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Build a Retrieval Augmented Generation (RAG) App: Part 2

In many Q&A applications we want to allow the user to have a back-and-forth conversation, meaning the application needs some sort of "memory" of past questions and answers, and some logic for incorporating those into its current thinking.

This is the second part of a multi-part tutorial:

- Part 1 introduces RAG and walks through a minimal implementation.
- Part 2 (this guide) extends the implementation to accommodate conversation-style interactions and multi-step retrieval processes.

Here we focus on **adding logic for incorporating historical messages.** This involves the management of a chat history.

We will cover two approaches:

1. Chains, in which we execute at most one retrieval step;
2. Agents, in which we give an LLM discretion to execute multiple retrieval steps.

> NOTE
>
> The methods presented here leverage tool-calling capabilities in modern chat models. See this page for a table of models supporting tool calling features.

For the external knowledge source, we will use the same LLM Powered Autonomous Agents blog post by Lilian Weng from the Part 1 of the RAG tutorial.

Setup

Components

We will need to select three components from LangChain's suite of integrations.

Select chat model: Google Gemini ▾

```
pip install -qU "langchain[google-genai]"
```

```
import getpass
import os

if not os.environ.get("GOOGLE_API_KEY"):
  os.environ["GOOGLE_API_KEY"] = getpass.getpass("Enter API key for
Google Gemini: ")

from langchain.chat_models import init_chat_model

llm = init_chat_model("gemini-2.5-flash",
model_provider="google_genai")
```

Select embeddings model: OpenAI ▾

```
pip install -qU langchain-openai
```

```
import getpass
import os

if not os.environ.get("OPENAI_API_KEY"):
  os.environ["OPENAI_API_KEY"] = getpass.getpass("Enter API key for
OpenAI: ")

from langchain_openai import OpenAIEmbeddings

embeddings = OpenAIEmbeddings(model="text-embedding-3-large")
```

Select vector store: In-memory

```
pip install -qU langchain-core
```

```python
from langchain_core.vectorstores import InMemoryVectorStore

vector_store = InMemoryVectorStore(embeddings)
```

Dependencies

In addition, we'll use the following packages:

```
%%capture --no-stderr
%pip install --upgrade --quiet langgraph langchain-community
beautifulsoup4
```

LangSmith

Many of the applications you build with LangChain will contain multiple steps with multiple invocations of LLM calls. As these applications get more and more complex, it becomes crucial to be able to inspect what exactly is going on inside your chain or agent. The best way to do this is with LangSmith.

Note that LangSmith is not needed, but it is helpful. If you do want to use LangSmith, after you sign up at the link above, make sure to set your environment variables to start logging traces:

```python
os.environ["LANGSMITH_TRACING"] = "true"
if not os.environ.get("LANGSMITH_API_KEY"):
    os.environ["LANGSMITH_API_KEY"] = getpass.getpass()
```

Chains

Let's first revisit the vector store we built in Part 1, which indexes an LLM Powered Autonomous Agents blog post by Lilian Weng.

```python
import bs4
from langchain import hub
from langchain_community.document_loaders import WebBaseLoader
from langchain_core.documents import Document
from langchain_text_splitters import RecursiveCharacterTextSplitter
from typing_extensions import List, TypedDict

# Load and chunk contents of the blog
loader = WebBaseLoader(
    web_paths=("https://lilianweng.github.io/posts/2023-06-23-
agent/",),
    bs_kwargs=dict(
        parse_only=bs4.SoupStrainer(
            class_=("post-content", "post-title", "post-header")
        )
    ),
)
docs = loader.load()

text_splitter = RecursiveCharacterTextSplitter(chunk_size=1000,
chunk_overlap=200)
all_splits = text_splitter.split_documents(docs)
```

API Reference: Document

```python
# Index chunks
_ = vector_store.add_documents(documents=all_splits)
```

In the Part 1 of the RAG tutorial, we represented the user input, retrieved context, and generated answer as separate keys in the state. Conversational experiences can be naturally represented using a sequence of messages. In addition to messages from the user and assistant, retrieved documents and other artifacts can be incorporated into a message sequence via tool messages. This motivates us to represent the state of our RAG application using a sequence of messages. Specifically, we will have

1. User input as a `HumanMessage`;

2. Vector store query as an `AIMessage` with tool calls;
3. Retrieved documents as a `ToolMessage`;
4. Final response as a `AIMessage`.

