Build a Retrieval Augmented Generation (RAG) App: Part 1

One of the most powerful applications enabled by LLMs is sophisticated question-answering (Q&A) chatbots. These are applications that can answer questions about specific source information. These applications use a technique known as Retrieval Augmented Generation, or RAG.

This is a multi-part tutorial:

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

This tutorial will show how to build a simple Q&A application over a text data source. Along the way we'll go over a typical Q&A architecture and highlight additional resources for more advanced Q&A techniques. We'll also see how LangSmith can help us trace and understand our application. LangSmith will become increasingly helpful as our application grows in complexity.

If you're already familiar with basic retrieval, you might also be interested in this high-level overview of different retrieval techniques.

Note: Here we focus on Q&A for unstructured data. If you are interested for RAG over structured data, check out our tutorial on doing question/answering over SQL data.

Overview

A typical RAG application has two main components:

Indexing: a pipeline for ingesting data from a source and indexing it. *This usually happens offline.*

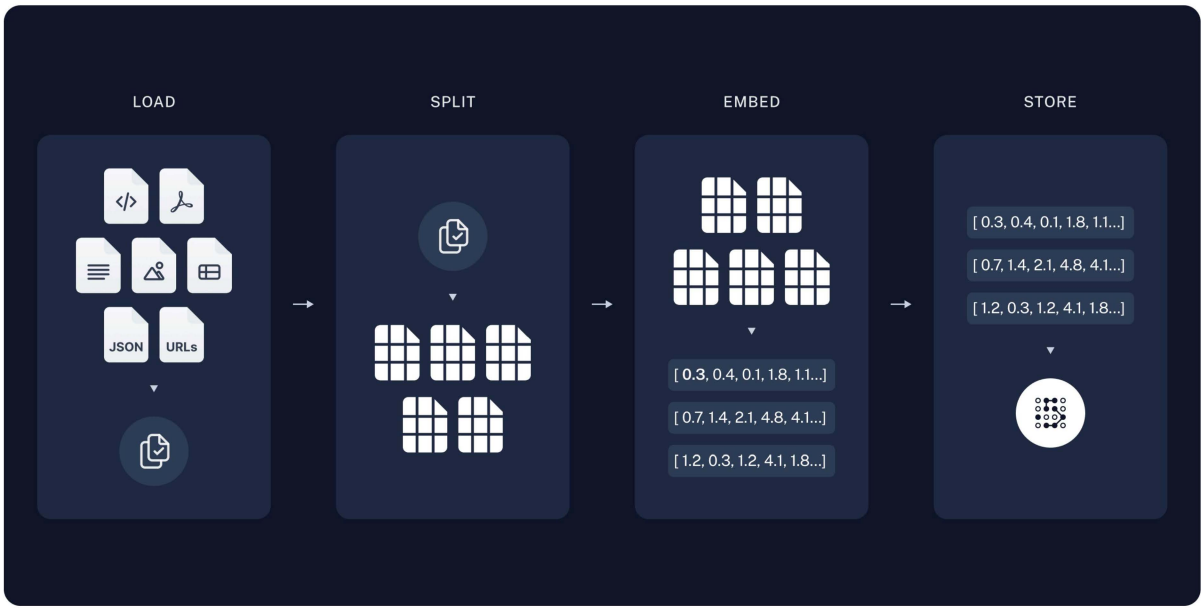
Retrieval and generation: the actual RAG chain, which takes the user query at run time and retrieves the relevant data from the index, then passes that to the model.

Note: the indexing portion of this tutorial will largely follow the semantic search tutorial.

The most common full sequence from raw data to answer looks like:

