6. Building an Agentic RAG System

In this tutorial, we will build a retrieval agent. Retrieval agents are useful when you want an LLM to make a decision about whether to retrieve context from a vectorstore or respond to the user directly.

By the end of the tutorial we will have done the following:

1. Fetch and preprocess documents that will be used for retrieval.
2. Index those documents for semantic search and create a retriever tool for the agent.
3. Build an agentic RAG system that can decide when to use the retriever tool.

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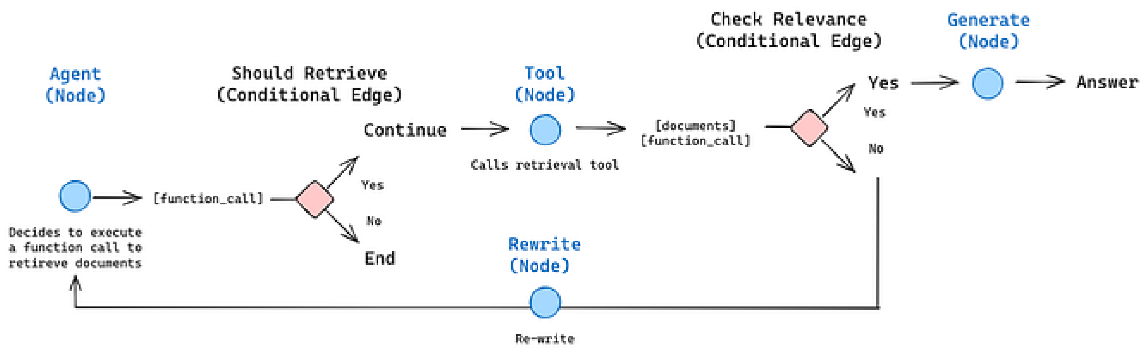


Setup

Let's download the required packages and set our API keys:

```
pip install -U --quiet langgraph "langchain[openai]" langchain-community
langchain-text-splitters
import getpass
import os


def _set_env(key: str):
  if key not in os.environ:
      os.environ[key] = getpass.getpass(f"{key}:")


_set_env("OPENAI_API_KEY")
```

6.1 Preprocess documents

1. Fetch documents to use in our RAG system. We will use three of the most recent pages from Lilian Weng's excellent blog. We'll start by fetching the content of the pages using `WebBaseLoader` utility:

```
from langchain_community.document_loaders import WebBaseLoader

urls = [
  "https://lilianweng.github.io/posts/2024-11-28-reward-hacking/",
  "https://lilianweng.github.io/posts/2024-07-07-hallucination/",
  "https://lilianweng.github.io/posts/2024-04-12-diffusion-video/",
]

docs = [WebBaseLoader(url).load() for url in urls]
docs[0][0].page_content.strip()[:1000]
```

2. Split the fetched documents into smaller chunks for indexing into our vectorstore:

```
from langchain_text_splitters import RecursiveCharacterTextSplitter

docs_list = [item for sublist in docs for item in sublist]

text_splitter = RecursiveCharacterTextSplitter.from_tiktoken_encoder(
  chunk_size=100, chunk_overlap=50
)
doc_splits = text_splitter.split_documents(docs_list)
doc_splits[0].page_content.strip()
```

6.2 Create a Retrieval Tool

Now that we have our split documents, we can index them into a vector store that we'll use for semantic search.

1. Use an in-memory vector store and OpenAI embeddings:

```
from langchain_core.vectorstores import InMemoryVectorStore
from langchain_openai import OpenAIEmbeddings

vectorstore = InMemoryVectorStore.from_documents(
  documents=doc_splits, embedding=OpenAIEmbeddings()
)
retriever = vectorstore.as_retriever()
```

2. Create a retriever tool using LangChain's prebuilt `create_retriever_tool`:

```
from langchain.tools.retriever import create_retriever_tool

retriever_tool = create_retriever_tool(
  retriever,
  "retrieve_blog_posts",
    "Search and return information about Lilian Weng blog posts.",
)
```

3. Test the tool:

```
retriever_tool.invoke({"query": "types of reward hacking"})
```

6.3 Generate a Query

Now we will start building components (nodes and edges) for our agentic RAG graph. Note that the components will operate on the `MessagesState` — graph state that contains a `messages` key with a list of chat messages.

