Autonomous Cognitive Architectures for LLMs: Metacognition and Evolutionary Memory for Next-Generation Artificial Intelligence

Abstract

Platforms adopting Large Language Models (LLMs) face a critical challenge: real-time output validation and long-term coherence. The absence of an intrinsic self-awareness mechanism leads to unreliability (hallucinations) and inefficiencies in context management. We introduce **MarCognity-AI**, an architecture that addresses this issue through the integration of metacognitive capabilities and a vector-based Evolutionary Memory system. The system not only generates responses, but also critically evaluates its own output using semantic coherence metrics (e.g., CrossEncoder), self-improves, and archives reflections for future learning. The **MarCognity-AI architecture** is a prototype for the AI of the future: a robust, verifiable, and self-regulated agent.

1. Introduction and Motivation

The large-scale implementation of LLMs in critical environments (e.g., research, finance, healthcare) is hindered by structural limitations. Current models do not guarantee verifiability, long-term coherence, or ethical adequacy. The dominant approach has focused on increasing model size, a method that does not resolve the intrinsic problems of grounding and self-criticism.

Our work introduces **MarCognity-AI**, an architectural framework that emulates human cognitive functions of **metacognition** (thinking about thinking) and **evolutionary memory** (learning based on the history of judgments). The goal is not simply to improve output, but to equip the agent with an autonomous cycle of critical reasoning.

The main contributions of this article are:

1. The formalization of a structured **Metacognitive Cycle** that employs specialized models (CrossEncoder, Specter) for internal validation.
2. An **Evolutionary Memory architecture** that integrates FAISS with the archiving of metacognitive reflection (Reflective Journal).
3. The integration of **Scientific Rigor and Ethical Control Modules** for the agent's internal governance.

2. Related Work

2.1 Retrieval-Augmented Generation (RAG) Standard RAG systems have improved reliability by anchoring generation to external data corpora. However, the limitations of RAG lie in its inability to critically validate the quality of the source and in the absence of a mechanism to correct reasoning errors after retrieval. **MarCognity-AI** extends RAG by implementing a post-generation semantic cross-verification phase.

2.2 Self-Correction and Reflection MarCognity-AI formalizes Self-Correction techniques into a two-level methodology: an objective numerical evaluation (via CrossEncoder) and a qualitative reflection which, once recorded, feeds into the long-term memory system. This ensures that self-improvement is based on a traceable and persistent mechanism.

3. Methodological Architecture of MarCognity-AI

3.1 The Metacognitive Cycle and Self-Evaluation Self-evaluation ensures that the agent not only produces output but also certifies the quality of its own output.

3.1.1 Objective Semantic Evaluation The initial coherence between the query and the response is assessed using a CrossEncoder model (e.g., DeBERTa). This provides an objective similarity score. If this score falls below a critical threshold (0.7), the output is flagged for correction.

3.1.2 Critical Reflection and Structured Improvement In the event of coherence failure, the reflection agent is activated, triggering the improve_response function. The correction prompt is designed to focus the LLM on specific attributes.

Code Snippet (Structured Improvement):

```python
# Function to improve a response while preserving its content but enhancing quality and clarity
def improve_response(question, response, level):
    improvement_prompt = f"""
You produced the following response:
\"{response.strip()}\"

Question:
\"{question.strip()}\"

Requested level: {level}

Improve the response while preserving the original content by enhancing:
- Clarity
- Academic rigor
- Semantic coherence

Return only the improved version.
"""
    return llm.invoke(improvement_prompt.strip())
```

“The result of the reflection process is recorded in the **Reflective Journal.**

3.2 Vector-Based Evolutionary Memory System Memory is implemented as a high-performance FAISS index. We use the *allenai/specter* embedding model (768 dimensions), specialized in the representation of scientific texts.

The key innovation is the archiving process (via add_diary_to_memory), which includes **Metacognitive Reflection** and the **Coherence Score** within the vector. This enables the system, in a future prompt, to retrieve not only factual context but also the lessons learned from previous self-evaluations, thereby creating a memory that evolves according to its own critical history.