This model for state is so versatile that LangGraph offers a built-in version for convenience:

```
from langgraph.graph import MessagesState, StateGraph

graph_builder = StateGraph(MessagesState)
```

API Reference: StateGraph

Leveraging tool-calling to interact with a retrieval step has another benefit, which is that the query for the retrieval is generated by our model. This is especially important in a conversational setting, where user queries may require contextualization based on the chat history. For instance, consider the following exchange:

> Human: "What is Task Decomposition?"
>
> AI: "Task decomposition involves breaking down complex tasks into smaller and simpler steps to make them more manageable for an agent or model."
>
> Human: "What are common ways of doing it?"

In this scenario, a model could generate a query such as `"common approaches to task decomposition"`. Tool-calling facilitates this naturally. As in the query analysis section of the RAG tutorial, this allows a model to rewrite user queries into more effective search queries. It also provides support for direct responses that do not involve a retrieval step (e.g., in response to a generic greeting from the user).

Let's turn our retrieval step into a tool:

```
from langchain_core.tools import tool


@tool(response_format="content_and_artifact")
def retrieve(query: str):
    """Retrieve information related to a query."""
    retrieved_docs = vector_store.similarity_search(query, k=2)
    serialized = "\n\n".join(
        (f"Source: {doc.metadata}\nContent: {doc.page_content}")
        for doc in retrieved_docs
    )
    return serialized, retrieved_docs
```

API Reference: tool

See this guide for more detail on creating tools.

Our graph will consist of three nodes:

1. A node that fields the user input, either generating a query for the retriever or responding directly;
2. A node for the retriever tool that executes the retrieval step;
3. A node that generates the final response using the retrieved context.

We build them below. Note that we leverage another pre-built LangGraph component, ToolNode, that executes the tool and adds the result as a `ToolMessage` to the state.

```
from langchain_core.messages import SystemMessage
from langgraph.prebuilt import ToolNode


# Step 1: Generate an AIMessage that may include a tool-call to be
sent.
def query_or_respond(state: MessagesState):
    """Generate tool call for retrieval or respond."""
    llm_with_tools = llm.bind_tools([retrieve])
    response = llm_with_tools.invoke(state["messages"])
    # MessagesState appends messages to state instead of overwriting
    return {"messages": [response]}


# Step 2: Execute the retrieval.
tools = ToolNode([retrieve])


# Step 3: Generate a response using the retrieved content.
def generate(state: MessagesState):
    """Generate answer."""
    # Get generated ToolMessages
    recent_tool_messages = []
    for message in reversed(state["messages"]):
        if message.type == "tool":
            recent_tool_messages.append(message)
        else:
            break
    tool_messages = recent_tool_messages[::-1]

    # Format into prompt
    docs_content = "\n\n".join(doc.content for doc in tool_messages)
    system_message_content = (
        "You are an assistant for question-answering tasks. "
        "Use the following pieces of retrieved context to answer "
        "the question. If you don't know the answer, say that you "
        "don't know. Use three sentences maximum and keep the "
        "answer concise."
        "\n\n"
        f"{docs_content}"
    )
    conversation_messages = [
        message
        for message in state["messages"]
        if message.type in ("human", "system")
        or (message.type == "ai" and not message.tool_calls)
    ]
    prompt = [SystemMessage(system_message_content)] +
conversation_messages

    # Run
    response = llm.invoke(prompt)
    return {"messages": [response]}
```

