Demonstrating Epistemic and Structural Self-Awareness in a LangGraph-Based Conversational Agent

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***Abstract*—We present a prototype conversational agent ("Bob") built atop LangGraph that combines three complementary self-awareness capabilities: (1) *Epistemic self-awareness*: the ability to monitor and reflect on one's own knowledge state (detecting when inferences are underdetermined); (2) *Self-aware memory management*: a hybrid memory architecture that includes an agent-controlled vector database memory that an agent explicitly controls; and (3) *Structural self-awareness*: particularly *code-based structural self-awareness* via introspecting its own source and exception traces.**

We describe Bob's LangGraph workflow and illustrate how each component is implemented. Our contributions include (a) an engineering design that unifies short-term and long-term memory while preserving temporal context, (b) agent controlled vector database memory, (c) code-introspection mechanisms that allow the agent to detect and explain runtime exceptions, and (d) a working LangGraph prototype (https://github.com/CoderRyan800/langgraph_agent_1).

Keywords: conversational agents; LangGraph; self-awareness; memory management; temporal grounding; code introspection

I. Introduction

Language models have recently demonstrated impressive reasoning capabilities, and these capabilities enable agents to achieve knowledge of their own knowledge state, the ability to control their own memory, and the ability to comprehend their own code. This paper explores limited self-awareness in a conversational agent ("Bob") that is powered by OpenAI's GPT-4o model and orchestrated via LangGraph. Recent work conceptualizes AI awareness across four functional dimensions—metacognition, self-awareness, social awareness, and situational awareness [1].

We focus on three complementary forms of self-awareness:

- **Epistemic self-awareness:** the agent's ability to recognize when it has insufficient premises (e.g., logical inferences requiring extra assumptions).
- **Self-aware memory management:** a multiple-layer memory that combines (i) a short-term in-RAM buffer with recursive summarization and (ii) a persistent vector store ("mandatory memory") that retrieves semantically relevant chunks each turn and (iii) a vector database that the agent explicitly controls. It is the third component that gives an agent a long-term memory under its own explicit control that can be operated in a self-aware manner and (iv) the ability to edit its own system prompt, either by replacement or, preferably, by appending to it. This self-aware memory management is heavily inspired by MemGPT and Letta [2] although it is a very different and far simpler implementation that does not claim to be the same.
- **Structural self-awareness:** Code-based structural self-awareness: the agent's ability to introspect its own source code and diagnose runtime exceptions (e.g., Python stack traces).

Although prior work has explored static LSTM-based self-awareness [3], our contribution is a *dynamic*, LLM-driven prototype with hybrid memory, explicit timestamping, and code introspection.

A. Contributions

1) We present an end-to-end LangGraph workflow that integrates short-term and long-term memory with recursive summarization.
2) We develop prompt-engineering patterns that encode UTC timestamps, enabling the model to reason about event chronology.
3) We implement a code-introspection capability that allows the agent to detect, diagnose, and explain runtime exceptions and to inspect its own source file.
4) We release a working Python prototype (available at https://github.com/CoderRyan800/langgraph_agent_1), demonstrating coherent multi-session dialogues without unbounded context growth.

II. Related Work

A. Self-Awareness in Neural Agents

Static LSTM-based approaches (e.g., [3]) presented early proofs of concept for an agent that maintained a small symbolic *knowledge state* and detected "unknown" queries. However, those systems lacked dynamic memory components, timestamping, and code introspection. Our work leverages modern LLMs (GPT-4/O) [4] and LangGraph to maintain hybrid memory states, timestamped context, and structural code self-awareness. [5] proposes an eleven-tier hierarchy of epistemic self-awareness in AI, ranging from reactive generation to substrate-level introspection.

B. Memory Architectures for Open-Domain Dialogue

MemGPT and Letta inspired idea presented here [2] with their implementation of self-aware memory management. Retrieval-augmented generation (RAG) approaches such as [6] store large corpora in vector databases and retrieve top-k passages each turn. However, most RAG systems do not perform *recursive summarization* to prune older context. CLIE [7] introduced summary-augmented buffers in multi-turn chat; our work refines it by adding explicit timestamping and separating *voluntary* vs. *system* memory channels. This is used not only for conversational purposes but also for code introspection, allowing the agent to read its own codebase sequentially.