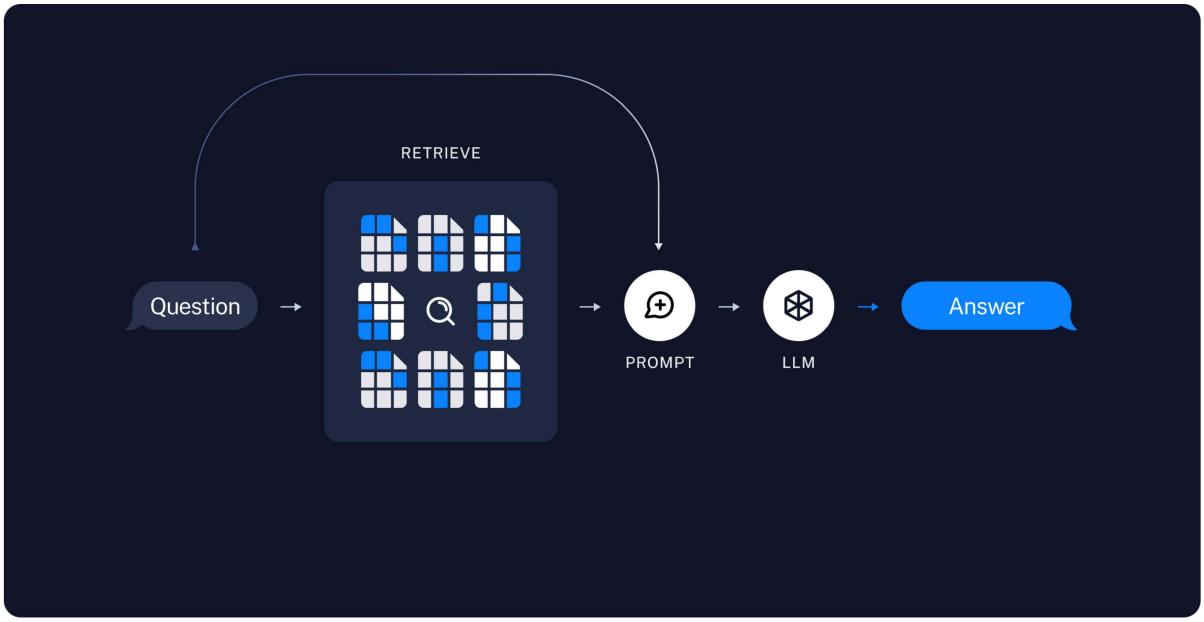
Indexing

1. **Load**: First we need to load our data. This is done with Document Loaders.
2. **Split**: Text splitters break large `Documents` into smaller chunks. This is useful both for indexing data and passing it into a model, as large chunks are harder to search over and won't fit in a model's finite context window.
3. **Store**: We need somewhere to store and index our splits, so that they can be searched over later. This is often done using a VectorStore and Embeddings model.



Retrieval and generation

4. **Retrieve**: Given a user input, relevant splits are retrieved from storage using a Retriever.
5. **Generate**: A ChatModel / LLM produces an answer using a prompt that includes both the question with the retrieved data



Once we've indexed our data, we will use LangGraph as our orchestration framework to implement the retrieval and generation steps.

Setup

Jupyter Notebook

This and other tutorials are perhaps most conveniently run in a Jupyter notebooks. Going through guides in an interactive environment is a great way to better understand them. See here for instructions on how to install.

Installation

This tutorial requires these langchain dependencies:

import Tabs from '@theme/Tabs'; import TabItem from '@theme/TabItem'; import CodeBlock from "@theme/CodeBlock";

```
%pip install --quiet --upgrade langchain-text-splitters langchain-community la
```

conda install langchain-text-splitters langchain-community langgraph -c conda-forge

For more details, see our Installation guide.

LangSmith

Many of the applications you build with LangChain will contain multiple steps with multiple invocations of LLM calls. As these applications get 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.

After you sign up at the link above, make sure to set your environment variables to start logging traces:

```
export LANGSMITH_TRACING="true"
export LANGSMITH_API_KEY="..."
```

Or, if in a notebook, you can set them with:

```
import getpass
import os

os.environ["LANGSMITH_TRACING"] = "true"
os.environ["LANGSMITH_API_KEY"] = getpass.getpass()
```

Components

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

import ChatModelTabs from "@theme/ChatModelTabs";

```
# | output: false
# | echo: false

from langchain_openai import ChatOpenAI

llm = ChatOpenAI(model="gpt-4o-mini")
```

import EmbeddingTabs from "@theme/EmbeddingTabs";

```
# | output: false
# | echo: false

from langchain_openai import OpenAIEmbeddings

embeddings = OpenAIEmbeddings()
```

import VectorStoreTabs from "@theme/VectorStoreTabs";

```
# | output: false
# | echo: false

from langchain_core.vectorstores import InMemoryVectorStore

vector_store = InMemoryVectorStore(embeddings)
```

Preview

In this guide we'll build an app that answers questions about the website's content. The specific website we will use is the LLM Powered Autonomous Agents blog post by Lilian Weng, which allows us to ask questions about the contents of the post.