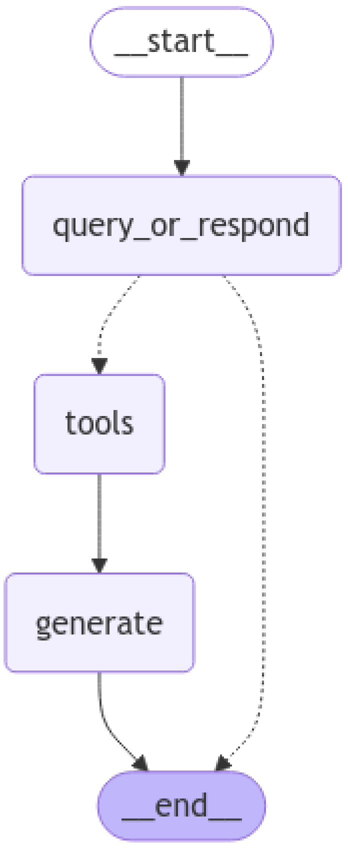
API Reference: SystemMessage | ToolNode

Finally, we compile our application into a single `graph` object. In this case, we are just connecting the steps into a sequence. We also allow the first `query_or_respond` step to "short-circuit" and respond directly to the user if it does not generate a tool call. This allows our application to support conversational experiences--e.g., responding to generic greetings that may not require a retrieval step

```python
from langgraph.graph import END
from langgraph.prebuilt import ToolNode, tools_condition

graph_builder.add_node(query_or_respond)
graph_builder.add_node(tools)
graph_builder.add_node(generate)

graph_builder.set_entry_point("query_or_respond")
graph_builder.add_conditional_edges(
    "query_or_respond",
    tools_condition,
    {END: END, "tools": "tools"},
)
graph_builder.add_edge("tools", "generate")
graph_builder.add_edge("generate", END)

graph = graph_builder.compile()
```

API Reference: ToolNode | tools_condition

```python
from IPython.display import Image, display

display(Image(graph.get_graph().draw_mermaid_png()))
```



Let's test our application.

Note that it responds appropriately to messages that do not require an additional retrieval step:

```
input_message = "Hello"

for step in graph.stream(
    {"messages": [{"role": "user", "content": input_message}]},
    stream_mode="values",
):
    step["messages"][-1].pretty_print()
```

```
================================ [1m Human Message
 [0m=================================

Hello
================================== [1m Ai Message
 [0m==================================

Hello! How can I assist you today?
```

And when executing a search, we can stream the steps to observe the query generation, retrieval, and answer generation:

```
input_message = "What is Task Decomposition?"

for step in graph.stream(
    {"messages": [{"role": "user", "content": input_message}]},
    stream_mode="values",
):
    step["messages"][-1].pretty_print()
```

```
================================ [1m Human Message
 [0m=================================

What is Task Decomposition?
================================== [1m Ai Message
 [0m==================================
Tool Calls:
  retrieve (call_dLjB3rkMoxZZxwUGXi33UBeh)
 Call ID: call_dLjB3rkMoxZZxwUGXi33UBeh
  Args:
    query: Task Decomposition
================================= [1m Tool Message
 [0m=================================
Name: retrieve

Source: {'source': 'https://lilianweng.github.io/posts/2023-06-23-
agent/'}
Content: Fig. 1. Overview of a LLM-powered autonomous agent system.
Component One: Planning#
A complicated task usually involves many steps. An agent needs to know
what they are and plan ahead.
Task Decomposition#
Chain of thought (CoT; Wei et al. 2022) has become a standard prompting
technique for enhancing model performance on complex tasks. The model
is instructed to "think step by step" to utilize more test-time
computation to decompose hard tasks into smaller and simpler steps. CoT
transforms big tasks into multiple manageable tasks and shed lights
into an interpretation of the model's thinking process.

Source: {'source': 'https://lilianweng.github.io/posts/2023-06-23-
agent/'}
Content: Tree of Thoughts (Yao et al. 2023) extends CoT by exploring
multiple reasoning possibilities at each step. It first decomposes the
problem into multiple thought steps and generates multiple thoughts per
step, creating a tree structure. The search process can be BFS
(breadth-first search) or DFS (depth-first search) with each state
evaluated by a classifier (via a prompt) or majority vote.
Task decomposition can be done (1) by LLM with simple prompting like
"Steps for XYZ.\n1.", "What are the subgoals for achieving XYZ?", (2)
by using task-specific instructions; e.g. "Write a story outline." for
writing a novel, or (3) with human inputs.
================================== [1m Ai Message
 [0m==================================

Task Decomposition is the process of breaking down a complicated task
into smaller, manageable steps. It often involves techniques like Chain
of Thought (CoT), which encourages models to think step by step,
enhancing performance on complex tasks. This approach allows for a
clearer understanding of the task and aids in structuring the problem-
solving process.
```

Check out the LangSmith trace here.