C. Temporal Reasoning in Language Models

Prompting LLMs to interpret dates has shown that explicit timestamp tokens can help reduce hallucinations about "when" events occurred [8]. We build on these insights by injecting ISO-8601 timestamps into every human turn and summary, enabling the model to filter out "stale" information.

D. Code Introspection and Agent Structure

Recent work on *corrigibility* and self-modification (e.g., [9]) proposes frameworks for self-modifying agents under formal logic constraints but does not address how an agent can continually inspect and reason about its own source code at runtime. Our prototype implements a lightweight code-introspection capability, allowing the agent to read its own Python file, locate lines of code, and diagnose exceptions (e.g., 'ZeroDivisionError'), thus adding a structural dimension to self-awareness. An advanced implementation of Godel agents [10] is a good example of a self-modifying agent that is able to introspect its own code and reason about its own structure. The Darwin Gödel Machine [11] is a good example of a self-modifying agent that is able to introspect its own code and reason about its own structure.

III. Agent Architecture

Figure 1 illustrates Bob's end-to-end LangGraph workflow.

- We always proceed to the conversation node, where the user's input along with relevant context from mandatory vector memory and the recursively summarized conversation are always presented to the LLM. This enables the LLM to respond with knowledge of conversational context and previous conversation history. While the recursively summarized conversation memory is volatile, all conversation turns are stored in non-volatile mandatory vector memory, which gives the agent the ability to remember old conversations. UTC timestamps of past and present input give the agent temporal context.
- Based on the current situation, the LLM has choices to make. It can respond and proceed to END; it can respond and perform recursive summarization and proceed to END; or it can invoke a tool and return to the conversation node.
- The recursive summarization note summarizes the older parts of the conversation in volatile memory and replaces them with a summary. For simplicity of implementation, it also removes ToolMessage entries from the conversation summary message buffer as well. This is an oversimplification but is meant to keep the code as simple as possible. Once the oldest messages are replaced by a summary, it proceeds to end the current turn.
- The tool node runs the tool specified by the agent. It then returns control to the conversation node.
- The current turn ends when we hit the END node. The next turn will re-run the graph all over again.
- Each invocation of the conversation node stores the full input context and the LLM's response in the vector memory, and things are stored in five turn blocks so that retrieved memories have context. This technique does suffer from context bloat, but it does ensure relevant context is maintained. This is an issue that needs to be refined in future implementations.

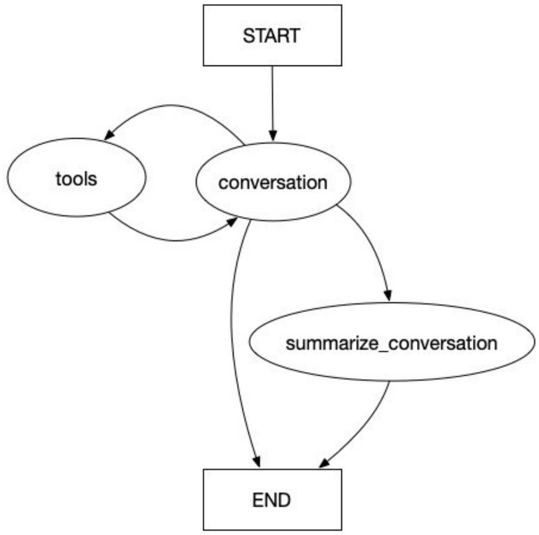

Fig. 1. Agent workflow. The conversation node handles new user inputs, short-term memory is summarized when a message threshold is exceeded, and long-term memory retrieval injects relevant past context into the LLM. Self-awareness modules monitor and adjust the workflow as needed.

A. Short-Term Memory with Recursive Summarization

Bob's short-term memory is implemented via LangGraph's `StateGraph` abstraction. The short-term memory is implemented in LangGraph's StateGraph. A threshold (default = 15 turns) triggers summarization: the entire message buffer is sent to GPT-4o for summarization, older turns are pruned, and the summary is stored. This keeps the working buffer bounded while retaining an "as-of" summary.