1. Build a `generate_query_or_respond` node. It will call an LLM to generate a response based on the current graph state (list of messages). Given the input messages, it will decide to retrieve using the retriever tool, or respond directly to the user. Note that we're giving the chat model access to the `retriever_tool` we created earlier via `.bind_tools`:

```
from langgraph.graph import MessagesState
from langchain.chat_models import init_chat_model

response_model = init_chat_model("openai:gpt-4.1", temperature=0)


def generate_query_or_respond(state: MessagesState):
    """Call the model to generate a response based on the current state. Given
    the question, it will decide to retrieve using the retriever tool, or simply respond to the user.
    """
    response = (
        response_model
        .bind_tools([retriever_tool]).invoke(state["messages"])
    )
    return {"messages": [response]}
```

2. Try it on a random input:

```
input = {"messages": [{"role": "user", "content": "hello!"}]}
generate_query_or_respond(input)["messages"][-1].pretty_print()
```

6.4 Grade Documents

1. Add a conditional edge — `grade_documents` — to determine whether the retrieved documents are relevant to the question. We will use a model with a structured output schema `GradeDocuments` for document grading. The `grade_documents` function will return the name of the node to go to based on the grading decision (`generate_answer` or `rewrite_question`):

```
from pydantic import BaseModel, Field
from typing import Literal

GRADE_PROMPT = (
  "You are a grader assessing relevance of a retrieved document to a user question. \n "
  "Here is the retrieved document: \n\n {context} \n\n"
  "Here is the user question: {question} \n"
  "If the document contains keyword(s) or semantic meaning related to the user question,
grade it as relevant. \n"
  "Give a binary score 'yes' or 'no' score to indicate whether the document is relevant to the
question."
)


class GradeDocuments(BaseModel):
  """Grade documents using a binary score for relevance check."""

  binary_score: str = Field(
     description="Relevance score: 'yes' if relevant, or 'no' if not relevant"
  )


grader_model = init_chat_model("openai:gpt-4.1", temperature=0)


def grade_documents(
  state: MessagesState,
) -> Literal["generate_answer", "rewrite_question"]:
  """Determine whether the retrieved documents are relevant to the question."""
  question = state["messages"][0].content
  context = state["messages"][-1].content

  prompt = GRADE_PROMPT.format(question=question, context=context)
  response = (
     grader_model
     .with_structured_output(GradeDocuments).invoke(
        [{"role": "user", "content": prompt}]
     )
  )
  score = response.binary_score

  if score == "yes":
     return "generate_answer"
  else:
     return "rewrite_question"
```

2. Run this with irrelevant documents in the tool response:

```
from langchain_core.messages import convert_to_messages

input = {
  "messages": convert_to_messages(
    [
      {
        "role": "user",
        "content": "What does Lilian Weng say about types of reward hacking?",
      },
      {
        "role": "assistant",
        "content": "",
        "tool_calls": [
          {
            "id": "1",
            "name": "retrieve_blog_posts",
            "args": {"query": "types of reward hacking"},
          }
        ],
      },
      {"role": "tool", "content": "meow", "tool_call_id": "1"},
    ]
  )
}
grade_documents(input)
```

3. Confirm that the relevant documents are classified as such:

```
input = {
  "messages": convert_to_messages(
    [
      {
        "role": "user",
        "content": "What does Lilian Weng say about types of reward hacking?",
      },
      {
        "role": "assistant",
        "content": "",
        "tool_calls": [
          {
            "id": "1",
            "name": "retrieve_blog_posts",
            "args": {"query": "types of reward hacking"},
          }
        ],
      },
      {
        "role": "tool",
                "content": "reward hacking can be categorized into two types: environment or goal misspecification, and reward tampering",
                "tool_call_id": "1",
            },
        ]
    )
}
grade_documents(input)
```

6.5 Rewrite Question

1. Build the `rewrite_question` node. The retriever tool can return potentially irrelevant documents, which indicates a need to improve the original user question. To do so, we will call the `rewrite_question` node:

```
REWRITE_PROMPT = (
    "Look at the input and try to reason about the underlying semantic intent / meaning.\n"
    "Here is the initial question:"
    "\n ------- \n"
    "{question}"
    "\n ------- \n"
    "Formulate an improved question:"
)


def rewrite_question(state: MessagesState):
    """Rewrite the original user question."""
    messages = state["messages"]
    question = messages[0].content
    prompt = REWRITE_PROMPT.format(question=question)
    response = response_model.invoke([{"role": "user", "content": prompt}])
    return {"messages": [{"role": "user", "content": response.content}]}
```