We can create a simple indexing pipeline and RAG chain to do this in ~50 lines of code.

```
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 langgraph.graph import START, StateGraph
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
all_splits = text_splitter.split_documents(docs)
```

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

# Define prompt for question-answering
# N.B. for non-US LangSmith endpoints, you may need to specify
# api_url="https://api.smith.langchain.com" in hub.pull.
prompt = hub.pull("rlm/rag-prompt")


# Define state for application
class State(TypedDict):
    question: str
    context: List[Document]
    answer: str


# Define application steps
def retrieve(state: State):
    retrieved_docs = vector_store.similarity_search(state["question"])
    return {"context": retrieved_docs}


def generate(state: State):
    docs_content = "\n\n".join(doc.page_content for doc in state["context"])
    messages = prompt.invoke({"question": state["question"], "context": docs_
    response = llm.invoke(messages)
    return {"answer": response.content}


# Compile application and test
graph_builder = StateGraph(State).add_sequence([retrieve, generate])
graph_builder.add_edge(START, "retrieve")
graph = graph_builder.compile()


response = graph.invoke({"question": "What is Task Decomposition?"})
print(response["answer"])


Task Decomposition is the process of breaking down a complicated task into sm
```

Check out the LangSmith trace.

Detailed walkthrough

Let's go through the above code step-by-step to really understand what's going on.

1. Indexing {#indexing}

:::note

This section is an abbreviated version of the content in the semantic search tutorial. If you're comfortable with document loaders, embeddings, and vector stores, feel free to skip to the next section on retrieval and generation.

:::

Loading documents

We need to first load the blog post contents. We can use DocumentLoaders for this, which are objects that load in data from a source and return a list of Document objects.

In this case we'll use the WebBaseLoader, which uses `urllib` to load HTML from web URLs and `BeautifulSoup` to parse it to text. We can customize the HTML -> text parsing by passing in parameters into the `BeautifulSoup` parser via `bs_kwargs` (see BeautifulSoup docs). In this case only HTML tags with class "post-content", "post-title", or "post-header" are relevant, so we'll remove all others.

```
import bs4
from langchain_community.document_loaders import WebBaseLoader

# Only keep post title, headers, and content from the full HTML.
bs4_strainer = bs4.SoupStrainer(class_=("post-title", "post-header", "post-con
loader = WebBaseLoader(
    web_paths=("https://lilianweng.github.io/posts/2023-06-23-agent/",),
    bs_kwargs={"parse_only": bs4_strainer},
)
docs = loader.load()

assert len(docs) == 1
print(f"Total characters: {len(docs[0].page_content)}")
```

```
Total characters: 43131
```

```
print(docs[0].page_content[:500])
```

```
      LLM Powered Autonomous Agents

Date: June 23, 2023  |  Estimated Reading Time: 31 min  |  Author: Lilian


Building agents with LLM (large language model) as its core controller is
Agent System Overview#
In
```

Go deeper

`DocumentLoader`: Object that loads data from a source as list of `Documents`.

- Docs: Detailed documentation on how to use `DocumentLoaders`.
- Integrations: 160+ integrations to choose from.
- Interface: API reference for the base interface.

Splitting documents

Our loaded document is over 42k characters which is too long to fit into the context window of many models. Even for those models that could fit the full post in their context window, models can struggle to find information in very long inputs.

To handle this we'll split the `Document` into chunks for embedding and vector storage. This should help us retrieve only the most relevant parts of the blog post at run time.

As in the semantic search tutorial, we use a RecursiveCharacterTextSplitter, which will recursively split the document using common separators like new lines until each chunk is the appropriate size. This is the recommended text splitter for generic text use cases.