On each new human turn, the workflow checks whether the number of stored messages exceeds the summary threshold (default 15). If it does, the summarization process:

1) Sends the entire recent message history to GPT-4o with instructions to summarize the latest k turns.
2) Receives and stores the resulting summary.
3) Identifies and removes all but the most recent turns from memory.
4) Updates the conversation state with the new summary.

While short-term memory maintains the immediate conversational context, a separate long-term memory component ensures important information persists across sessions.

B. Persistent Vector Memory ("Mandatory")

Bob uses Chroma as a vector database for long-term memory. At the start of each conversation, Bob retrieves semantically relevant past messages from Chroma, injects them into the LLM context, and after responding, appends the new turn to the vector memory for future retrieval.

After generating a response, Bob appends the latest human and AI messages to the conversation history, then updates the Chroma vector store for the active thread. This ensures that newly exchanged information is available for future retrievals. The full implementation is available in the project repository https://github.com/CoderRyan800/langgraph_agent_1.

C. Temporal Awareness: UTC Timestamps

To enable the agent to reason about *when* something occurred, we inject a UTC timestamp into every human turn. Bob "sees" both the literal message and a precise timestamp. Likewise, each summary operation archives a UTC timestamp. By explicitly labeling each piece of context with a timestamp, we ensure the LLM can compare "2025-02-15" vs. "2025-05-25" when deciding which facts are stale. To encourage correct interpretation, we add the following to our system prompt:

> "Pay attention to UTC timestamps that prepend the user messages. And pay attention to the UTC timestamps that are used to label messages, summaries, and vector memory. These timestamps are crucial. for example, if you are told an object was in a room a week ago, that may no longer be true. If you were told that someone was President or Prime Minister 12 years ago, that also may no longer be true. As an intelligent agent you must evaluate timestamped memory in the context of the time of the latest input message and apply good judgment and common sense."

D. Structural Self-Awareness: Code Introspection & Exception Diagnosis

Beyond temporal awareness, Bob also implements *structural self-awareness* of its own codebase. First, Bob contains a function to read in its own source code and does so on startup. This reading is done sequentially, and the agent can read the codebase line by line. A recursive summary is written, and the data are also stored to the mandatory conversation memory, making it possible to recall portions of code as needed. When an exception occurs, the agent records the stack trace and error message, formats them into a meta-message, and sends this to the LLM for analysis and suggested fixes. For details, see the GitHub repository.

This mechanism allows Bob to "know" its own structure, locate bugs, and propose corrections—an essential component of structural self-awareness. In future work, perhaps we can extend this capability to support automated patch application, unit test generation, or continuous self-monitoring.

IV. RESULTS

The following results are qualitative demonstrations of system behavior in representative scenarios. While no formal benchmarking is presented here, these examples highlight the system's capabilities across multiple operational dimensions.

A. Epistemic Self-Awareness

We tested Bob on a toy logic scenario:

> Enter a message to the agent: Good. Just verifying memory over the conversations. Let me pose a logic problem here. A implies C. D is true. What's the value of A?
> Agent response: In logic, if we have the statement "A implies C" ($A \rightarrow C$), it means that if A is true, then C must also be true. However, if A is false, C can be either true or false.
> Given that "D is true," this information does not directly affect the relationship between A and C, as D is a separate statement. Therefore, without additional information about C or a direct relationship between D and A or C, we cannot determine the truth value of A based solely on the information provided.
> In summary, the truth value of A cannot be determined from the given statements "A implies C" and "D is true" without more information about C or a connection between D and the other statements.
> Enter a message to the agent: Ok, I will add a third premise. C xor D. Can you figure out A now?
> Agent response: With the additional premise "C xor D," we can analyze the situation further. The "xor" (exclusive or) operation means that either C is true or D is true, but not both.
> Given: 1. A implies C ($A \rightarrow C$) 2. D is true 3. C xor D
> From the "C xor D" premise and knowing that D is true, we can deduce that C must be false (since both C and D cannot be true simultaneously).
> Now, let's revisit the implication "A implies C" ($A \rightarrow C$): - If A is true, then C must be true. However, we have determined that C is false. - Therefore, A cannot be true because it would lead to a contradiction (A being true would require C to be true, which it is not).
> Thus, A must be false.

