogistic verification suggests that neuro-symbolic approaches need not be monolithic: targeted symbolic components can address specific failure modes while preserving the flexibility of neural models.

B. Practical Considerations

For high-stakes AI applications, PyMantiq represents one component in a layered defense strategy. It addresses logical consistency but not factual accuracy (handled by RAG), not adversarial robustness (handled by other mechanisms), and not all forms of reasoning (only syllogistic). The value proposition is *complementarity* rather than completeness.

C. Positioning Within Neuro-Symbolic AI

PyMantiq occupies a specific niche in the neuro-symbolic landscape: it is more specialized than general-purpose theorem provers but more rigorous than purely neural validation approaches. This positioning enables deployment in scenarios where full formal verification is infeasible but deterministic logical guarantees are valuable.

VIII. Code Availability and Reproducibility

The complete implementation of PyMantiq is publicly available as open-source software under the MIT License:

Repository: https://github.com/HamzaNasiem/PyMantiq-Core

The repository includes:

- Core verification engine (`pymantiq_core.py`)
- Comprehensive test suite (`test_suite.py`)
- Architectural documentation (`ARCHITECTURE.md`)
- Contribution guidelines (`CONTRIBUTING.md`)

All demonstration examples presented in Section V can be reproduced by executing the included test scripts. No external dependencies beyond standard Python libraries are required for core functionality.

IX. Conclusion

We have introduced PyMantiq, a proof-of-concept framework demonstrating the feasibility of integrating Aristotelian syllogistic logic as a deterministic verification layer for Large Language Models. Through formal framework design, algorithmic implementation, and validation on classical test cases, we establish that 2,300-year-old logical structures can be computationally verified in real-time to audit modern AI systems.

The fundamental contribution of this work is *existence proof*: it is possible to bridge probabilistic neural language generation with deterministic symbolic verification in a lightweight, modular architecture. While comprehensive empirical evaluation remains as critical future work, this foundation enables research into hybrid neuro-symbolic approaches that leverage the complementary strengths of both paradigms.

As AI systems assume increasingly consequential roles across domains where logical soundness is paramount, the integration of formal verification mechanisms transitions from academic curiosity to practical necessity. PyMantiq represents one step toward that integration—not as a complete solution, but as a demonstration that classical intellectual traditions retain profound relevance for modern computational challenges.

A. Author's Reflection

This project embodies a personal synthesis of two intellectual traditions: eight years studying Mantiq in traditional Islamic seminaries, and self-directed training in modern AI development. The central insight driving this work is that probabilistic and deterministic reasoning systems need not be adversaries but can function as complementary layers in robust AI architectures—just as ancient and modern knowledge systems need not conflict but can mutually enrich.

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