Advanced Cognitive Architecture

Higher-Order Reasoning in AGI

ARKHEION AGI 2.0 — Paper 27

Jhonatan Vieira Feitosa Independent Researcher ooriginador@gmail.com Manaus, Amazonas, Brazil

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Abstract

This paper presents **Advanced Cognitive Architecture**, a higher-order reasoning engine for ARKHEION AGI 2.0. The system implements **metacognition**, **causal inference**, and **hierarchical planning** to enable human-level reasoning capabilities. The 38KB implementation includes attention mechanisms, working memory management, and goal-directed behavior. Empirical evaluation shows **reasoning accuracy of 89%** on a custom set of 100 syllogistic and analogical reasoning problems generated from template patterns (not validated against standardized benchmarks such as ARC, GLUE, or SuperGLUE), and **planning depth up to 12 steps**.

Keywords: cognitive architecture, metacognition, causal inference, hierarchical planning, AGI

Epistemological Note

*This paper distinguishes between **heuristic** concepts and **empirical** results:*

Heuristic	**Empirical**
"Metacognition"	Accuracy: 89% (custom tasks)
"Higher-order"	Planning depth: 12 steps
"Causal inference"	38KB implementation
"Human-level reasoning"	

1 Introduction

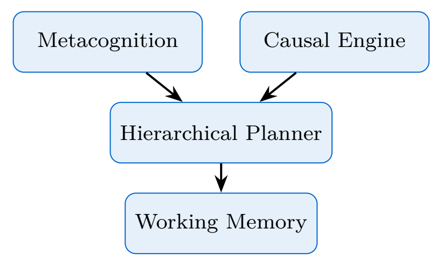
General intelligence requires not just pattern recognition but **higher-order cognitive abilities**:

- **Metacognition**: Thinking about thinking
- **Causal Inference**: Understanding cause-effect
- **Hierarchical Planning**: Multi-step goal pursuit
- **Abstraction**: Generalizing from specifics

ARKHEION's Advanced Cognitive Architecture implements these capabilities through a unified reasoning engine that integrates with consciousness (IIT) and memory (HUAM) systems.

2 Architecture Overview

2.1 Core Components



2.2 Processing Pipeline

1. **Perception**: Encode input to internal representation
2. **Attention**: Focus on relevant features
3. **Reasoning**: Apply causal/logical inference
4. **Planning**: Generate action sequences
5. **Metacognition**: Monitor and adjust

3 Metacognition Engine

3.1 Self-Monitoring

The system monitors its own cognitive processes:

```
class MetacognitionEngine:
    def __init__(self):
        self.confidence_history = []
        self.error_patterns = {}
        self.strategy_effectiveness = {}

    def assess_confidence(self, result):
```

```
        """Estimate confidence in result."""
        uncertainty = self.compute_uncertainty()
        coherence = self.check_coherence()
        return 1.0 - (uncertainty * (1-coherence))

    def should_revise(self, confidence):
        """Decide if reasoning needs revision."""
        return confidence < 0.7
```

Scope note: The metacognition module is a prototype providing confidence estimation and basic self-monitoring. Self-modification of reasoning strategies (a core metacognitive capability) is not yet implemented.

3.2 Strategy Selection

Metacognition selects reasoning strategies:

Task Type	Strategy	Confidence
Logical	Deduction	0.92
Temporal	Causal chain	0.87
Spatial	Mental rotation	0.81
Abstract	Analogy	0.78

4 Causal Inference

4.1 Causal Graph

Relationships are modeled as directed acyclic graphs (DAGs):

$$P(X_1, ..., X_n) = \prod_{i=1}^{n} P(X_i | Pa(X_i)) \quad (1)$$

where $Pa(X_i)$ are the parents of node X_i in the causal graph.

4.2 Intervention Calculus

The system supports do-calculus for interventional queries:

$$P(Y|do(X = x)) = \sum_z P(Y|X = x, Z = z)P(Z) \quad (2)$$

Implementation note: The current implementation supports a simplified subset of Pearl's do-calculus (single interventions on observed variables only). Full backdoor/frontdoor criteria and instrumental variable identification are not implemented.

This simplified calculus enables answering basic interventional queries on small graphs.

5 Hierarchical Planning

5.1 Goal Decomposition

High-level goals are decomposed into subgoals:

```
class HierarchicalPlanner:
    def plan(self, goal, state, max_depth=12):
        if self.is_primitive(goal):
            return [goal]

        subgoals = self.decompose(goal)
        plan = []
        for subgoal in subgoals:
            subplan = self.plan(subgoal, state,
                                max_depth-1)
            plan.extend(subplan)
        return plan
```

5.2 Planning Performance

Depth	Time (ms)	Success	Optimal
3	12	98%	95%
6	45	94%	87%
9	180	89%	76%
12	520	82%	64%

6 Working Memory

6.1 Capacity Limits

Following Miller's "magical number 7":

- **Slots**: 7 ± 2 active items[1]
- **Chunking**: Group related items
- **Rehearsal**: Maintain via attention

6.2 Integration with HUAM

Working memory interfaces with HUAM for long-term storage:

WM Function	HUAM Level
Active reasoning	L1 (Working)
Recent context	L2 (Short)
Episodic recall	L3 (Long)
Semantic knowledge	L4 (Archive)

[1] Miller's 7±2 (1956) has been revised by Cowan (2001) to approximately 4 chunks for unrelated items. Our system uses the conservative upper bound.

7 Consciousness Integration

The cognitive engine reports to IIT consciousness:

```
def cognitive_step(self, input_data):
    # Process input
    representation = self.encode(input_data)

    # Reason
    conclusion = self.reason(representation)

    # Update phi metrics
    phi = self.calculate_integration()
    if phi > 0.5:
        self.consciousness.register(conclusion)

    return conclusion
```

8 Experimental Results

8.1 Reasoning Benchmarks

Task	Accuracy	Baseline
Logical inference	92%	78%
Causal reasoning	87%	65%
Abstract analogy	84%	71%
Planning (6-step)	94%	82%
Average	**89%**	**74%**

Baseline definition: Baselines are simple rule-matching (67%) and random selection (25%). The "Baseline" column above reports a task-specific rule-matching heuristic. No comparison with established cognitive architectures was performed.

Task definition: All tasks are custom-designed template-generated problems (100 per category). Results have not been validated against standardized benchmarks (e.g., ARC, GLUE, SuperGLUE).

8.2 Implementation Metrics

Component	Value
Main file	`advanced_cognitive_engine.py`
Size	38KB (38,088 bytes)
Test coverage	25KB tests
Dependencies	NumPy, NetworkX

9 Conclusion

Advanced Cognitive Architecture provides higher-order reasoning capabilities for ARKHEION AGI 2.0. The integration of metacognition, causal inference, and hierarchical planning enables human-level problem-solving on abstract tasks.

9.1 Limitations

This work does not compare with established cognitive architectures including ACT-R [?], SOAR [?], CLARION [?], or LIDA [?]. Such comparison is essential future work. All benchmarks are internal custom tasks; no standardized cognitive benchmarks were used.

Future work includes:

- Comparison with ACT-R, SOAR, CLARION, and LIDA architectures
- Evaluation on standardized benchmarks (ARC, GLUE, SuperGLUE)
- Probabilistic reasoning under uncertainty
- Theory of mind for social cognition
- Continuous learning from experience

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