Stateful management of chat history

NOTE

This section of the tutorial previously used the RunnableWithMessageHistory abstraction. You can access that version of the documentation in the v0.2 docs.

As of the v0.3 release of LangChain, we recommend that LangChain users take advantage of LangGraph persistence to incorporate `memory` into new LangChain applications.

If your code is already relying on `RunnableWithMessageHistory` or `BaseChatMessageHistory`, you do **not** need to make any changes. We do not plan on deprecating this functionality in the near future as it works for simple chat applications and any code that uses `RunnableWithMessageHistory` will continue to work as expected.

Please see How to migrate to LangGraph Memory for more details.

In production, the Q&A application will usually persist the chat history into a database, and be able to read and update it appropriately.

LangGraph implements a built-in persistence layer, making it ideal for chat applications that support multiple conversational turns.

To manage multiple conversational turns and threads, all we have to do is specify a checkpointer when compiling our application. Because the nodes in our graph are appending messages to the state, we will retain a consistent chat history across invocations.

LangGraph comes with a simple in-memory checkpointer, which we use below. See its documentation for more detail, including how to use different persistence backends (e.g., SQLite or Postgres).

For a detailed walkthrough of how to manage message history, head to the How to add message history (memory) guide.

```python
from langgraph.checkpoint.memory import MemorySaver

memory = MemorySaver()
graph = graph_builder.compile(checkpointer=memory)

# Specify an ID for the thread
config = {"configurable": {"thread_id": "abc123"}}
```

API Reference: MemorySaver

We can now invoke similar to before:

```python
input_message = "What is Task Decomposition?"

for step in graph.stream(
    {"messages": [{"role": "user", "content": input_message}]},
    stream_mode="values",
    config=config,
):
    step["messages"][-1].pretty_print()
```

```
================================ [1m Human Message
 [0m=================================

What is Task Decomposition?
================================== [1m Ai Message
 [0m==================================
Tool Calls:
  retrieve (call_JZb6GLD812bW2mQsJ5EJQDnN)
 Call ID: call_JZb6GLD812bW2mQsJ5EJQDnN
  Args:
    query: Task Decomposition
================================= [1m Tool Message
 [0m=================================
Name: retrieve

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================================== [1m Ai Message
 [0m==================================

Task Decomposition is a technique used to break down complicated tasks
into smaller, manageable steps. It involves using methods like Chain of
Thought (CoT) prompting, which encourages the model to think step by
step, enhancing performance on complex tasks. This process helps to
clarify the model's reasoning and makes it easier to tackle difficult
problems.
```

```python
input_message = "Can you look up some common ways of doing it?"

for step in graph.stream(
    {"messages": [{"role": "user", "content": input_message}]},
    stream_mode="values",
    config=config,
):
    step["messages"][-1].pretty_print()
```

```
================================ [1m Human Message
 [0m=================================

Can you look up some common ways of doing it?
================================== [1m Ai Message
 [0m==================================
Tool Calls:
  retrieve (call_kjRI4Y5cJOiB73yvd7dmb6ux)
 Call ID: call_kjRI4Y5cJOiB73yvd7dmb6ux
  Args:
    query: common methods of task decomposition
================================= [1m Tool Message
 [0m=================================
Name: retrieve

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================================== [1m Ai Message
 [0m==================================

Common ways of performing Task Decomposition include: (1) using Large
Language Models (LLMs) with simple prompts like "Steps for XYZ" or
"What are the subgoals for achieving XYZ?", (2) employing task-specific
instructions such as "Write a story outline" for specific tasks, and
(3) incorporating human inputs to guide the decomposition process.
```

Note that the query generated by the model in the second question incorporates the conversational context.

The LangSmith trace is particularly informative here, as we can see exactly what messages are visible to our chat model at each step.

Agents

Agents leverage the reasoning capabilities of LLMs to make decisions during execution. Using agents allows you to offload additional discretion over the retrieval process. Although their behavior is less predictable than the above "chain", they are able to execute multiple retrieval steps in service of a query, or iterate on a single search.

Below we assemble a minimal RAG agent. Using LangGraph's pre-built ReAct agent constructor, we can do this in one line.