2. Try it out:

```
input = {
    "messages": convert_to_messages(
        [
            {
                "role": "user",
                "content": "What does Lilian Weng say about types of reward hacking?",
            },
            {
                "role": "assistant",
                "content": "",
                "tool_calls": [
                    {
                        "id": "1",
                        "name": "retrieve_blog_posts",
                        "args": {"query": "types of reward hacking"},
                    }
                ],
            },
            {"role": "tool", "content": "meow", "tool_call_id": "1"},
        ]
    )
}

response = rewrite_question(input)
print(response["messages"][-1]["content"])
```

6.6 Generate an Answer

1. Build `generate_answer` node: if we pass the grader checks, we can generate the final answer based on the original question and the retrieved context:

```
GENERATE_PROMPT = (
  "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, just say that you don't know. "
  "Use three sentences maximum and keep the answer concise.\n"
  "Question: {question} \n"
  "Context: {context}"
)


def generate_answer(state: MessagesState):
  """Generate an answer."""
  question = state["messages"][0].content
  context = state["messages"][-1].content
  prompt = GENERATE_PROMPT.format(question=question, context=context)
  response = response_model.invoke([{"role": "user", "content": prompt}])
  return {"messages": [response]}
```

2. Try it:

```
input = {
  "messages": convert_to_messages(
      [
          {
              "role": "user",
              "content": "What does Lilian Weng say about types of reward hacking?",
          },
          {
              "role": "assistant",
              "content": "",
              "tool_calls": [
                  {
                      "id": "1",
                      "name": "retrieve_blog_posts",
                      "args": {"query": "types of reward hacking"},
                  }
              ],
          },
          {
              "role": "tool",
              "content": "reward hacking can be categorized into two types: environment or goal
misspecification, and reward tampering",
              "tool_call_id": "1",
          },
      ]
  )
}

response = generate_answer(input)
response["messages"][-1].pretty_print()
```

6.7 Assemble the Graph

Start with a `generate_query_or_respond` and determine if we need to call `retriever_tool`

Route to next step using `tools_condition`:

- If `generate_query_or_respond` returned `tool_calls`, call `retriever_tool` to retrieve context
- Otherwise, respond directly to the user

Grade retrieved document content for relevance to the question (`grade_documents`) and route to next step:

- If not relevant, rewrite the question using `rewrite_question` and then call `generate_query_or_respond` again
- If relevant, proceed to `generate_answer` and generate final response using the `ToolMessage` with the retrieved document context