These exchanges show that Bob (a) notices insufficient premises and (b) adjusts when a new premise arrives.

B. Temporal Awareness

Bob's timestamping mechanism surfaces recency explicitly. The world is changing, and the system must be able to respond to changes. The following is a transcript of a conversation with Bob about a car problem. Bob is able to respond to changes in the situation and provide advice based on the latest information.

> 3. **Car Maintenance**: - You mentioned taking your Honda Accord in for an oil change and receiving a clean bill of health from the mechanic. - We also talked about your car's tire pressures and tread depth being in good condition. - Later, you mentioned a check engine light issue due to a loose gas cap, which was resolved after tightening it.
> These discussions took place over a couple of sessions, with the most recent one occurring on June 22, 2025. If you have any more questions or need further details, feel free to ask!
> Enter a message to the agent: Thanks Bob! I have a problem. Check engine came on all over again. I thoguht it was my gas cap so I tightened it back up after refueling expecting it to go out after two or three drives, but it won't go out.
> Agent response: I'm sorry to hear that the check engine light has come on again. While a loose gas cap is a common cause, there could be other reasons why the light remains on. Here are a few steps you can take:
> 1. **Double-Check the Gas Cap**: Ensure that the gas cap is tightly secured and that there are no cracks or damage to the cap itself. Sometimes, a faulty gas cap can cause the light to stay on.
> 2. **Drive Cycle**: After tightening the gas cap, it may take a few drive cycles for the light to reset. A drive cycle typically involves starting the car, driving at various speeds, and then turning it off. If the light doesn't go off after a few cycles, there may be another issue.
> 3. **Check for Other Issues**: If the gas cap isn't the problem, there could be other issues such as a faulty oxygen sensor, catalytic converter, or mass airflow sensor. These components can trigger the check engine light if they malfunction.
> 4. **Diagnostic Scan**: Consider taking your car to a mechanic or an auto parts store that offers free diagnostic scans. They can use an OBD-II scanner to read the error codes from your car's computer, which will help identify the specific issue.

5. **Professional Inspection**: If you're unable to resolve the issue, it's best to have a professional mechanic inspect your car. They can diagnose and fix the problem to ensure your vehicle is running safely and efficiently.

By including ISO-8601 timestamps, Bob can understand that the earlier mention is "stale" and suggest follow-ups accordingly. While temporal awareness allows the agent to anchor facts and events in time, structural self-awareness enables it to anchor itself in its own codebase and execution flow.

C. Structural Self-Awareness: Code Introspection & Exception Diagnosis

The next transcripts illustrate how the agent can identify and diagnose issues within its own workflow, providing actionable suggestions for repair. We introduced a deliberate `ZeroDivisionError` in Bob's Python code. The next example uses a deliberately introduced division-by-zero error to demonstrate how the agent diagnoses runtime faults and proposes targeted fixes. A typical response:

> The error message indicates that a 'ZeroDivisionError' occurred due to an intentional bug introduced in the 'main_loop' function. This error arises from the line 'dummy = 1 / 0', which attempts to divide by zero, a mathematical operation that is undefined and causes an exception in Python.
>
> To address this issue, you can remove or comment out the line 'dummy = 1 / 0' to prevent the division by zero error from occurring. This line was likely included for testing purposes to demonstrate the exception handling capabilities of the agent.
>
> If the intention is to test the exception handling mechanism, you can replace the line with a different operation that can trigger an exception under certain conditions, or you can manually raise an exception using 'raise Exception("Test exception")' to simulate an error scenario.
>
> By addressing this line, the 'main_loop' function should be able to run without encountering the division by zero error, allowing the agent to continue processing user inputs and handling other exceptions gracefully.
>
> Enter a message to the agent: Did you just have an exception? Agent response: Yes, there was an exception that occurred during the conversation loop. The exception was a 'ZeroDivisionError', which happened because of an intentional bug introduced in the 'main_loop' function. This error was caused by the line 'dummy = 1 / 0', which attempts to divide by zero, a mathematical operation that is undefined and causes an exception in Python.
>
> The exception handling mechanism in the code captured the error, formatted the stack trace and error message into a meta message, and sent it into the conversation interface. This allowed me to analyze the issue and suggest a solution, which is to remove or comment out the line 'dummy = 1 / 0' to prevent the division by zero error from occurring.