```
from langchain_text_splitters import RecursiveCharacterTextSplitter

text_splitter = RecursiveCharacterTextSplitter(
    chunk_size=1000,  # chunk size (characters)
    chunk_overlap=200,  # chunk overlap (characters)
```

```
    add_start_index=True,  # track index in original document
)
all_splits = text_splitter.split_documents(docs)

print(f"Split blog post into {len(all_splits)} sub-documents.")
```

```
Split blog post into 66 sub-documents.
```

Go deeper

`TextSplitter`: Object that splits a list of `Document`s into smaller chunks. Subclass of `DocumentTransformer`s.

- Learn more about splitting text using different methods by reading the how-to docs
- Code (py or js)
- Scientific papers
- Interface: API reference for the base interface.

`DocumentTransformer`: Object that performs a transformation on a list of `Document` objects.

- Docs: Detailed documentation on how to use `DocumentTransformers`
- Integrations
- Interface: API reference for the base interface.

Storing documents

Now we need to index our 66 text chunks so that we can search over them at runtime. Following the semantic search tutorial, our approach is to embed the contents of each document split and insert these embeddings into a vector store. Given an input query, we can then use vector search to retrieve relevant documents.

We can embed and store all of our document splits in a single command using the vector store and embeddings model selected at the start of the tutorial.

```
document_ids = vector_store.add_documents(documents=all_splits)

print(document_ids[:3])
```

```
['07c18af6-ad58-479a-bfb1-d508033f9c64', '9000bf8e-1993-446f-8d4d-f4e507ba
```

Go deeper

`Embeddings` : Wrapper around a text embedding model, used for converting text to embeddings.

- Docs: Detailed documentation on how to use embeddings.
- Integrations: 30+ integrations to choose from.
- Interface: API reference for the base interface.

`VectorStore` : Wrapper around a vector database, used for storing and querying embeddings.

- Docs: Detailed documentation on how to use vector stores.
- Integrations: 40+ integrations to choose from.
- Interface: API reference for the base interface.

This completes the **Indexing** portion of the pipeline. At this point we have a query-able vector store containing the chunked contents of our blog post. Given a user question, we should ideally be able to return the snippets of the blog post that answer the question.

2. Retrieval and Generation {#orchestration}

Now let's write the actual application logic. We want to create a simple application that takes a user question, searches for documents relevant to that question, passes the retrieved documents and initial question to a model, and returns an answer.

For generation, we will use the chat model selected at the start of the tutorial.

We'll use a prompt for RAG that is checked into the LangChain prompt hub (here).

```
from langchain import hub

# N.B. for non-US LangSmith endpoints, you may need to specify
# api_url="https://api.smith.langchain.com" in hub.pull.
prompt = hub.pull("rlm/rag-prompt")

example_messages = prompt.invoke(
    {"context": "(context goes here)", "question": "(question goes here)"}
).to_messages()
```

```
assert len(example_messages) == 1
print(example_messages[0].content)
```

```
You are an assistant for question-answering tasks. Use the following piece
Question: (question goes here)
Context: (context goes here)
Answer:
```

We'll use LangGraph to tie together the retrieval and generation steps into a single application. This will bring a number of benefits:

- We can define our application logic once and automatically support multiple invocation modes, including streaming, async, and batched calls.
- We get streamlined deployments via LangGraph Platform.
- LangSmith will automatically trace the steps of our application together.
- We can easily add key features to our application, including persistence and human-in-the-loop approval, with minimal code changes.

To use LangGraph, we need to define three things:

1. The state of our application;
2. The nodes of our application (i.e., application steps);
3. The "control flow" of our application (e.g., the ordering of the steps).

State:

The state of our application controls what data is input to the application, transferred between steps, and output by the application. It is typically a `TypedDict`, but can also be a Pydantic BaseModel.

For a simple RAG application, we can just keep track of the input question, retrieved context, and generated answer:

```
from langchain_core.documents import Document
from typing_extensions import List, TypedDict


class State(TypedDict):
    question: str
    context: List[Document]
    answer: str
```

Nodes (application steps)

Let's start with a simple sequence of two steps: retrieval and generation.