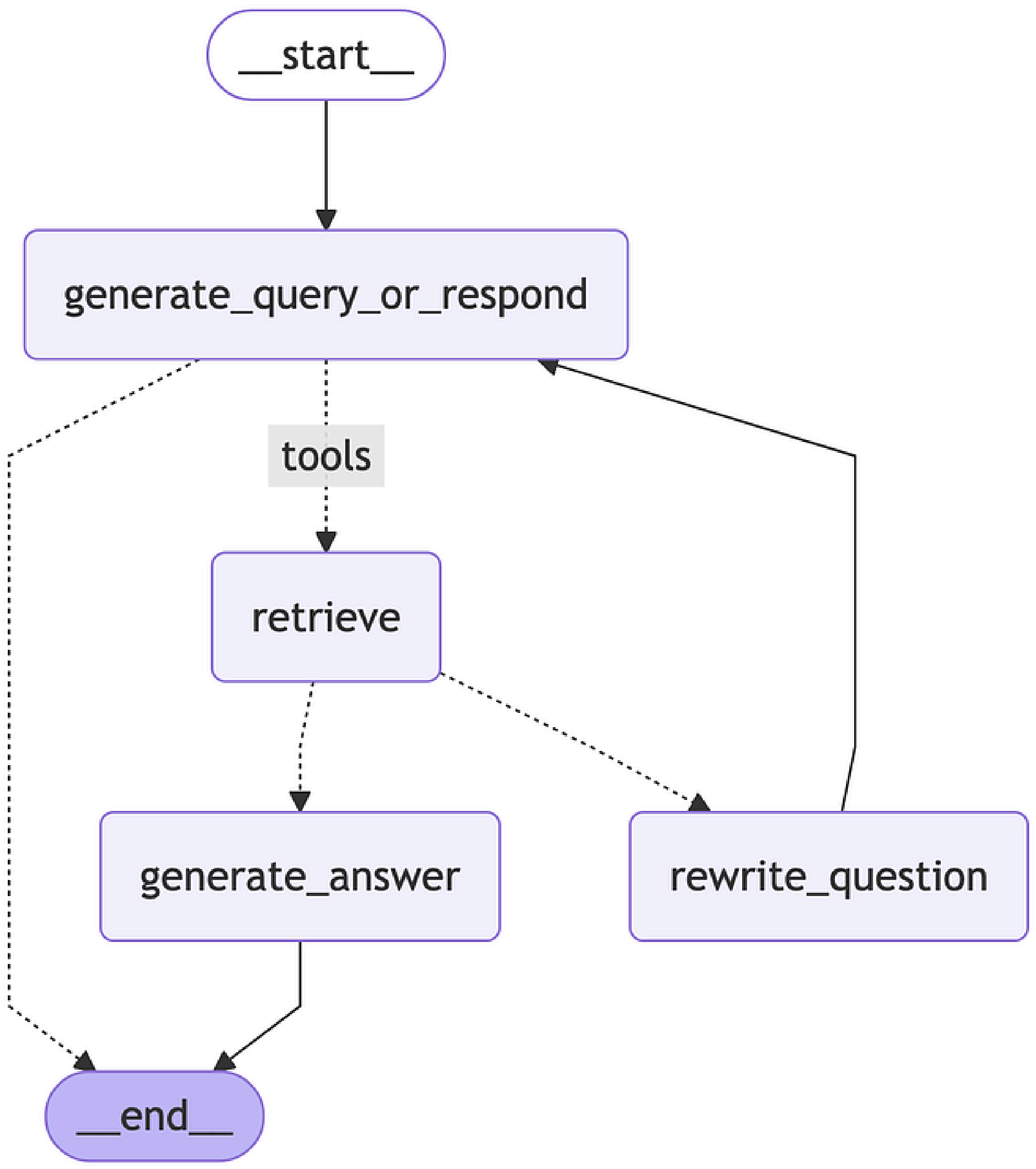
```
from langgraph.graph import StateGraph, START, END
from langgraph.prebuilt import ToolNode
from langgraph.prebuilt import tools_condition

workflow = StateGraph(MessagesState)

# Define the nodes we will cycle between
```

```
workflow.add_node(generate_query_or_respond)
workflow.add_node("retrieve", ToolNode([retriever_tool]))
workflow.add_node(rewrite_question)
workflow.add_node(generate_answer)

workflow.add_edge(START, "generate_query_or_respond")

# Decide whether to retrieve
workflow.add_conditional_edges(
  "generate_query_or_respond",
  # Assess LLM decision (call `retriever_tool` tool or respond to the user)
  tools_condition,
  {
     # Translate the condition outputs to nodes in our graph
     "tools": "retrieve",
     END: END,
  },
)

# Edges taken after the `action` node is called.
workflow.add_conditional_edges(
  "retrieve",
  # Assess agent decision
  grade_documents,
)
workflow.add_edge("generate_answer", END)
workflow.add_edge("rewrite_question", "generate_query_or_respond")

# Compile
graph = workflow.compile()
```

Visualize the graph:

```
from IPython.display import Image, display

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

Press enter or click to view image in full size



6.8 Run the Agentic RAG

```
for chunk in graph.stream(
    {
        "messages": [
            {
                "role": "user",
                "content": "What does Lilian Weng say about types of reward hacking?",
            }
        ]
    }
):
    for node, update in chunk.items():
        print("Update from node", node)
        update["messages"][-1].pretty_print()
        print("\n\n")
```

Output:

```
Update from node generate_query_or_respond
================================== Ai Message
==================================
Tool Calls:
 retrieve_blog_posts (call_cZehDWOxAfSV1RQdw1RHzKwG)
Call ID: call_cZehDWOxAfSV1RQdw1RHzKwG
 Args:
  query: types of reward hacking



Update from node retrieve
================================= Tool Message
=================================
Name: retrieve_blog_posts

Detecting Reward Hacking#

In-Context Reward Hacking#

(Note: Some work defines reward tampering as a distinct category of misalignment behavior
from reward hacking. But I consider reward hacking as a broader concept here.)
At a high level, reward hacking can be categorized into two types: environment or goal
misspecification, and reward tampering.

Why does Reward Hacking Exist?#



Update from node generate_answer
================================== Ai Message
==================================

Lilian Weng categorizes reward hacking into two types: environment or goal
misspecification, and reward tampering. She considers reward hacking as a broader concept
that includes both of these categories. Some work defines reward tampering separately, but
Weng includes it under the umbrella of reward hacking.
```