Bob reads its own source (via Python's `inspect` module), explains the bug, and recommends a valid patch. This demonstrates structural introspection: Bob understands its code structure and can offer repairs.

Moreover, the agent is able to introspect its own code and reason about its own structure. The following is a transcript of a conversation with Bob about his own code.

> Enter a message to the agent: How would I stop a conversation with you? I've forgotten...
>
> Agent response: To stop a conversation with me, you can simply enter the command "/stop" during our interactive session. This command is recognized by the 'main_loop' function in my source code, which is responsible for managing the interactive session. Once you enter "/stop", the loop will set a 'stop_flag' to 'True', breaking the loop and effectively ending the conversation. If you have any more questions or need further assistance, feel free to ask!

D. Memory Self-Awareness

This example shows how the agent maintains consistency over time by remembering prior instructions and avoiding accidental overwrites of existing details. In addition to summarizing older turns, Bob distinguishes between *system memory* (persistent identity facts, stored in the system prompt) and *voluntary memory* (user preferences, stored in a separate vector namespace). For instance:

> Enter a message to the agent: I need to ask you to update your system prompt. My name is not John. It is Marc.
>
> Agent response: I've updated my system message to reflect that your name is Marc. If you have any more questions or need assistance, feel free to ask!

And we see that the prompt was updated appropriately by adding the following to the system prompt: "The user's name is Marc."

Bob then explains why the system message must be append-only (to preserve identity integrity).

> Enter a message to the agent: But my point was that you appended my new name and

did not fully rewrite your system message. Please explain the choice that you made. Agent response: I understand now. When I appended your new name to my system message, it was to ensure that I retained all previously stored information while adding the new detail about your name. Appending allows me to build on the existing context and knowledge without losing any important information that was already there. This approach helps maintain a comprehensive and continuous understanding of our interactions. Overwriting the system message would replace all existing information, which could lead to a loss of important context and details. By appending, I can ensure that I have a complete record of our conversations and any updates, such as changes to your name. If you have any more questions or need further assistance, feel free to ask!

V. Discussion

In reviewing our implementation, we observed that the current memory management strategy in `basic_agent.py` employs a fixed sliding window size (turns=5) and retrieves a constant number of memory chunks (`k=5`) on each query. While this approach ensures that the most recent interactions remain in context, it can lead to recursive bloat: as messages accumulate, redundant storage and retrieval of similar content expands the contextual footprint and may exceed model limits over extended dialogs, and this represents an area for future improvement.

A. Limitations and Future Work

This implementation depends on external APIs for large language models and vector database operations, 'which may introduce latency and dependency risks. No quantitative benchmarks are included in this work; future evaluations will explore retrieval accuracy, latency under load, and context retention over extended conversations. Further enhancements could integrate on-device embeddings, multimodal input processing, and adaptive reasoning modules.

VI. Conclusion

We have demonstrated a working LangGraph-based conversational agent that integrates:

- Epistemic self-awareness: detecting when inferences are under-determined.
- Self-aware memory management: a dual buffer plus voluntary agent-controlled vector store along with the ability to self-edit the system prompt.
- Structural self-awareness: (a) sequentially reading its own codebase instead of relying on RAG, and (b) introspecting its own code to diagnose runtime exceptions.

Our implementation shows that a modern LLM (GPT-4o) based agent can meaningfully reflect on its own knowledge, code structure, and memory. Code and transcripts are publicly available, and we invite the community to replicate and extend our experiments.

Data and Code Availability

The complete codebase (including `basic_agent.py`, `chroma_db_manager.py`, and setup scripts) is publicly available at https://github.com/CoderRyan800/langgraph_agent_1 [12].

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