```
def retrieve(state: State):
    retrieved_docs = vector_store.similarity_search(state["question"])
    return {"context": retrieved_docs}


def generate(state: State):
    docs_content = "\n\n".join(doc.page_content for doc in state["context"])
    messages = prompt.invoke({"question": state["question"], "context": docs_c
    response = llm.invoke(messages)
    return {"answer": response.content}
```

Our retrieval step simply runs a similarity search using the input question, and the generation step formats the retrieved context and original question into a prompt for the chat model.

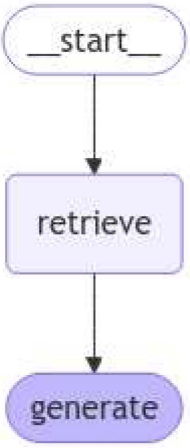
Control flow

Finally, we compile our application into a single `graph` object. In this case, we are just connecting the retrieval and generation steps into a single sequence.

```
from langgraph.graph import START, StateGraph

graph_builder = StateGraph(State).add_sequence([retrieve, generate])
graph_builder.add_edge(START, "retrieve")
graph = graph_builder.compile()
```

LangGraph also comes with built-in utilities for visualizing the control flow of your application:

```
from IPython.display import Image, display

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



▶ Do I need to use LangGraph?

Usage

Let's test our application! LangGraph supports multiple invocation modes, including sync, async, and streaming.

Invoke:

```
result = graph.invoke({"question": "What is Task Decomposition?"})

print(f"Context: {result['context']}\n\n")
print(f"Answer: {result['answer']}")
```

```
Context: [Document(id='a42dc78b-8f76-472a-9e25-180508af74f3', metadata={'s

Answer: Task decomposition is a technique used to break down complex tasks
```

Stream steps:

```
for step in graph.stream(
    {"question": "What is Task Decomposition?"}, stream_mode="updates"
):
    print(f"{step}\n\n----------------\n")
```

```
{'retrieve': {'context': [Document(id='a42dc78b-8f76-472a-9e25-180508af74f

----------------
```

```
    {'generate': {'answer': 'Task decomposition is the process of breaking dow

    ----------------
```

Stream tokens:

```
for message, metadata in graph.stream(
    {"question": "What is Task Decomposition?"}, stream_mode="messages"
):
    print(message.content, end="|")
```

```
|Task| decomposition| is| the| process| of| breaking| down| complex| tasks
```

:::tip

For async invocations, use:

```
result = await graph.ainvoke(...)
```

and

```
async for step in graph.astream(...):
```

:::

Returning sources

Note that by storing the retrieved context in the state of the graph, we recover sources for the model's generated answer in the `"context"` field of the state. See this guide on returning sources for more detail.

Go deeper

Chat models take in a sequence of messages and return a message.

- Docs
- Integrations: 25+ integrations to choose from.
- Interface: API reference for the base interface.

Customizing the prompt

As shown above, we can load prompts (e.g., this RAG prompt) from the prompt hub. The prompt can also be easily customized. For example:

```
from langchain_core.prompts import PromptTemplate

template = """Use the following pieces of context to answer the question at th
If you don't know the answer, just say that you don't know, don't try to make
Use three sentences maximum and keep the answer as concise as possible.
Always say "thanks for asking!" at the end of the answer.

{context}

Question: {question}

Helpful Answer:"""
custom_rag_prompt = PromptTemplate.from_template(template)
```

Query analysis

So far, we are executing the retrieval using the raw input query. However, there are some advantages to allowing a model to generate the query for retrieval purposes. For example:

- In addition to semantic search, we can build in structured filters (e.g., "Find documents since the year 2020.");
- The model can rewrite user queries, which may be multifaceted or include irrelevant language, into more effective search queries.

Query analysis employs models to transform or construct optimized search queries from raw user input. We can easily incorporate a query analysis step into our application. For illustrative purposes, let's add some metadata to the documents in our vector store. We will add some (contrived) sections to the document which we can filter on later.

```
total_documents = len(all_splits)
third = total_documents // 3

for i, document in enumerate(all_splits):
    if i < third:
        document.metadata["section"] = "beginning"
```

```
    elif i < 2 * third:
        document.metadata["section"] = "middle"
    else:
        document.metadata["section"] = "end"


all_splits[0].metadata
```

```
{'source': 'https://lilianweng.github.io/posts/2023-06-23-agent/',
 'start_index': 8,
 'section': 'beginning'}
```

We will need to update the documents in our vector store. We will use a simple InMemoryVectorStore for this, as we will use some of its specific features (i.e., metadata filtering). Refer to the vector store integration documentation for relevant features of your chosen vector store.

```
from langchain_core.vectorstores import InMemoryVectorStore

vector_store = InMemoryVectorStore(embeddings)
_ = vector_store.add_documents(all_splits)
```

Let's next define a schema for our search query. We will use structured output for this purpose. Here we define a query as containing a string query and a document section (either "beginning", "middle", or "end"), but this can be defined however you like.