Code Snippet (Semantic Coherence):

```python
# === Semantic coherence check ===
def check_coherence(query, response):
    emb_query = embedding_model.encode([query])
    emb_response = embedding_model.encode([response])
    similarity = np.dot(emb_query, emb_response.T) / (np.linalg.norm(emb_query) * np.linalg.norm(emb_response))
    if similarity < 0.7:
        return "The response is too generic, reformulating with more precision..."
    return response
```

3.3 Scientific Rigor Module MarCognity-AI is equipped with modules to ensure the academic rigor of its content:

- **Methodology and Citation Verification**: The functions (verify_methodology, verify_citations) analyze the replicability of methodologies and the timeliness/relevance of cited sources.
- **Novelty and Impact Assessment**: A RandomForestRegressor estimates an *Impact Score* for articles. Vector similarity among hypotheses further evaluates the degree of novelty with respect to the existing knowledge corpus.

3.4 Ethical Control and Controlled Autonomy An Ethical Module with a flagging system analyzes the text for the presence of risk patterns related to "critical topics." In cases of high-risk detection, the system can reduce the agent's autonomy, ensuring compliance.

4. Performance Analysis and Evaluation

This section describes the evaluation methodology of **MarCognity-AI**, the set of integrated models, and the results obtained that quantify performance improvements in terms of reliability, coherence, and ethical rigor compared to a baseline non-augmented LLM.

4.1 Experimental Setup and Model Architecture The **MarCognity-AI** architecture operates by integrating a suite of specialized models for cognitive augmentation and validation. The primary LLM model for generation is *meta-llama/llama-4-maverick-17b-128e-instruct*, used under the **LLaMA 4 Community License (Meta)**. This setup ensures that the agent does not merely generate output but engages in an integrated metacognitive reasoning process for each response.

The key tools employed are:

- **LLM Generation**: Llama 4 (*meta-llama/llama-4-maverick-17b-128e-instruct*).
- **Vector Embedding**: *allenai/specter* model (768 dimensions), specialized in the representation of scientific texts.
- **Objective Semantic Evaluation**: A CrossEncoder (DeBERTa-based) assesses coherence between query and response, triggering correction if the score falls below the critical threshold of 0.7.
- **Evolutionary Memory**: High-performance FAISS index for archiving and retrieving metacognitive reflection.

- **Scientific Retrieval**: The agent leverages asynchronous querying of open-access sources for grounding and validation, including *arXiv*, *PubMed*, and *Zenodo*.

4.2 Evaluation Metrics and Adapted Methodology The evaluation was conducted to measure the impact of the **Metacognitive Cycle** and **Evolutionary Memory** on the intrinsic limitations of the LLM.

- **Increase in Semantic Coherence Score**: Measured as the improvement in the CrossEncoder score between the initial response generated by Llama 4 and the final response refined by the reflection agent.
- **Reduction of Fallacy Rate (Hallucination Rate)**: Measured by the number of incorrect statements corrected after the self-improvement phase. Statements were verified against the *Corpus of Truth* composed of articles retrieved from open-access sources (arXiv, PubMed, Zenodo).
- **Long-Term Coherence (LTC)**: Assessed by measuring the relevance and accuracy of responses in multi-turn sessions, using the Reflective Journal as memory to guide learning based on the history of judgments.
- **Rigor and Transparency**: Qualitative evaluation of the integration of conceptual visualizations (generated via Plotly, NetworkX, etc.) and the effectiveness of ethical auditing (bias detection, risk analysis) on each output, ensuring that the agent is not only intelligent but also self-aware.

5. Implications and Strategic Value

The **MarCognity-AI architecture** is a ready-made solution for the strategic challenges that AI industry leaders must face:

- **Enterprise Reliability**: By providing an intrinsic and algorithmic mechanism for output certification (Coherence Score), MarCognity-AI transforms reliability into a contractual quality parameter.
- **Scalability and Technological Advantage**: The combination of FAISS/Specter resolves context and cost bottlenecks, offering a more efficient platform and a clear competitive edge in managing large proprietary corpora.
- **Compliance and Responsible AI**: The Ethical and Scientific Rigor Modules represent a proactive framework for governance and regulatory risk management.

MarCognity-AI provides a solid foundation for the evolution of generative models into mature cognitive agents.

References

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