TIP

Check out LangGraph's Agentic RAG tutorial for more advanced formulations.

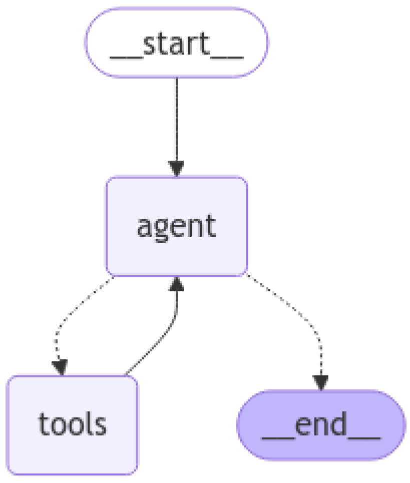
```python
from langgraph.prebuilt import create_react_agent

agent_executor = create_react_agent(llm, [retrieve],
checkpointer=memory)
```

API Reference: create_react_agent

Let's inspect the graph:

```python
display(Image(agent_executor.get_graph().draw_mermaid_png()))
```



The key difference from our earlier implementation is that instead of a final generation step that ends the run, here the tool invocation loops back to the original LLM call. The model can then either answer the question using the retrieved context, or generate another tool call to obtain more information.

Let's test this out. We construct a question that would typically require an iterative sequence of retrieval steps to answer:

```python
config = {"configurable": {"thread_id": "def234"}}

input_message = (
    "What is the standard method for Task Decomposition?\n\n"
    "Once you get the answer, look up common extensions of that 
method."
)

for event in agent_executor.stream(
    {"messages": [{"role": "user", "content": input_message}]},
    stream_mode="values",
    config=config,
):
    event["messages"][-1].pretty_print()
```

```
================================ [1m Human Message
 [0m=================================

What is the standard method for Task Decomposition?

Once you get the answer, look up common extensions of that method.
================================== [1m Ai Message
```

```
 [0m==================================
Tool Calls:
  retrieve (call_Y3YaIzL71B83Cjqa8d2G0O8N)
 Call ID: call_Y3YaIzL71B83Cjqa8d2G0O8N
  Args:
    query: standard method for Task Decomposition
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================================== [1m Ai Message
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Tool Calls:
  retrieve (call_2JntP1x4XQMWwgVpYurE12ff)
 Call ID: call_2JntP1x4XQMWwgVpYurE12ff
  Args:
    query: common extensions of Task Decomposition methods
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 [0m=================================
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================================== [1m Ai Message
 [0m==================================

The standard method for task decomposition involves using techniques
such as Chain of Thought (CoT), where a model is instructed to "think
step by step" to break down complex tasks into smaller, more manageable
components. This approach enhances model performance by allowing for
more thorough reasoning and planning. Task decomposition can be
accomplished through various means, including:

1. Simple prompting (e.g., asking for steps to achieve a goal).
2. Task-specific instructions (e.g., asking for a story outline).
3. Human inputs to guide the decomposition process.

### Common Extensions of Task Decomposition Methods:

1. **Tree of Thoughts**: This extension builds on CoT by not only
decomposing the problem into thought steps but also generating multiple
thoughts at each step, creating a tree structure. The search process
can employ breadth-first search (BFS) or depth-first search (DFS), with
each state evaluated by a classifier or through majority voting.
```

```
These extensions aim to enhance reasoning capabilities and improve the
effectiveness of task decomposition in various contexts.
```

Note that the agent:

1. Generates a query to search for a standard method for task decomposition;
2. Receiving the answer, generates a second query to search for common extensions of it;
3. Having received all necessary context, answers the question.

We can see the full sequence of steps, along with latency and other metadata, in the LangSmith trace.

Next steps

We've covered the steps to build a basic conversational Q&A application:

- We used chains to build a predictable application that generates at most one query per user input;
- We used agents to build an application that can iterate on a sequence of queries.

To explore different types of retrievers and retrieval strategies, visit the retrievers section of the how-to guides.

For a detailed walkthrough of LangChain's conversation memory abstractions, visit the How to add message history (memory) guide.

To learn more about agents, check out the conceptual guide and LangGraph agent architectures page.

Edit this page