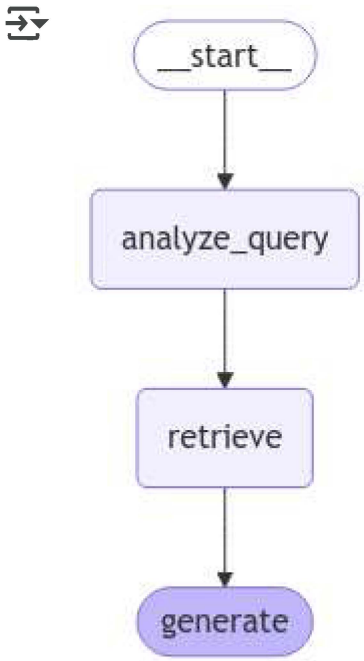
```
from typing import Literal

from typing_extensions import Annotated


class Search(TypedDict):
    """Search query."""

    query: Annotated[str, ..., "Search query to run."]
    section: Annotated[
        Literal["beginning", "middle", "end"],
        ...,
        "Section to query.",
    ]
```

Finally, we add a step to our LangGraph application to generate a query from the user's raw input:

```
class State(TypedDict):
    question: str
    # highlight-next-line
    query: Search
    context: List[Document]
    answer: str


# highlight-next-line
def analyze_query(state: State):
    # highlight-next-line
    structured_llm = llm.with_structured_output(Search)
    # highlight-next-line
    query = structured_llm.invoke(state["question"])
    # highlight-next-line
    return {"query": query}


def retrieve(state: State):
    # highlight-start
    query = state["query"]
    retrieved_docs = vector_store.similarity_search(
        query["query"],
        filter=lambda doc: doc.metadata.get("section") == query["section"],
    )
    # highlight-end
    return {"context": retrieved_docs}


def generate(state: State):
    docs_content = "\n\n".join(doc.page_content for doc in state["context"])
    messages = prompt.invoke({"question": state["question"], "context": docs_c
    response = llm.invoke(messages)
    return {"answer": response.content}


# highlight-start
graph_builder = StateGraph(State).add_sequence([analyze_query, retrieve, gener
graph_builder.add_edge(START, "analyze_query")
# highlight-end
graph = graph_builder.compile()
```

▶ Full Code:

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



We can test our implementation by specifically asking for context from the end of the post. Note that the model includes different information in its answer.

```
for step in graph.stream(
    {"question": "What does the end of the post say about Task Decomposition?"
    stream_mode="updates",
):
    print(f"{step}\n\n----------------\n")
```

```
{'analyze_query': {'query': {'query': 'Task Decomposition', 'section': 'en

----------------

{'retrieve': {'context': [Document(id='d6cef137-e1e8-4ddc-91dc-b62bd33c602

----------------

{'generate': {'answer': 'The end of the post highlights that task decompos

----------------
```

In both the streamed steps and the LangSmith trace, we can now observe the structured query that was fed into the retrieval step.

Query Analysis is a rich problem with a wide range of approaches. Refer to the how-to guides for more examples.

Next steps

We've covered the steps to build a basic Q&A app over data:

- Loading data with a Document Loader
- Chunking the indexed data with a Text Splitter to make it more easily usable by a model
- Embedding the data and storing the data in a vectorstore
- Retrieving the previously stored chunks in response to incoming questions
- Generating an answer using the retrieved chunks as context.

In Part 2 of the tutorial, we will extend the implementation here to accommodate conversation-style interactions and multi-step retrieval processes.

Further reading:

- Return sources: Learn how to return source documents
- Streaming: Learn how to stream outputs and intermediate steps
- Add chat history: Learn how to add chat history to your app
- Retrieval conceptual guide: A high-level overview of specific retrieval